Modeling the Impact of Generative AI on Global Wages and Trade: A GTAP Framework with Occupational Details

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September 2026

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ABSTRACT

This paper examines the impacts of AI-driven productivity increases on global patterns of trade, income, and wages, using an implementation of CGE modeling that disaggregates the U.S. labor force into 22 occupations and leveraging recent research into the adoption of AI by workers and its labor market impacts. AI exposure and its associated productivity impacts tend to be concentrated in high-skill, high-wage occupations, most notably computer science and mathematics, business and finance, and architecture and engineering. These occupations are used most intensively in the production of services and certain knowledge-intensive goods like computer, electronic, and optical products. While AI increases real GDP in all regions of the world, gains are highest in the United States and other high-income countries that have high exposure to AI. AI reshapes the U.S. pattern of comparative advantage in favor of business services. Increased import demand in high-income countries induces an increase in China's manufacturing output and exports. Skill premiums decrease universally across all countries and regions. The results for GDP, output, and exports are highly robust to whether capital-skill (K-S) complementarity is included in the model. However, wages are sensitive to the model specifications. While all wages increase in the traditional GTAP model, wages for skilled labor often decrease in the model with K-S complementarity, with declines concentrated in the most AI-exposed occupations.

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Acknowledgement: This research would not have been possible without the methodological advancements pioneered by Dr. Marinos Tsigas, as described further in the text of this paper. Dr. Tsigas passed away in 2025, and the authors gratefully acknowledge his important contributions to the methodology underlying this research. The authors would also like to thank Huyen Nguyen and Meryem Demirkaya in the Office of Economics for their contributions to the development of the GTAP database, which was used to disaggregate U.S. labor categories in the GTAP model employed in this paper.

Introduction

This paper examines how technology-driven labor-productivity shocks — illustrated by the adoption of generative AI— reshapes global wage differentials, upstream and downstream production linkages, and cross-border trade patterns. Much of the existing literature on the impact of generative AI has focused on measuring AI exposure by occupation (Hampole et al., 2025; Auer et al., 2024) and on estimating how generative AI affects labor demand and labor productivity (Chen et al., 2024; Bick et al., 2025, Acemoglu et al., 2026). However, to date there is little research about how generative AI diffusion propagates through supply chains, alters cross-border trade patterns and international competitiveness, or shifts wage gaps within and between countries. Because occupations differ sharply in their exposure to AI in the United States—and generative AI changes their productivity in heterogeneous ways—capturing AI's upstream and downstream effects, along with the resulting shifts in cross-border trade patterns, requires modeling U.S. labor at the occupational level. To address this research gap, this paper examines the diffusion of generative AI in a computable general equilibrium (CGE) model with capital-skill complementarity that incorporates the Demirkaya et al. (2025) GTAP database with 22 U.S. occupational categories.

CGE models are widely used for forward-looking counterfactual analysis, providing insight into how changes in trade policies affect U.S. sectoral output, trade, and overall macroeconomic outcomes. Among these, the GTAP CGE model is a multi-country, multi-sector framework frequently applied to estimate the impact of a variety of economic shocks (van Tongeren et al., 2017). Although wage and employment are an integral part of the general equilibrium effects captured in the GTAP CGE model, the standard GTAP CGE model is limited in its capacity to analyze how policy shocks affect workers in various occupations differently, as it only includes five labor categories: technicians/professionals, officials and managers, clerks, service workers, and agricultural and other unskilled workers.

To address this limitation, our paper extends the U.S. labor categories in the GTAP model utilizing the Demirkaya et al. (2025) GTAP database, which allows us to disaggregate U.S. labor into 22 different occupational categories.[1] This detailed breakdown of occupations makes it possible to examine how the spread of generative AI impacts various occupations in the United States.

[1] The Standard Occupational Classification (SOC) system is used by the U.S. Bureau of Labor Statistics to group U.S. workers into 22 occupational categories for the Occupational Employment and Wage Statistics (OEWS) survey.

Our results are driven by the fact that AI exposure and its associated productivity impacts tend to be concentrated in high-skill, high-wage occupations, such as management, computer science and mathematics, business and finance, and architecture and engineering. These occupations are used most intensively in the production of services and certain knowledge-intensive goods like computer, electronic, and optical products. Substitution of AI for labor causes relative wages to fall in these occupations. While AI Increases real GDP in all regions of the world, gains are highest in the United States and other high-income countries that have a comparative advantage in the production and export of services.

The remainder of this paper is organized as follows. Section 2 reviews the relevant literature on both the impacts of generative AI and the evolution of labor market extensions in CGE models. Section 3 outlines our modeling framework, detailing the disaggregation of U.S. labor categories and our approach to incorporating capital-skill complementarity. Section 4 describes the two simulation exercises and the calibration of the AI-induced labor productivity shocks. The first simulation examines how the global diffusion of generative AI reshapes international trade patterns and wage disparities both within and between countries. The second simulation applies the same AI-induced labor productivity shocks as the first, but uses a standard GTAP model without capital-skill complementarity, allowing us to assess the robustness of the trade and labor market results to the inclusion of this mechanism. Section 5 presents and discusses the simulation results. Section 6 concludes the paper.

Literature Review

The existing literature on generative AI has primarily focused on quantifying occupational exposure to AI, estimating its effects on labor demand and productivity, and analyzing macroeconomic implications through various empirical and modeling approaches. There have been a handful of papers that use general equilibrium methods to examine AI and trade, and are thus comparable to our paper. We discuss these at the end of this literature review.

Recent estimates of AI's productivity effects vary considerably across studies. Acemoglu (2025) finds that AI-driven productivity growth remains modest, amounting to no more than a 0.71 percent increase in total factor productivity (TFP) over ten years, or 0.07 percent per year, with diminishing returns expected as AI extends from easy-to-learn tasks to harder-to-learn tasks. Aghion and Bunuel (2024) offer a median estimate of 0.68 percent TFP growth per year—substantially higher than Acemoglu's. Misch et al. (2025) apply the method of Acemoglu (2024) to estimate AI-induced productivity gains for 31 European countries, and they estimate medium-term productivity gains of approximately 1.1 percent in the medium term, around 60 percent higher than Acemoglu's estimate for the United States, with significant variation by country and sector. The author finds that AI-induced productivity gains are highest in high-wage countries with high exposure to financial services. For instance, Luxembourg experiences a 2 percent increase in productivity—four times higher than Romania. Importantly, Misch et al. (2025) find that the main driver of the differences in cross-country productivity rates to be AI adoption rates, with industrial composition being second, and occupational composition within industry third.

Another strand of literature focuses on estimating occupational exposure to AI. Auer et al. (2024) use the O*NET database to classify 711 U.S. occupations by cognitive skill requirements, finding that computer and mathematical roles exhibit the highest exposure, while construction and agriculture are least affected. Using O*NET and the Current Population Survey, Elondou et al. (2023) estimate that 80 percent of U.S. workers could have at least 10 percent of their tasks exposed to large language models, while 19 percent of workers could have 50 percent or more of their tasks affected. Hampole et al. (2025) find that occupations with many AI-exposed tasks experience depressed labor demand. This effect is offset when exposure is concentrated in a few tasks, so that workers can reallocate their time to tasks that require human capabilities. They provide a heat mapping of the intensity of 20 different AI applications to the 22 Standard Occupational Classification (SOC) occupational categories, which we exploit in constructing our estimates of productivity impact by occupation.

A third strand of the literature finds that, when occupations are classified at a sufficiently detailed level, the effects of AI on labor demand are heterogeneous, with AI substituting for some occupations while complementing others. For instance, Chen et al. (2025) merge the O*NET database with ChatGPT queries to identify occupations with the potential for task automation by generative AI. The authors find a 17 percent decrease in job postings for the top quartile of occupations where generative AI is likely to promote task automation, and a 22 percent increase in job postings where generative AI is likely to augment human labor. They conclude that the impact of generative AI on labor demand is heterogeneous, with AI substituting for some occupations and complementing others. Mäkelä and Stephany (2025), examining 12 million U.S. online job vacancies from 2018-2023, again identify examples of both substitution and complementarity with AI across sectors, occupations and regions. Importantly, this heterogeneity may also arise within occupations, depending on workers' levels of experience. Brynjolfsson et al. (2025), for example, find that early-career workers (aged 22–25) in AI-exposed occupations experience employment declines, whereas more experienced workers do not. Davis (2026) similarly finds that jobs with high experience premiums see a 0.2 percentage point increase in wage growth with increased AI exposure, while jobs with zero experience premium face a 0.28 percentage point reduction in wage growth with increased AI exposure. Taken together, these findings suggest that AI may substitute for less-experienced workers while complementing more-experienced workers within the same broad occupational categories. This pattern is consistent with the conceptual framework proposed by Acemoglu et al. (2026), who characterize AI as an "expertise-leveling" technology. Because AI can supplement or democratize core technical tasks, it risks displacing entry-level roles that traditionally served as a pipeline for young professionals, while simultaneously acting as a complement to the senior-level human judgment held by more experienced workers.

A fourth strand of literature estimated the AI adoption rate and how it affects worker productivity. Bick et al. (2025) use Real-Time Population Survey data to estimate both the generative AI adoption rate and its effect on worker productivity. The authors find that as of late 2024, 45 percent of U.S. adults use generative AI; 27 percent of employed persons use generative AI for work at least once in the previous week, and 10 percent use it daily. Respondents report time savings equivalent to 1.4 percent of total work hours, implying that generative AI raises average U.S. labor productivity by 1.4 percent across all workers.

