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

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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, 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, which have a comparative advantage in the production and export of services. Meanwhile, AI reduces wage gaps within countries but increases wage gaps between countries. It reduces wage gaps within countries because AI reduces the demand for high-income labor and increases the relative demand for low-income labor. It increases wage gaps between countries since high-income countries have a comparative advantage in services, and this advantage increases with AI.

JEL categories: F16, C68, O33

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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.

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[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 presents two simulation exercises and the calibration of AI-induced labor productivity shocks implemented in the two simulations: the first focuses on the United States, exploring how AI-driven labor productivity gains in various occupations affect U.S. output, cross-border trade patterns, and wage differentials across occupations; the second takes a global perspective, examining how generative AI diffusion across countries reshape global trade patterns, and wage gaps both within and between nations. Section 5 discusses the simulation results, and 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.

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. Following Elondou et al. (2023), 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. 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 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. 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.

Recent empirical research—including Maliar et al. (2022), Ohanian et al. (2023), and Berlingieri et al. (2024)—demonstrates that capital tends to be 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. These empirical studies estimate the substitution elasticity between capital and skilled labor, thereby enabling more accurate integration of this mechanism into forward-looking general equilibrium models for conducting counterfactual analyses.

To date, the existing CGE literature has not modified the substitution possibilities between various types of labor and capital to reflect capital-skill complementarity, as informed by empirical estimates of the substitution elasticities between capital and skilled labor. Furthermore, no existing research in the AI literature analyzes generative AI's impact on cross-border trade, or wage gaps within and across countries. Our work addresses these two gaps in the literature by: (1) expanding GTAP model labor data, with a 2019 baseline, into 22 occupational groups using Demirkaya et al. (2025), while incorporating the mechanism that higher-skilled labor is less substitutable with capital by applying empirically estimated elasticities to capture capital–skill complementarity and simulate resulting changes in skill premiums as a result of policy changes; and (2) analyzing the effects of generative AI diffusion on global trade patterns and wage disparities within and between countries.

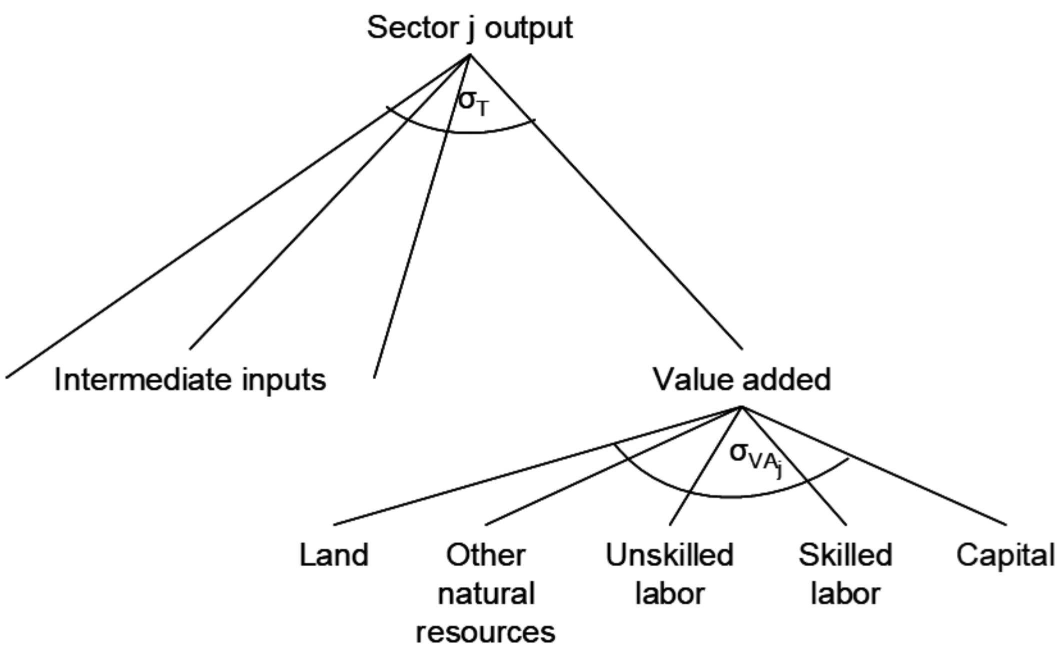
In the next two sections, we detail our method for dividing labor data in the GTAP model into 22 different occupations, along with the structural enhancements we've introduced to better reflect the capital-skill complementarity mechanism. We also describe our process for calibrating generative AI-driven 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 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).

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

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), Ohanian et al. (2023), and Berlingieri et al. (2024)—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.