Misra et al. (2025) present a dataset tracking AI adoption in 147 countries using customer-authorized Microsoft data on visits to generative AI platforms like ChatGPT, Gemini, Claude, and Copilot. The authors find that AI adoption, measured by user share, is strongly correlated with per capita income and internet penetration, indicating that a lack of electrification and broadband availability constrains AI adoption in low- and middle-income countries. Over twenty high-income countries have AI user shares exceeding that of the United States. One caveat is that the data do not distinguish between workplace use of AI, which is of direct relevance to our study, and household use. We use a modified version of the Misra et al. data to calibrate our country-specific productivity effects.

With regards to the literature on labor market extensions in CGE models, there have been several efforts within the CGE literature to incorporate more detailed labor categories into various CGE models to capture how trade-induced gains and losses affect different types of workers differently. For instance, Carrico and Tsigas (2010) broke down U.S. labor statistics in the GTAP version 8 database, which is based on 2007 data, into 22 different occupations. They then used the modified GTAP model to simulate scenarios involving both U.S. trade liberalization and worldwide trade liberalization and presented the simulated wage results by different occupations. Dixon and Rimmer (2022) developed an extension of the USAGE model called USAGE-OCC, a recursive dynamic two-region CGE model, encompassing the United States and the rest of the world. The U.S. economy in this model includes U.S. occupation-industry matrices for 2019, identifying employment and wage bills in 233 BLS occupations and 392 BEA industries. The authors simulate a hypothetical scenario of a 10 percent increase in the real wage rates for the lowest paid occupations. The simulation results indicate that employment in all occupations in the United States is adversely affected, with low-wage occupations being more negatively impacted compared to high-wage occupations. Gurevich, Riker, and Tsigas (2021) split the labor market data in the GTAP model into male and female labor categories. For both male and female labor, the authors further divided these categories into five broad occupational groups based on the U.S. census definition, with each occupational group further split into low- and high-skilled workers. They simulated the effects of past U.S. trade agreements and found considerable heterogeneity in how gains from trade varied among different worker groups.

The dramatic rise in the U.S. skill premium that began around the 1980s prompted scholars to investigate its underlying drivers. Krusell et al. (2000), Maliar et al. (2022), and Ohanian et al. (2023) demonstrated empirically that capital is less substitutable with skilled labor and more substitutable with unskilled labor. This phenomenon, known as capital-skill complementarity, has been incorporated into structural general equilibrium models with labor extensions, such as the one developed by Dix Carneiro et al. (2023), which distinguishes between two broad labor types —unskilled and skilled labor. Dix Carneiro et al. (2023) indicated that with capital-skill complementarity, the decline in the relative price of capital led to an increase in the relative demand for skilled labor, driving up their wages. These empirical studies estimate the substitution elasticity between capital and skilled labor, which can be incorporated into forward-looking general equilibrium models for conducting counterfactual analyses.

The most comparable paper to our paper is Bekkers et al. (2025), which examines AI, economic growth, and international trade in a general equilibrium framework. They capture the effects of AI by introducing an “AI services sector,” which uses labor, capital, electricity services, and ICT equipment as inputs, and sells its output to other sectors. As an input, AI services are complementary with labor, and more complementary with skilled labor. Purchases of AI services not only raise the productivity of other inputs directly, but also reduce various types of costs associated with international trade. Much of Bekkers et al. is devoted to the potential gains in global GDP from lagging countries’ catching up in AI performance to leading regions. Their “tech divergence” scenario, in which such catch-up does not happen, is most comparable to our work. Similar to our paper, in all their simulation scenarios, they find that AI raises the returns to capital and reduces the skill premium.

Cerruti et al. (2025) explore the consequences of countries' unequal ability to exploit AI productivity gains using the IMF's Global Integrated Monetary and Fiscal model (GIMF),a multi-sector, multi-region dynamic general equilibrium model. Inequality is modeled as having three dimensions – exposure (share of highly AI-exposed occupations), preparedness (institutions, digital infrastructure, and workplace skills), and access (advanced hardware, data centers, and global partnerships.) Growth effects are estimated to be greatest in the United States, followed by Europe and other advanced economies, China, and low-income countries. Productivity and growth effects are more than twice as large for the United States as for low-income countries.

Rockall et al. (2025) use a general equilibrium model of heterogeneous households with a task-based production function to examine competing narratives about the impact of AI on inequality. AI can displace high-income workers, but it can also increase the productivity of high-income workers. The model is applied to the United Kingdom, an economy with both high AI exposure and rich micro data. High-income workers in the UK are more exposed to AI but less exposed to automation relative to low-income workers. Taking into account firms' decisions about how much AI to adopt sharpens the tradeoff between inequality and inefficiency. Lennox et al. (2026) employ a task-based multi-sector CGE model for Australia, in which AI adoption can either augment tasks, automate tasks, or augment equipment. The effect of AI is largely within occupations rather than between occupations. Task augmentation dominates task automation. Bogmans et al. (2026) use the energy-focused, multi-country IMF-ENV model to examine the impact of AI on energy use and greenhouse gas emissions.

To date, the existing CGE literature has not modified the substitution possibilities between various types of labor and capital to reflect capital-skill complementarity, using empirically estimated substitution elasticities. In addition, there has been limited research on the effects of generative AI on international trade and wage gaps within and across countries. To our knowledge, Bekkers et al. (2025) is the only study to examine AI, economic growth, and international trade within a general equilibrium framework. Our paper addresses these gaps in two ways. First, we extend the GTAP model by disaggregating U.S. labor into 22 occupational groups using data from Demirkaya et al. (2025). We also incorporate capital-skill complementarity by applying empirically estimated substitution elasticities, allowing the model to capture differences in substitutability between capital and workers with different skill levels and to simulate the resulting changes in skill premiums. Second, we analyze how the diffusion of generative AI reshapes global trade patterns and wage disparities within and between countries.

In the next two sections, we detail our method for dividing labor data in the GTAP model into 22 different occupations, along with the structural enhancements we've introduced to better reflect the capital-skill complementarity mechanism. We also describe our process for calibrating generative AI-driven labor productivity shocks at the U.S. occupation level, as well as productivity shocks specific to different types of labor in major advanced and developing economies—including Canada, Mexico, the EU, and China—before presenting our simulation findings.

Structure of the Modified GTAP Model with 22 Different Occupations and Capital-Skill Complementarity

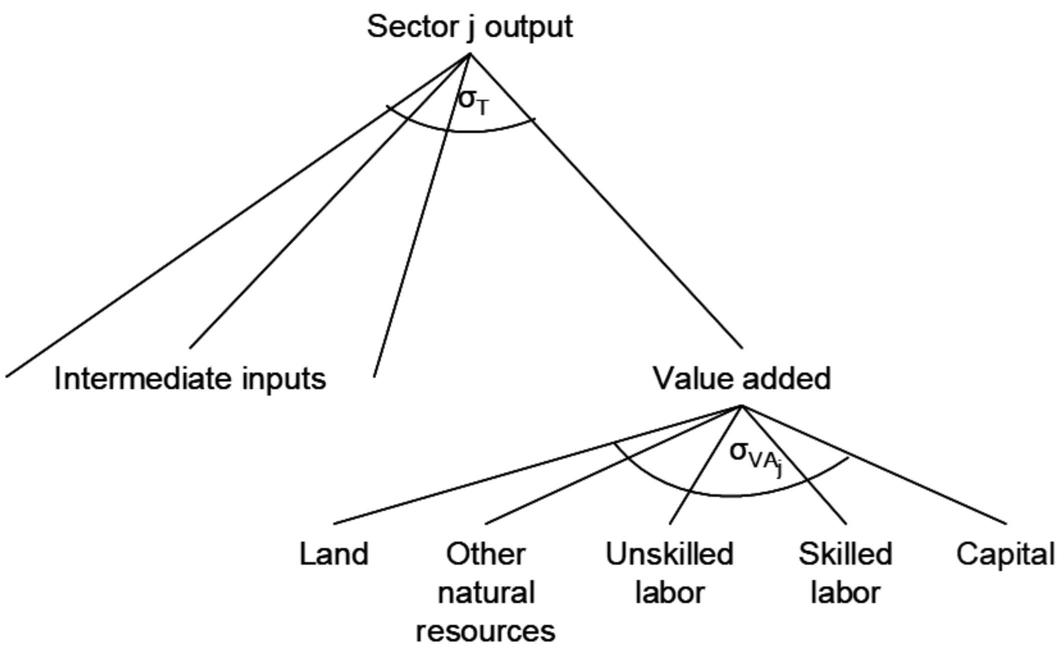
Our enhanced GTAP framework incorporates (i) a comprehensive U.S. labor dataset encompassing 22 occupations and 65 sectors, which was developed by Demirkaya et al. (2025), and (ii) an enhanced labor market feature reflecting capital-skill complementarity. The list of 22 U.S. labor occupations is shown in Appendix Table 1. Two microeconomic assumptions underpin our labor market modeling within this enhanced GTAP framework. First, each occupation is treated as an endowment, meaning workers in occupation i cannot transition to occupation j. Second, workers within each occupation type are assumed to be perfectly mobile across industries within the same economy. For other countries and regions in our model, the five original GTAP labor categories are aggregated into two: unskilled and skilled labor. Similarly, each labor type is regarded as an endowment such that unskilled labor cannot transform into skilled labor, and vice versa. Workers of each labor type remain perfectly mobile across industries within their respective economies but are region-specific.

As previously noted, we revised the modeling of primary factor demand at the sector level to integrate the capital-skill complementarity mechanism.[2] The following outlines how our enhanced GTAP framework differs from the standard GTAP model. The standard GTAP model employs a two-level nested-CES (constant elasticity of substitution) production function for each producing sector. Figure 1 illustrates the substitution possibilities among inputs in the standard GTAP model. At the first (lower) level of the nest, demands for primary factors are derived from a CES production function with an elasticity of substitution denoted by σ_{VAj}. In the standard GTAP database, σ_{VAj} values are positive and less than one for agricultural sectors and greater than one for manufacturing and services sectors. At the second (upper) level, demands for multiple intermediate inputs and the value-added composite—the composite of all primary factors—are determined by a CES

[2] In the GTAP model framework, primary factors include various types of labor, capital, land and natural resources.

production function with elasticity of substitution σ_T. In the standard GTAP model, σ_T is set to zero, which indicates that all intermediate inputs are complementary to the value-added composite and both are utilized in fixed proportions.

Figure 1 Input substitution possibilities for producing sectors in the standard GTAP model



Source: Hertel and Tsigas (1997).

In our enhanced GTAP model framework, we refine the sector-level modeling of primary factor demands to reflect the capital-skill complementarity mechanism. Specifically, we adjust substitution possibilities in production between various labor occupations and other primary factors. This approach is informed by empirical studies—including Krusell et al. (2000), Maliar et al. (2022), and Ohanian et al. (2023)—which indicate that capital is generally less substitutable with skilled labor and more substitutable with unskilled labor.

For the United States, we distinguish between lower- and higher-skilled occupational groups by using weighted mean wages as a proxy for skill levels and sort our twenty-two occupations based on the mean wage. This methodology follows after Deitz and Orr (2006), who used median wage data to categorize manufacturing employment into high-, mid-, or low-skilled groups.

We divide the 22 U.S. labor occupations into two categories, as outlined in Table 1. We consider occupations classified under Group 1 as well substitutable with capital, whereas those in Group 2 are less substitutable. These two labor groups are categorical groupings as opposed to aggregations of occupations.

Table 1 Grouping U.S. labor occupations in two groups for the U.S. Economy

Group 1 (Occupations with low average wages)	Group 2 (Occupations with high average wages)
Social services	Management
Healthcare support	Business and Finance
Protective services	Computer and mathematical
Food preparation and serving	Architecture and Engineering
Building and Grouds clean and Maintenance	Life, Physical and Social Sciences
Personal care and Service	Legal
Sales and related	Education
Office and Administrative support	Art, Design, Entertainment, Sports and Media
Farm, Fishing and Forestry	Healthcare Practitioners and Technical
Construction and Extraction	
Installation, maintenance and repair	
Production	
Transport and material moving	

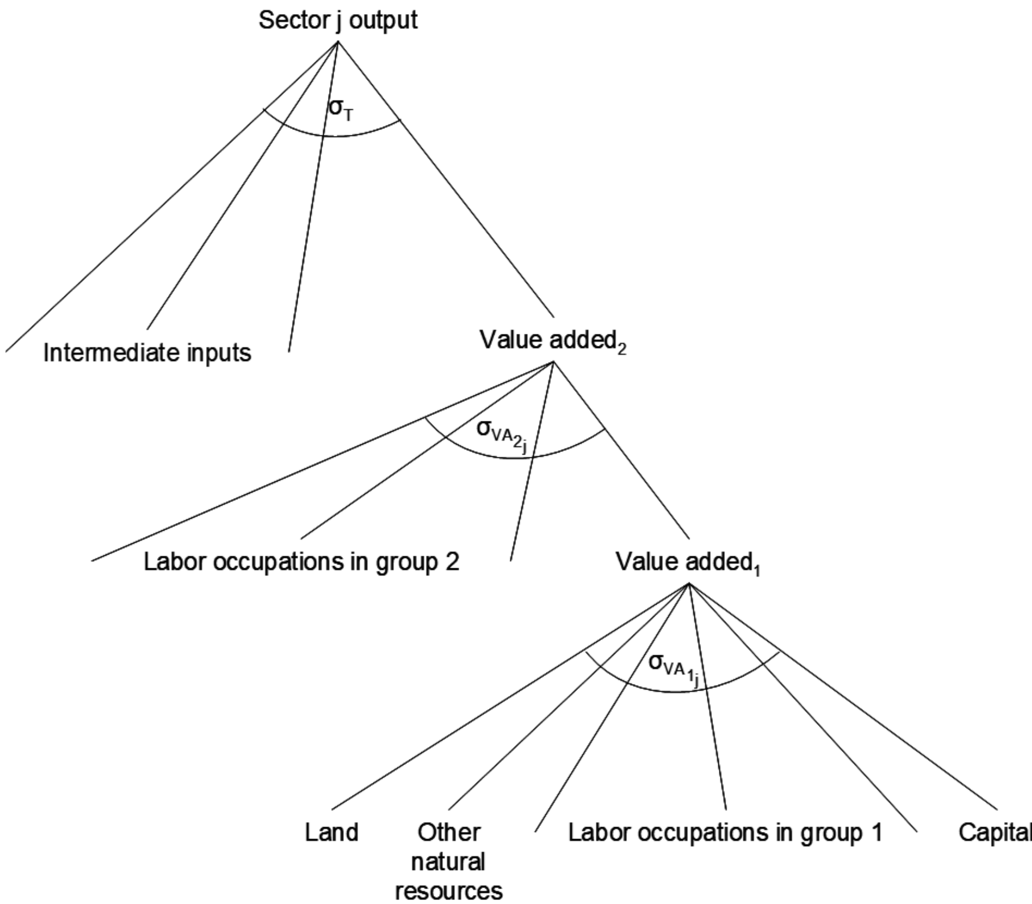
Source: Authors' calculations.

Figure 2 sketches the substitution possibilities among inputs in our enhanced version of the GTAP model for the United States. At the lowest nest level, primary factor demands—covering land, natural resources, capital, and unskilled labor types highly substitutable with capital (see group 1, table 1)—are set by a CES function with elasticity σ_{VA1j}, matching σ_{VAj} in figure 1. The middle level nest includes skilled labor types less substitutable with capital (see group 2, table 1), using elasticity σ_{VA2j} set to 0.67 based on estimates from Krusell et al. (2000) and supported by recent empirical literature showing capital is less substitutable with skilled labor than unskilled labor.[3] At the top level of the nest, demands for intermediate inputs and value added composite (Value added_2) are derived from a CES production function with elasticity of substitution σ_T which is zero for all sectors.[4]

[3] The elasticity σ_{VA2j} of 0.67 is lower than most GTAP default elasticities used in the lowest nest of the production function. In that lowest nest, the elasticities are 1.12 for processed foods; 1.26 for other manufacturing sectors and for electricity, water, and gas distribution; 1.68 for wholesale and retail trade, accommodation, land, water and air transport services, and warehousing; and 1.40 for all other services. For primary agricultural sectors, the corresponding elasticities are smaller, between 0.2 and 0.3. We set this parameter to 0.67, following the landmark empirical estimation by Krusell et al. (2000) and its subsequent adoption in the structural general equilibrium model of Dix-Carneiro et al. (2023). Conceptually, a lower elasticity in the middle level nest implies stronger labor-market effects: the smaller the elasticity, the larger the impact of changes in economic policies on occupational-level real wages.

[4] If $\sigma_{VA1j} = \sigma_{VA2j}$, the production function collapses to the same structure as in the standard GTAP model.

Figure 2 Input substitution possibilities for producing sectors in our enhanced version of the GTAP model for the United States



Notes: Group 1 consists of 13 occupations. Group 2 consists of 9 labor types. For the detailed contents of each categorical grouping, see Table 1.

In our enhanced version of the GTAP model framework, all other regions have only two labor types, unskilled and skilled labor, and we again incorporate the capital-skill complementarity mechanism as in Dix Carneiro et al. (2023). The substitution-possibility mechanism mirrors the structure shown in Figure 2. At the lowest level of the nest, demands for the primary factors are derived from a CES production function with elasticity of substitution σ_{VA1j}. The values of the parameter σ_{VA1j} are the same with the values of parameter σ_{VAj} in figure 1. The lowest level of the nest includes primary factors of capital, land, other natural resources and one of the two labor types -- unskilled labor. The middle level of the nest includes another labor type --skilled labor, which is less substitutable with capital and other primary factors. Similar to the United States, CES elasticity of substitution, σ_{VA2j}, in the middle level of the nest is set at 0.67. At the third and highest level of the nest, demands for intermediate inputs and value added (Value added$_2$) are derived from a CES production function with elasticity of substitution σ_T which is zero for all sectors. Meanwhile, in both the standard GTAP model and in our enhanced GTAP model framework, manufacturing and services sectors employ only labor and capital and they do not employ land and other natural resources. In our enhanced GTAP model framework, we use the GTAP version 12 database, which is based on the 2019 baseline year—the same year as the U.S. occupational-level wage and employment data developed by Demirkaya et al. (2025). We aggregate the original 160 regions into seven: the United States, Canada, Mexico, China, EU27, the United Kingdom, and the Rest of the World. We maintain the 65 GTAP sectors in the GTAP version 12 database.

Calibration of AI-Induced Labor Productivity Shocks Implemented in Two Global Simulations

To examine the impact of generative AI diffusion on cross-border trade patterns and wage disparities within and between nations, we conduct two global simulations: The first simulation applies generative AI-induced labor productivity shocks across 22 occupations in the United States and to both skilled and unskilled labor in all other countries and regions, using the enhanced GTAP model with capital-skill complementarity. The second simulation applies the same productivity shocks but employs a standard GTAP model without capital-skill complementarity.

Conducting these two simulations allows us to assess the role of capital-skill complementarity in shaping the economic effects of generative AI. This approach follows Dix-Carneiro et al. (2023), who compared the simulation results from a structural general equilibrium model with capital-skill complementarity to an alternative specification that removes this mechanism by adopting Cobb–Douglas production functions for capital, skilled labor, and unskilled labor. Their comparison demonstrated how capital-skill complementarity influences simulation outcomes. Similarly, by comparing the results from our two model specifications, we not only illustrate the impact of generative AI diffusion on cross-border trade patterns and labor market outcomes across countries, but also assess the robustness of these findings to the inclusion of the capital-skill complementarity mechanism.

It is worth noting, however, that our modeling approach does not account for within-occupation heterogeneity. Specifically, because our model disaggregates U.S. workers into 22 broad occupational categories, it cannot capture the possibility that, within a given occupation, AI may substitute for certain types of workers—such as less-experienced, entry-level workers—while complementing more experienced workers. A more detailed occupational classification could potentially allow the model to better reflect the empirical evidence that AI can have both substitution and complementarity effects within the same broad occupational category. However, we do not evaluate this possibility in our paper due to data limitations that prevent us from further disaggregating the occupational categories.

We took the following steps to calibrate U.S. occupation-level generative AI-induced labor productivity shocks. Hampole et al. (2025) calculated an AI exposure score for each of 22 U.S. occupations, where a higher score indicates greater exposure to AI (see Table 2). We convert the scores, presented in a heat map in the original paper, into numerical form. The results show that AI exposure is concentrated in a handful of occupation groups — computer and mathematics (70), business and finance (61), management (31), and architecture and engineering (26) and sales (25).

Meanwhile, Bick et al. (2025) estimate that generative AI raised average U.S. labor productivity by 1.4 percent annually across all workers. This estimate is at the high end of estimates for the immediate period after the public introduction of ChatGPT in November 2022, and the authors indicate that their estimates do not capture potential productivity gains from using GenAI to reorganize or completely automate production processes, and therefore likely represent a lower bound over longer horizons. While the available literature shows a broad consensus with regard to what occupations will be affected by AI, there is a wide divergence of views about how rapidly productivity gains will be achieved, or about their ultimate magnitude over longer periods of time.

To translate the labor productivity increase from Bick et al. (2025) into occupation-specific labor productivity shocks, we use Hampoles et al. (2025)'s AI exposure score by occupation and assume that occupations with higher exposure to generative AI should experience proportionally larger labor productivity gains, while those with little or no exposure should see smaller labor productivity effects. Formally, let E_i denote the AI exposure score for occupation i, and let s_i denote each occupation's employment share.[5] The occupation-level labor productivity shock for each U.S. occupation i takes the proportional form: $g_i = kE_i$, where k is a scaling parameter.

We determine k such that the employment-weighted average of g_i equals to the aggregate generative AI-driven labor productivity gain of 1.4 percent from Bick et al. (2025):

$$\sum s_i g_i = 0.014$$

[5] Each occupation's share of total employment is calculated as the number of U.S. workers in that occupation divided by total U.S. employment. Data on the number of workers in each of the 22 U.S. occupations come from Demirkaya et al. (2025) and form part of the baseline statistics in our enhanced GTAP framework.

Substituting $g_i = kE_i$ gives:

$$k = \frac{0.014}{\sum_i s_i E_i}$$

Thus, the generative AI-driven occupation-specific labor productivity shock is:

$$g_i = \frac{0.014}{\sum_j s_j E_j} E_i$$

The generative AI-driven labor productivity shock for each of the 22 U.S. occupations, as calculated, is presented in the final column of Table 2 below. These estimates are implemented as the AI-induced labor productivity shocks for the United States in the two global simulations using our enhanced GTAP framework.

Table 2: AI Exposure Score, Occupational Share of Total U.S. Employment and Occupation-Specific Labor Productivity Shock

List of Occupations	Number of U.S. Workers	Share of Total Employment (in percent)	AI Exposure Score	Labor Productivity Shock
1 management	10,282,305	6.8%	31	2.7
2 business and finance	8,189,010	5.4%	61	5.3
3 computer and mathematics	4,546,141	3.0%	70	6.1
4 architecture and engineering	2,583,426	1.7%	26	2.3
5 physical and social sciences	1,285,598	0.8%	10	0.9
6 community and social service	2,239,401	1.5%	1	0.1
7 legal	1,142,795	0.8%	2	0.2
8 education	8,810,000	5.8%	0	0.0
9 entertain	1,978,653	1.3%	9	0.8
10 healthcare practitioners	8,380,473	5.5%	6	0.5
11 healthcare support	6,513,253	4.3%	4	0.3
12 protective services	3,495,709	2.3%	10	0.9
13 food preparation services	13,478,247	8.9%	1	0.1
14 building and grounds cleaning	6,173,843	4.1%	0	0.0
15 personal care and services	3,278,392	2.2%	1	0.1
16 sales	14,417,650	9.5%	25	2.2
17 office and administrative support	19,663,740	13.0%	24	2.1

18 farming occupations	1,457,648	1.0%	0	0.0
19 construction and extraction	6,219,439	4.1%	0	0.0
20 installation, maintenance and repair	5,767,052	3.8%	13	1.1
21 production occupations	9,120,132	6.0%	14	1.2
22 transportation and material moving	12,558,071	8.3%	3	0.3

Source: The number of U.S. workers is sourced from Demirkaya et al. (2025) and serves as part of the baseline statistics in our enhanced GTAP framework. The AI exposure score is taken from Hampole et al. (2025), converted to numerical form by the authors. The occupational share of total employment and the occupation-level labor productivity shock are calculated by the authors.

Meanwhile, for the two global simulations, we not only apply generative AI-induced labor productivity shocks to the 22 occupations in the United States, but also to both skilled and unskilled labor in other countries/regions. To calculate the generative AI-induced labor productivity shock to both skilled and unskilled labor in other regions, we make use of the AI user share by country calculated by Misra et al. (2025), who present a dataset tracking AI adoption in 147 countries using customer-authorized Microsoft data on visits to generative AI platforms like ChatGPT, Gemini, Claude, and Copilot from laptops and mobiles. The broad country coverage of the Misra et al. data make it a convenient starting point for calibrating country-specific AI productivity effects. However, visits by devices to generative AI platforms provide an incomplete picture of AI adoption.

There is substantial evidence that the United States is the global leader in AI by a large margin. In a major report from the Institute for Human-Centered AI at Stanford University, Maslej et al. (2025) note that in 2024, U.S.-based institutions produced 40 notable AI models, as compared to China's 15 and Europe's combined total of three. In the past decade, more notable machine learning models have originated from the United States than any other country. In addition, the United States leads in highly cited research publications, while China leads in overall AI publications and citations. Koetsier (2025) finds that the United States has 50 percent of global computational power, compared to 3 percent for China. China leads in the number of AI data center clusters, with 46 percent of the global total, with 38 percent in the United States. There is, however, a substantial difference in the scale of data clusters, with computational power per data cluster being much higher in the United States than in China.

Misra et al. (2025) provides AI user shares for the United States, China, Mexico, EU27, Canada, the United Kingdom and the Rest of the World (table 3).

Table 3: AI User Share in Misra et al. (2025) and AI User Share Adopted in Our Paper

Region	AI User Share in Misra et al. (2025), in percent	AI User Share adopted in this paper, in percent
United States	26.27	26.27
China	15.40	15.40
Mexico	16.72	16.72
EU27	27.62	26.27
Canada	33.54	26.27
The United Kingdom	36.38	26.27
ROW	13.48	13.48

Note: The AI User Share in Misra et al. (2025) for the EU27 is calculated by taking the simple average of the AI User Share data from the 22 EU member countries reported by Misra et al. (2025). For the Rest of the World (ROW), the AI User Share is computed as the simple average across all other countries for which Misra et al. (2025) provided AI User Share data.

Table 3 above shows that, according to the AI user share data from Misra et al. (2025), the percentages for EU27, Canada, and Britain are higher than that of the United States. However, the data from Misra et al. (2025) do not separate workplace use of AI—which is directly relevant to our study—from household use. Given the advanced adoption of AI in workplaces in the United States, we assume that the United States represents the global frontier of AI-induced productivity gains. Thus, in this first attempt at calibrating the model, we adjust the numbers by applying the U.S. AI user share rate to EU27, Canada, and the United Kingdom for the purposes of our paper. A revised country-specific shock taking into account additional indicators of AI adoption would likely show higher rates of AI adoption in the United States and China, and lower rates in Canada, EU27, and the United Kingdom, relative to other countries.

As indicated before, Bick et al. (2025) found that generative AI increases average U.S. labor productivity by 1.4 percent across all workers. Applying the same method above using AI exposure score, we calculate that generative AI boosts labor productivity by 2.4 percent for skilled labor and by 1.0 percent for unskilled labor in the United States.[6] Assuming that productivity gains from AI are proportional to its usage rates, we calculate corresponding labor productivity shocks for other regions by scaling with their respective AI user share ratios.[7] Table 4 presents the calculated gains in labor productivity for both skilled and

[6] As discussed above and shown in Table 1, we group the 22 U.S. occupations into skilled and unskilled labor by using weighted mean wages as a proxy for skill levels and ranking the occupations accordingly. This approach follows Deitz and Orr (2006), who used median wage data to classify manufacturing jobs into high-, mid-, and low-skilled categories. The AI-induced labor productivity shocks for the 22 occupations are then aggregated into productivity shocks for skilled and unskilled labor using the occupational shares in the GTAP model's baseline statistics.

[7] Using China as an example, China's AI User Share is 15.4 percent, compared with 26.27 percent in the United States. Because the AI-induced labor productivity gain for skilled labor in the United States is 2.4 percent, then the

unskilled workers in China, Mexico, EU27, Canada, the United Kingdom, and the Rest of the World. In the two global simulations—these labor productivity shocks are implemented alongside U.S. occupation-level productivity shocks spanning 22 different occupations, using, respectively, our enhanced GTAP framework with capital-skill complementarity and the standard GTAP model without capital-skill complementarity.

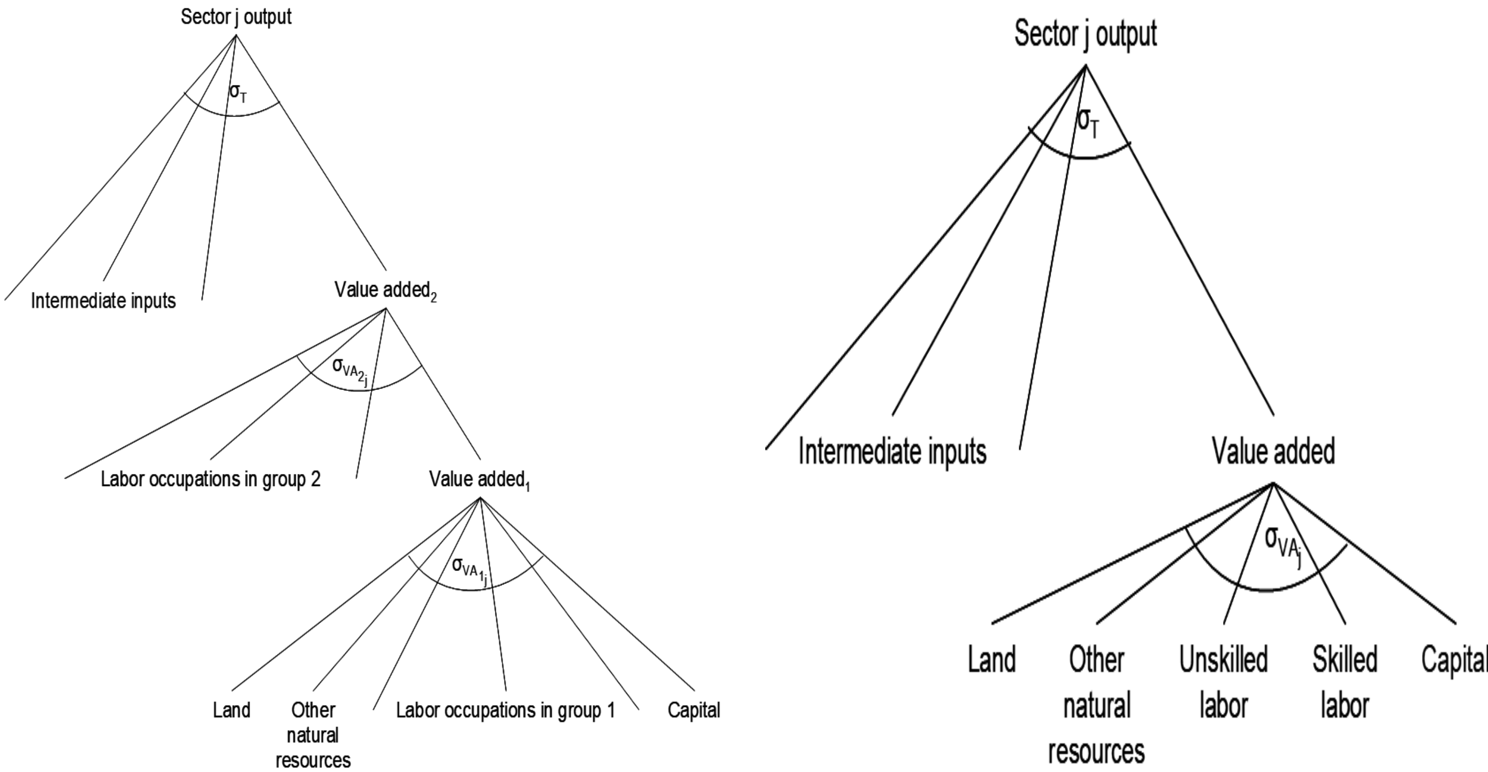
Table 4: Generative AI-driven Labor Productivity Shocks for China, Mexico, EU27, Canada, the United Kingdom and the Rest of the World

	Labor Productivity Shock for Skilled Labor (in percent)	Labor Productivity Shock for Unskilled Labor (in percent)
China	1.4	0.6
Mexico	1.5	0.6
EU27	2.4	1.0
Canada	2.4	1.0
The United Kingdom	2.4	1.0
ROW	1.2	0.5

To clarify our implementation of the second global simulation using the standard GTAP model without capital-skill complementarity, Figure 3a, which illustrates the input substitution structure in the enhanced GTAP model, is presented alongside Figure 3b, which shows the corresponding input substitution structure in the standard GTAP model. When we run the second global simulation, we set σ_{VA1j} and σ_{VA2j} equal to σ_{VAj}, using the default elasticities from the standard GTAP model. This adjustment causes the input substitution possibilities for producing sectors in Figure 3a to collapse to Figure 3b. Regarding labor categories, the United States continues to feature 22 different occupations, while all other countries and regions remain divided into two categories: skilled and unskilled labor.

corresponding gain for China is scaled by the ratio of their AI User Shares. This gives: 2.4*(15.4/26.27)= 1.4 percent.

Figure 3a (left) and 3b (right): Input substitution possibilities for producing sectors in our enhanced version of the GTAP model VS. the standard GTAP model



Note: Figure 3a is the same as Figure 2 and Figure 3b is the same as Figure 1.

Discussion of Simulation Results

Changes in Welfare and Real GDP: Simulation 1 and 2

Results from Simulations 1 and 2 indicate that changes in welfare and real GDP are robust to whether capital-skill complementarity is incorporated into the model, as the macroeconomic results of the two simulations are qualitatively very similar (see Tables 5, 6a and 6b). With an AI-induced labor productivity gain globally, all countries and regions experience an increase in welfare and real GDP (see table 5, 6a and 6b). The biggest gains in real GDP, in percentage change terms, are in advanced economies such as the United States, EU27 countries, Canada and the UK, which have higher AI-induced labor productivity gains compared to emerging and developing economies such as China and Mexico (see table 6a and 6b below). Advanced economies saw increases in real GDP ranging from 0.9 percent to 1.2 percent, while China and Mexico experienced gains of 0.4 percent and 0.3 percent, respectively (table 6a and 6b).

Table 5: Change in Welfare by Country/Region, Relative to the Baseline, in billion dollars, Simulation 1 with capital-skill complementarity and Simulation 2 without capital-skill complementarity

Change in Welfare, in billion dollars	Simulation 1	Simulation 2
China	52.2	54.9
Canada	22.2	21.9
Mexico	3.5	3.8
USA	219.4	220.1
UK	28.0	27.7
EU27	132.5	131.7
ROW	116.6	119.9

Table 6a: Change in Real GDP by Country/Region, Relative to the Baseline, in percent and in billion dollars, Simulation 1

6a. Change in Real GDP	in percent	in billion dollars
China	0.4	59.9
Canada	1.2	20.8
Mexico	0.3	3.8
USA	1.0	215.4
UK	1.0	28.1
EU27	0.9	135.0
ROW	0.4	111.4

Table 6b: Change in Real GDP by Country/Region, Relative to the Baseline, in percent and in billion dollars, Simulation 2

6b. Change in Real GDP	in percent	in billion dollars
China	0.4	61.1
Canada	1.2	20.7
Mexico	0.3	3.8
USA	1.0	218.6
UK	1.0	28.0
EU27	0.9	135.2
ROW	0.4	112.5

Changes in Real Wages by Labor Type and By Country/Region: Simulation 1 and 2

The most notable difference between the two global simulations—with and without capital-skill complementarity—appears in the labor market results, particularly in real wage changes. In Simulation 1, which incorporates capital-skill complementarity, real wages for skilled labor decline in five of the model's seven regions, increasing only in Canada and marginally in the United Kingdom (Figure 4). In the more detailed representation of the United States, these wage declines are concentrated in computer and mathematics occupations and business and financial occupations, which have the highest AI exposure. Real wages also decline modestly for architecture and engineering and management occupations. Specifically, in the United States, real wages decrease by 1.8 percent for computer and mathematics occupations, 1.3 percent for business and financial occupations, and 0.1 percent for architecture and engineering occupations (Figure 5).

By contrast, Simulation 2, which uses the standard GTAP model without capital-skill complementarity, shows that real wages for skilled labor increase in all seven regions. Moreover, the percentage increase in skilled wages exceeds that of unskilled wages in every region (Figure 6). In the more detailed U.S. results, real wages rise across all occupations, with the largest gains occurring in the occupations most exposed to AI—computer and mathematics occupations and business and financial occupations—which experience wage increases of 1.7 percent and 1.6 percent, respectively (Figure 7).

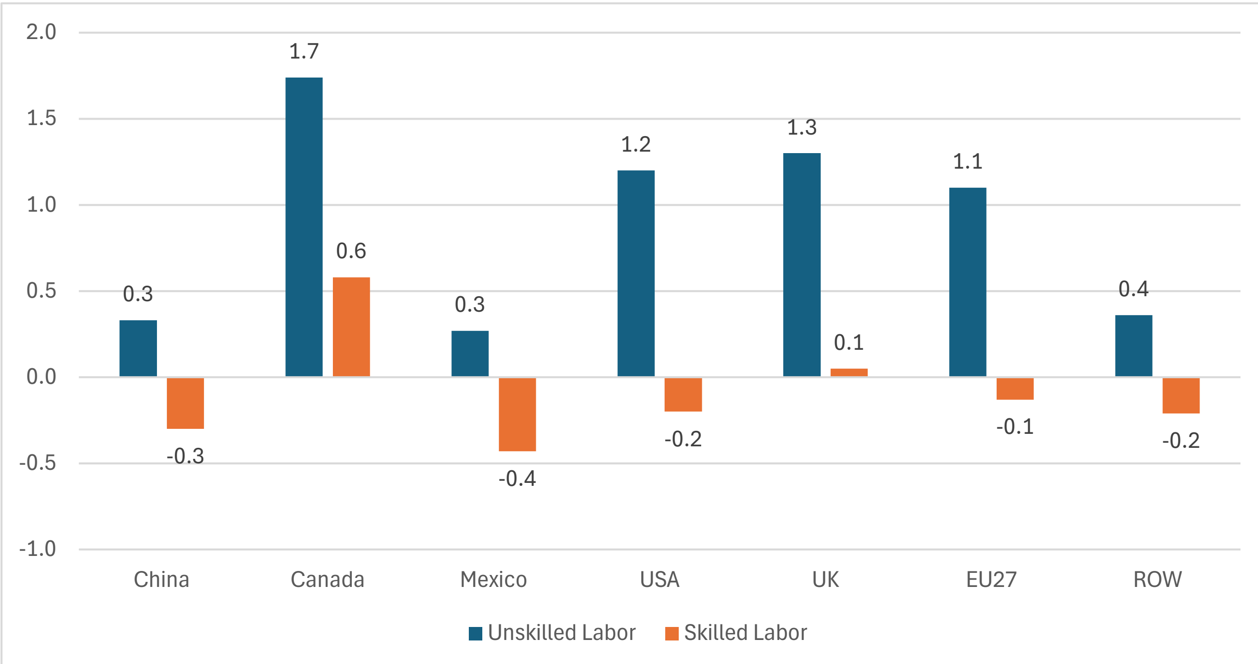
The skill premium declines in all regions under Simulation 1 but increases in all regions under Simulation 2.[8] Thus, when capital-skill complementarity is incorporated, real wages for unskilled labor rise relative to real wages for skilled labor across all regions, implying a reduction in global wage inequality. In contrast, under the standard GTAP specification, real wages for skilled labor rise relative to real wages for unskilled labor in every region, indicating an increase in global wage inequality (figure 4 and 6).

The stark difference in real wage outcomes arises because, as GDP and welfare increase in all regions, the price of capital also rises. Under the capital-skill complementarity mechanism, the higher cost of capital reduces firms' demand for skilled labor while increasing the relative demand for unskilled labor. As a result, real wages for skilled labor decline relative to real wages for unskilled labor. These findings are consistent with those of Dix Carneiro et al. (2023), who compared simulation results from a structural general equilibrium model with capital-skill complementarity to a model that eliminates this complementarity by assuming Cobb–Douglas production functions for capital, skilled

[8] Skill premium in the United States, Canada, UK, the EU27 declines by 1.4 percent, 1.2 percent, 1.3 percent and 1.2 percent, respectively in simulation 1, while skill premium in China and Mexico declines by only 0.6 percent and 0.7 percent, respectively in simulation 1. Skill premium in the United States, Canada, UK, the EU27 increases by 0.2, 0.3, 0.3 and 0.3 percent, respectively in simulation 2, while skill premium in China and Mexico increases by 0.2 and 0.1 percent, respectively, in simulation 2.

labor, and unskilled labor. Similar to our results, they found that removing capital-skill complementarity reversed the direction of real wage changes for skilled labor.

Figure 4: Change in Real Wages Across Regions, in percent, relative to the baseline, simulation 1



Note: U.S. results are the weighted-average of changes in real wages of the 9 high-skilled occupations and 13 low-skilled occupations.

Figure 5: Change in U.S. Real Wages, in percent, relative to the baseline, simulation 1

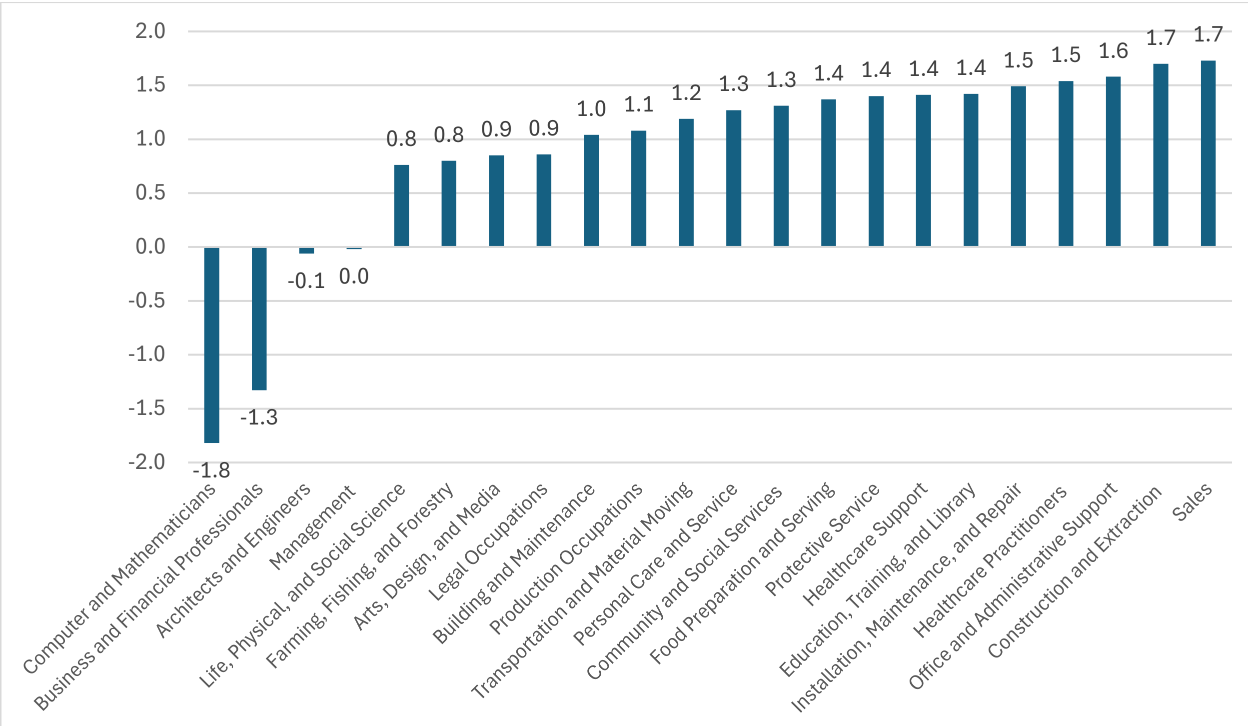


Figure 6: Change in Real Wages Across Regions, in percent, relative to the baseline, simulation 2 run with the standard GTAP model

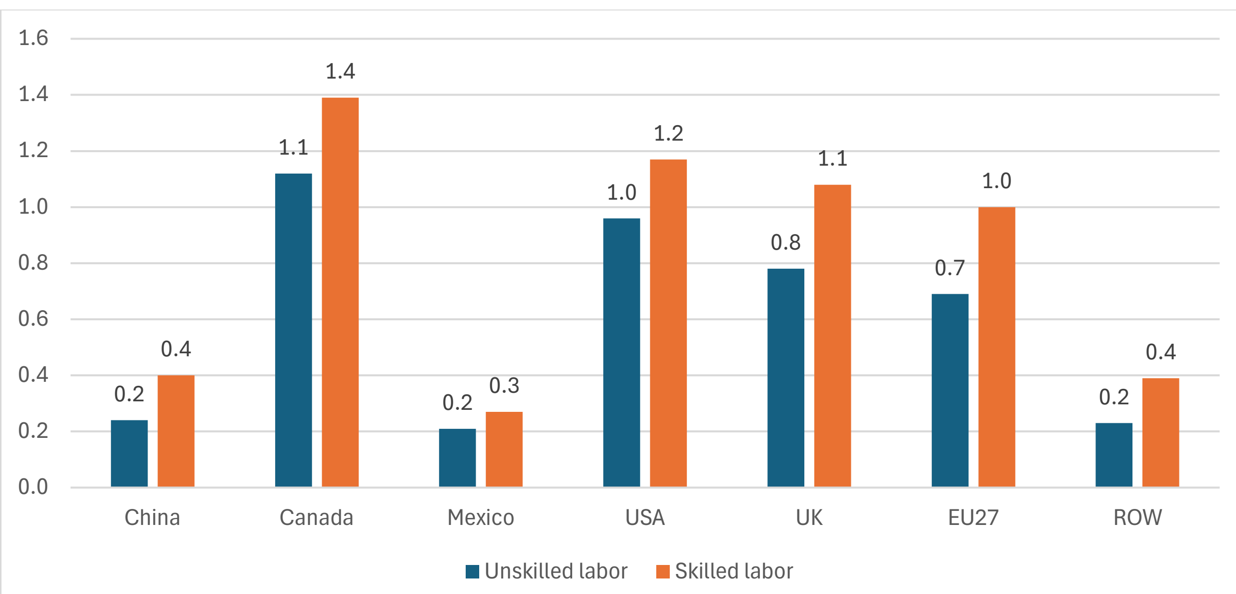
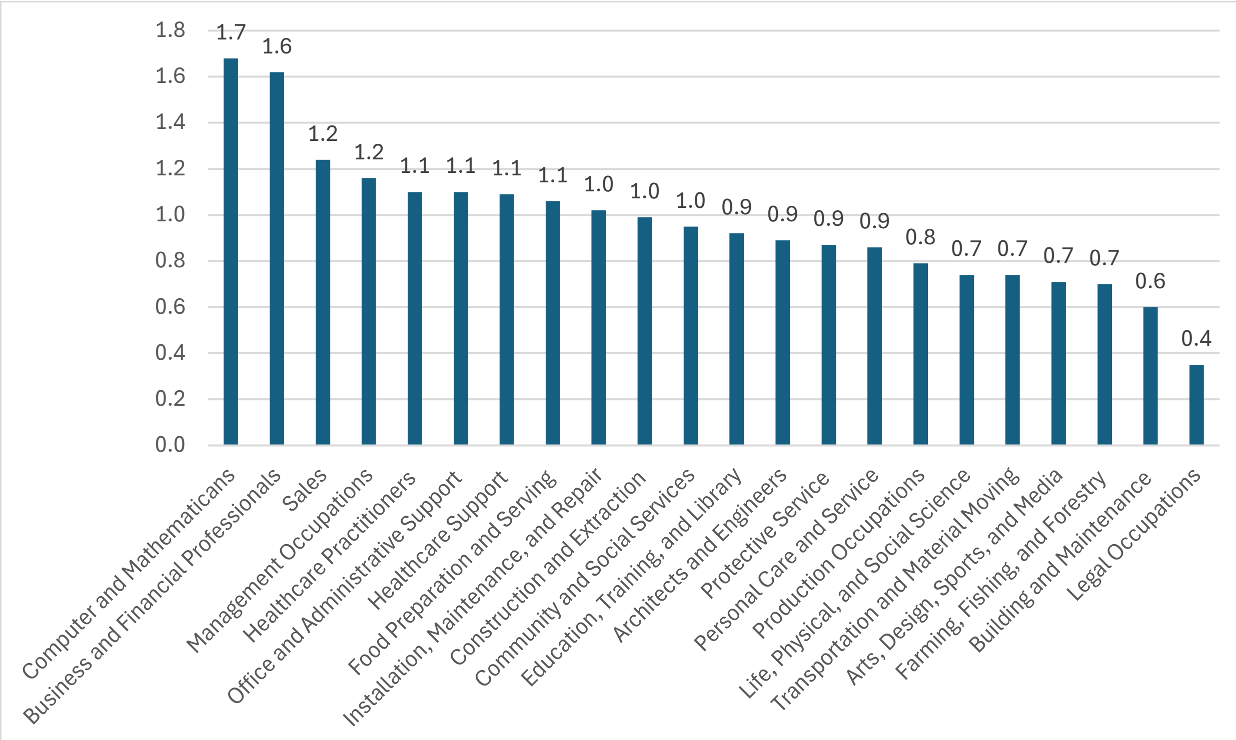


Figure 7: Change in U.S. Real Wages, in percent, relative to the baseline, simulation 2 run with the standard GTAP model



Changes in Output and Trade: Simulation 1 and 2

Results from Simulations 1 and 2 also indicate that changes in output and trade are largely robust to whether capital-skill complementarity is incorporated into the model. A global labor productivity increase driven by AI boosts output worldwide, and advanced economies see a larger percentage increase than developing regions (see Table 7 below). This is because labor productivity gains due to AI are greater in advanced economies compared to developing countries. For example, output rises between 0.8 and 1.1 percent in advanced economies, while China's and Mexico's outputs grow by only 0.4 percent and 0.3 percent, respectively.

Table 7: Changes in Total Output by Country/Region, Relative to the Baseline, in percent and in billion dollars, Simulation 1 and 2

Change in Output	Simulation 1		Simulation 2	
	in percent	in billion dollars	in percent	in billion dollars
China	0.4	155.8	0.4	156.0
Canada	1.1	32.4	1.1	33.7
Mexico	0.3	7.0	0.3	6.6
USA	1.0	359.0	1.0	366.8

UK	1.0	48.3	1.0	48.0
EU27	0.8	258.5	0.9	261.3
ROW	0.4	205.9	0.3	205.2

Table 8: Changes in Total Imports, by country/region, in percent and in billion dollars, relative to the baseline, simulation 1 and 2.

Change in Total Imports	Simulation 1		Simulation 2	
	in percent	in billion dollars	in percent	in billion dollars
China	0.1	2.0	0.2	5.0
Canada	1.2	6.3	1.2	6.2
Mexico	0.3	1.1	0.3	1.5
USA	1.4	41.0	1.1	33.4
UK	1.0	9.4	0.9	8.9
EU27	0.8	51.4	0.8	50.5
ROW	0.3	20.9	0.3	27.3

Regarding cross-border trade, total imports increase in all regions, and this result is robust to whether capital-skill complementarity is incorporated into the model (table 8). However, the magnitude of import growth differs substantially across regions. Advanced economies experience considerably larger increases in imports than developing economies (Table 8), with import growth ranging from 0.8 to 1.4 percent, compared with only 0.1 to 0.3 percent in China and Mexico.

This disparity reflects the larger AI-induced labor productivity gains in advanced economies, which translate into stronger real GDP growth and, consequently, greater domestic demand for imported goods. As discussed in the macroeconomic results above, estimated real GDP increases range from 0.9 to 1.2 percent for the four high-income, high-AI-exposure regions (United States, Canada, EU27, and the United Kingdom), compared with only 0.3 to 0.4 percent for the lower-AI-exposure, middle-income regions (China, Mexico, and the Rest of the World). The close correlation between GDP growth and import growth suggests that the sectoral results, which will be discussed later in the paper, are driven in part, by stronger import demand in high-income economies. Consequently, advanced economies experience substantially larger increases in imports than developing economies.

Table 9: Changes in Total Exports, by country/region, in percent and in billion dollars, relative to the baseline, simulation 1 and 2.

Change in Total Exports	Simulation 1		Simulation 2	
	in percent	in billion dollars	in percent	in billion dollars
China	1.2	32.4	0.9	24.6
Canada	-0.2	-1.0	0.3	1.5
Mexico	0.7	3.3	0.5	2.4
USA	-0.1	-3.3	0.3	6.2
UK	0.6	4.7	0.7	5.8
EU27	0.7	46.7	0.8	53.4
ROW	0.6	49.4	0.5	39.0

With respect to changes in total exports by country and region, the results from Simulations 1 and 2 are also largely robust to whether capital-skill complementarity is incorporated into the model (table 9). As will be discussed in greater detail in the country- and sector-level analysis in the next section, changes in exports are driven primarily by the structural changes induced by AI.

For example, China's fastest-growing sectors in terms of both output and exports are concentrated in highly tradable manufacturing industries, resulting in a larger increase in total exports in percentage change terms than in other regions. By contrast, output growth in the United States is concentrated primarily in less-traded service sectors. Consequently, total U.S. exports of goods and services either decline slightly by 0.1 percent in Simulation 1 or increase only modestly by 0.3 percent in Simulation 2 (table 9).

A more detailed examination of output and trade outcomes by country and sector confirms that these patterns are broadly unchanged regardless of whether capital-skill complementarity is included in the model. Due to space constraints, not all country- and sector-level results are reported in this paper; however, the complete set of results is available from the authors upon request.

Changes In Sectoral Comparative Advantage Induced By AI: Results from Simulation 1

Because the output and trade results are largely robust to whether capital-skill complementarity is incorporated into the model, this section reports detailed country- and sector-level results from Simulation 1, which uses our enhanced GTAP model with capital-skill complementarity. We focus on this specification because it is more consistent with the empirical evidence on labor market dynamics and with the approach adopted in previous general equilibrium studies, such as Dix Carneiro et al. (2023).

A closer look at sectoral results show that the effect of AI in our model is to shift comparative advantage in high-income countries to sectors with high AI exposure. These effects are mediated by the pre-existing pattern of trade and production, which affects the post-AI equilibrium. AI-induced productivity changes vary from sector to sector. The reason for this is that the share of labor which is highly exposed to AI varies substantially between sectors. For the United States for example, most of the AI productivity effects in our model are concentrated in two occupations: computer and mathematical occupations, and business and finance occupations (see Table 2 above).

We explore these effects in greater detail by examining the estimated impacts on U.S. trade. There are two main reasons for focusing on the United States. First, even in the baseline, prior to the introduction of AI-induced labor productivity shocks, the United States has a comparative advantage and a large market share in sectors expected to experience the largest AI-induced productivity gains, mainly business services of various types. Second, our ability to represent U.S. labor with 22 disaggregated occupations means that we can pinpoint these sectoral effects more precisely. For non-U.S. regions, we aggregate labor into two types, “skilled” and “unskilled.” If our country-specific estimates of AI exposure are correct, this means that we are able to capture aggregate productivity effects for the rest of the world reasonably well. However, this aggregation necessarily limits the precision of our estimates of sectoral productivity differences. Thus, at this stage in our work we present primarily aggregate effects for the non-U.S. regions.

Table 10 presents the effects of AI-induced productivity changes on the exports of the United States, highlighting the sectors with highest exposure to AI productivity effects. In Tables 10 and 11, “share of highly AI-exposed labor” is measured as the combined share of computer and mathematical occupations and business and finance occupations in the wage bill. Estimated increases in U.S. exports in the most AI-exposed sectors exceed the estimated 1.0 percent increase in U.S. real GDP, thus indicating structural change. These sectors include other financial services; insurance; computer, electronic, and optical products; and other business services. Thus, the U.S. comparative advantage shifts in the direction of business services more broadly. The overall shift in resources to these sectors induces decreases in exports in less AI-exposed sectors, both in manufacturing (e.g. chemicals, pharmaceuticals, non-ferrous metals) and in services such as education and hospitality that we estimate are less AI-exposed.

A comparison of Tables 10 and 11 shows that AI induces an improvement in the U.S. trade balance in other financial services and other business services. Meanwhile, insurance, information and communication, and computer, electronic, and optical products experience an expansion in two-way trade. The expansion of two-way trade in these sectors occurs because AI-induced productivity increases are modeled as taking place across all regions of the world, leading to increased production and exports. There are also increases in trade due to cross-sector value chain linkages. For example, firms in "other business services" may operate data centers and train AI models using imported semiconductors and other manufactured inputs.

Table 11 also shows increased U.S. imports across many manufacturing sectors, particularly motor vehicles and parts and machinery. Rising U.S. incomes increase domestic demand for these goods, while the expansion of AI-intensive service industries further boosts demand for manufactured intermediate inputs. As a result, manufacturing sectors in the rest of the world—particularly in countries such as China and Mexico that specialize in these industries—experience an increase in their net exports to meet higher U.S. demand in the post-AI equilibrium. The increase in the U.S. comparative advantage in services implies a corresponding shift in comparative advantage toward manufacturing in the rest of the world. Taking China as an example, the top 15 sectors with the highest export increases are all within highly tradable manufacturing, such as computer, electronic and optical products ($6.3 billion), electrical equipment ($3.3 billion), chemicals ($2.7 billion), other manufacturing ($2.4 billion), and machinery ($2.3 billion) (see Figure 8 below).

Table 10: Changes in U.S. Exports by Sector, relative to the baseline, Simulation 1

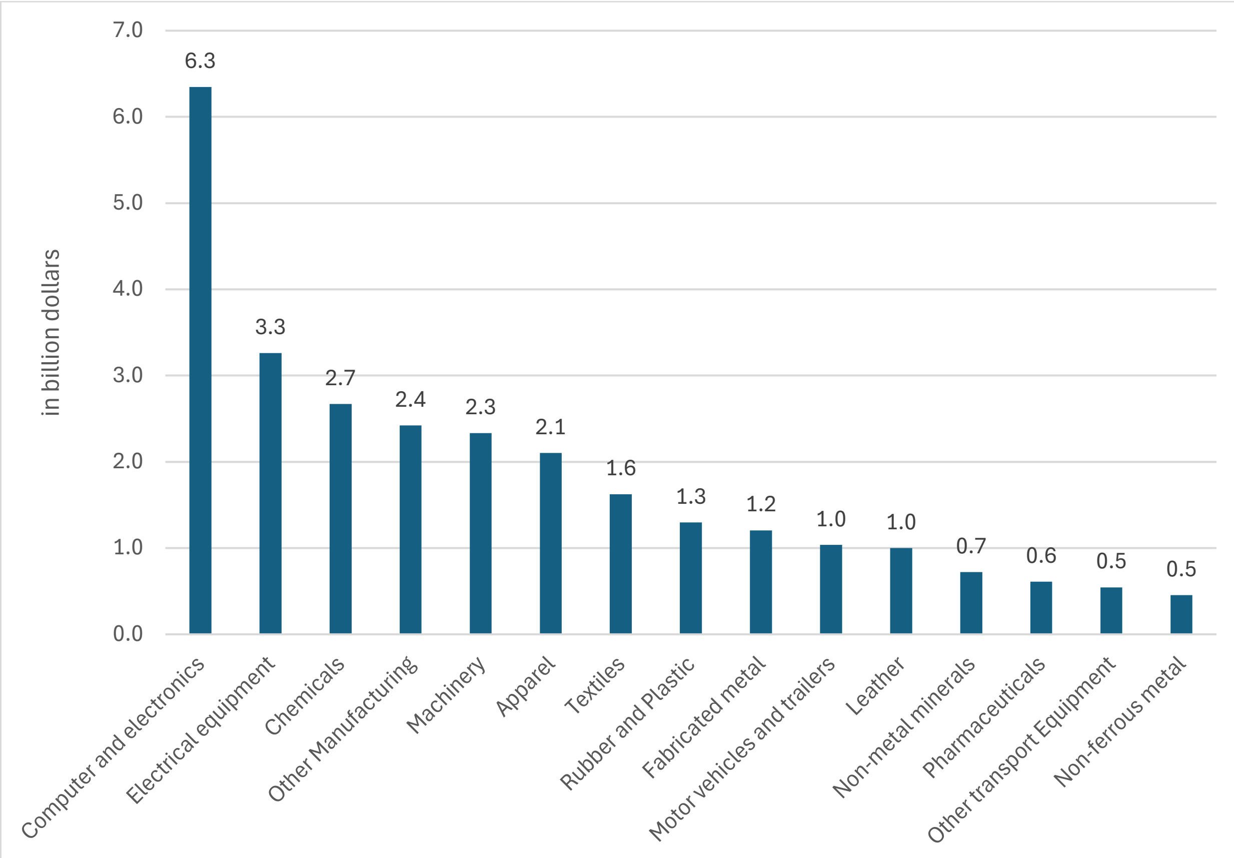
	change in value, in percent	**change in value, in million dollars**	**Share of highly AI-exposed labor, in percent**
Top 10 highly AI-exposed sectors			
Other financial services	2.5	2,404	40.7
Insurance	2.1	468	36.3
Information and communication	1.0	620	33.7
Computer, electronic, and optical products	2.1	4,703	28.4
Other business services	1.6	3,226	27.8
Other transport equipment	0.6	346	20.9
Gas manufacture/distribution	-1.2	-18	20.7
Other services	-0.3	-55	17.3
Electricity	-0.6	-8	12.3
Oil	0.2	84	11.9
Top 10 decreases in exports in other sectors			
Electrical equipment	-0.6	-411	9.9

Rubber and Plastic	-1.0	-420	5.8
Air transport	-0.8	-580	3.8
Motor vehicles and parts	-0.5	-712	5.0
Machinery	-0.5	-713	11.7
Non-ferrous metal	-2.2	-1,139	4.9
Education	-3.3	-1,315	4.8
Pharmaceuticals	-2.4	-1,500	11.6
Hospitality	-1.9	-2,151	0.7
Chemicals	-1.5	-2,324	7.5

Table 11: Change in U.S. Imports by Sector, relative to the baseline, Simulation 1

	change in value, in percent	**change in value, in million dollars**	**Share of highly AI-exposed labor, percent**
Top 10 highly AI-exposed sectors			
Other financial services	0.2	93	40.7
Insurance	0.7	336	36.3
Information and communication	1.2	806	33.7
Computer, electronic, and optical products	1.1	4,070	28.4
Other business services	0.8	1,191	27.8
Other transport equipment	1.1	895	20.9
Gas manufacture/distribution	1.8	1	20.7
Other services	2.1	428	17.3
Electricity	0.8	39	12.3
Oil	0.4	535	11.9
Top 10 increases in imports in other sectors			
Motor vehicles and parts	1.6	5,324	5.0
Machinery	1.5	3,023	11.7
Other manufacturing	1.5	2,885	8.2
Pharmaceuticals	1.9	2,496	11.6
Electrical equipment	1.4	2,362	9.9
Hospitality	2.2	2,120	0.7
Apparel	1.4	1,684	7.0
Chemicals	1.4	1,622	7.5
Rubber and plastic	1.8	1,377	5.8
Fabricated metal	1.8	1,240	5.1

Figure 8: Sectors with the Highest Chinese Exports, in billion dollars, Relative to the baseline, simulation 1



Concluding Remarks

This paper develops an enhanced static GTAP model that distinguishes 22 occupations in the United States and incorporates capital-skill complementarity into the production function. We use the model to examine how AI-driven labor productivity gains affect international trade and labor markets, comparing results with and without capital-skill complementarity to assess robustness.

The simulations show that welfare, real GDP, output, and trade effects are largely robust to the inclusion of capital-skill complementarity, whereas labor market outcomes are more sensitive. AI-driven productivity gains increase welfare and real GDP across all countries and regions, with advanced economies experiencing larger gains because of stronger productivity improvements. These gains raise domestic demand for imports while shifting comparative advantage toward sectors with high AI exposure for advanced economies.

In the United States, highly AI-exposed sectors—including other financial services, insurance, and other business services—experience the largest export gains. At the same time, the reallocation of resources toward these industries reduces exports from less AI-exposed sectors, including manufacturing as well as services such as education and hospitality. Rising incomes and domestic demand in advanced economies also increase their demand for imported manufacturing goods, while the expansion of AI-intensive service industries boosts demand for manufactured intermediate inputs. As a result, manufacturing-specialized economies such as China strengthen their comparative advantage and expand exports of highly tradable manufactured products, including computers, electronic and optical products, and electrical equipment.

As for future research, there are other papers using different methods than Hampole to compare U.S. occupations by AI intensity. For instance, Handa et al. (2025) analyze millions of Claude.ai conversations to identify AI usage patterns across the United States by occupation. The International Monetary Fund (2024) also developed an AI preparedness Index assessing the level of AI preparedness across 174 countries. One possible future work would be to apply alternative AI exposure scores to construct alternative AI-driven labor-productivity shocks and further test the robustness of our simulation results.

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Appendices:

Appendix Table 1: 22 U.S. Occupational Categories

SOC Major Group	SOC code	SOC Description
11	management	Management Occupations
13	bus_finance	Business and Financial Operations Occupations
15	comp_math	Computer and Mathematical Occupations
17	arch_enginr	Architecture and Engineering Occupations
19	sciences	Life, Physical, and Social Science Occupations
21	social_serv	Community and Social Services Occupations
23	legal	Legal Occupations
25	education	Education, Training, and Library Occupations
27	entertain	Arts, Design, Entertainment, Sports, and Media Occupations
29	health_prac	Healthcare Practitioners and Technical Occupations
31	health_sup	Healthcare Support Occupations
33	protective	Protective Service Occupations
35	food_service	Food Preparation and Serving Related Occupations
37	build_maint	Building and Grounds Cleaning and Maintenance Occupations
39	pers_care	Personal Care and Service Occupations
41	sales	Sales and Related Occupations
43	admin_supp	Office and Administrative Support Occupations
45	farm_occup	Farming, Fishing, and Forestry Occupations
47	constructn	Construction and Extraction Occupations
49	maint_repr	Installation, Maintenance, and Repair Occupations
51	production	Production Occupations
53	transport	Transportation and Material Moving Occupations

Source: Bureau of Labor Statistics (BLS) Occupational Employment Statistics (OES) survey.