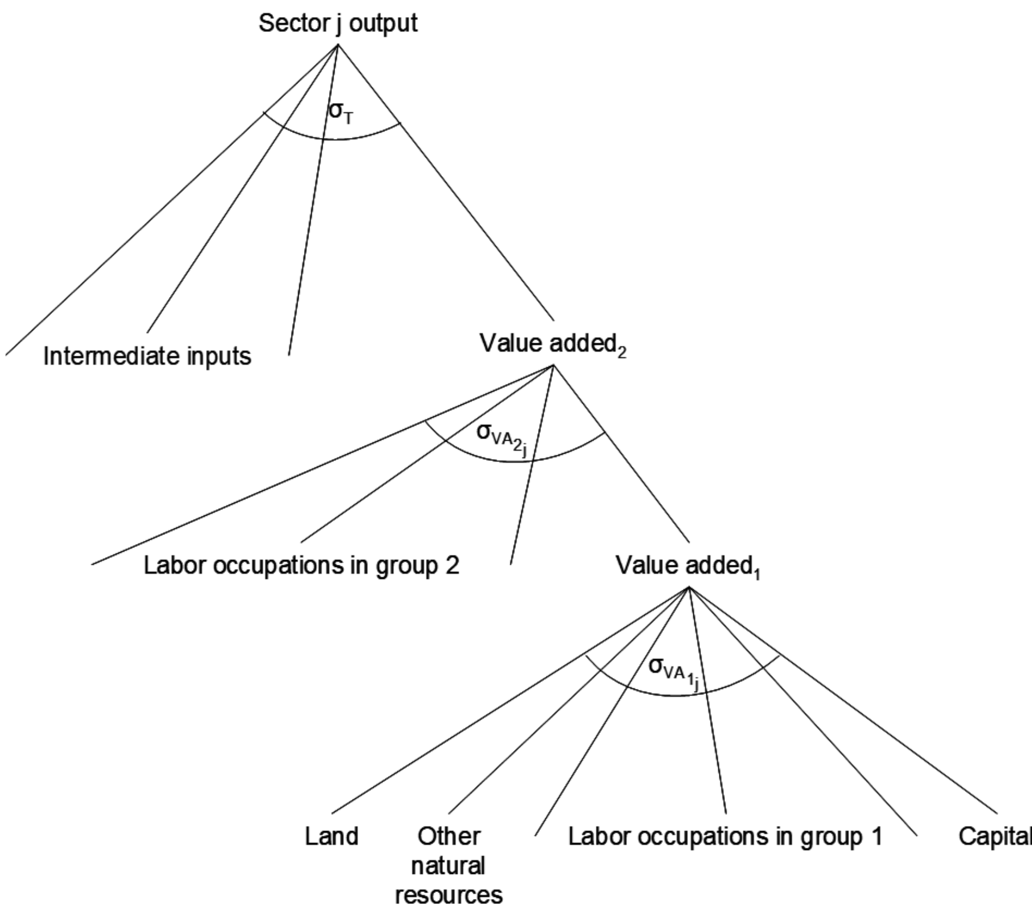
Table 1 Grouping U.S. labor occupations in two groups

Labor 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 0.39 based on estimates from Berlingieri et al. (2024) 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]

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.

[3] The elasticity σ_{VA2j} of 0.39 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 adopt the value 0.39 in this paper because it comes from the most recent empirical estimates based on relatively up-to-date data. 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.

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 0.39. 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 Simulations

To examine the impact of generative AI diffusion on cross-border trade patterns and wage disparities within and between nations, we conduct two simulations using the aforementioned enhanced GTAP model framework: 1) a U.S.-focused simulation implementing generative AI-driven labor productivity shocks across 22 different U.S. occupations; and 2) a global simulation applying generative AI-induced labor productivity shocks to the same 22 occupations in the United States, as well as to both skilled and unskilled labor in all other countries/regions.

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):

$$\sum s_i g_i = 0.014$$

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 and implemented within Simulation 1—the U.S.-focused scenario—using our enhanced GTAP framework.

[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.

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 occupations	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.

For the second simulation (the global simulation), we apply generative AI-induced labor productivity shocks to the same 22 occupations in the United States, as well as 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 unskilled workers in China, Mexico, EU27, Canada, the United Kingdom, and the Rest of the World. In simulation 2—the global simulation—these labor productivity shocks are implemented alongside U.S. occupation-level productivity shocks spanning 22 different occupations, utilizing our enhanced GTAP model framework.

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

[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 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.

Canada	2.4	1.0
The United Kingdom	2.4	1.0
ROW	1.2	0.5

Discussion of Simulation Results

1) U.S.-focused simulation implementing generative AI-driven labor productivity shocks across 22 different U.S. occupations

Change in Real Wages by Occupation

In the first U.S.-focused simulation, generative AI-driven labor productivity gains across occupations yields notable real wage effects. As discussed above, occupations with the greatest exposure to generative AI—namely computer and mathematics, business and finance, management, and architecture and engineering—experience proportionally the largest labor productivity gains, which are implemented as shocks to our enhanced GTAP framework. As workers in these occupations produce more output per unit of labor, firms require less of such labor to maintain the same output levels, leading to reduced labor demand for these occupations.

Our enhanced GTAP framework maintains the full employment assumption as in the standard GTAP model. Therefore, a decrease in labor demand in these occupations translates into a reduction in real wages.[8] As shown in figure 3 below, this generative AI diffusion leads to declines in real wages in the United States by 6.4 percent for computer and mathematics professionals, 5.2 percent for those in business and finance, 1.6 percent for managers, and 1.4 percent for architects and engineers.

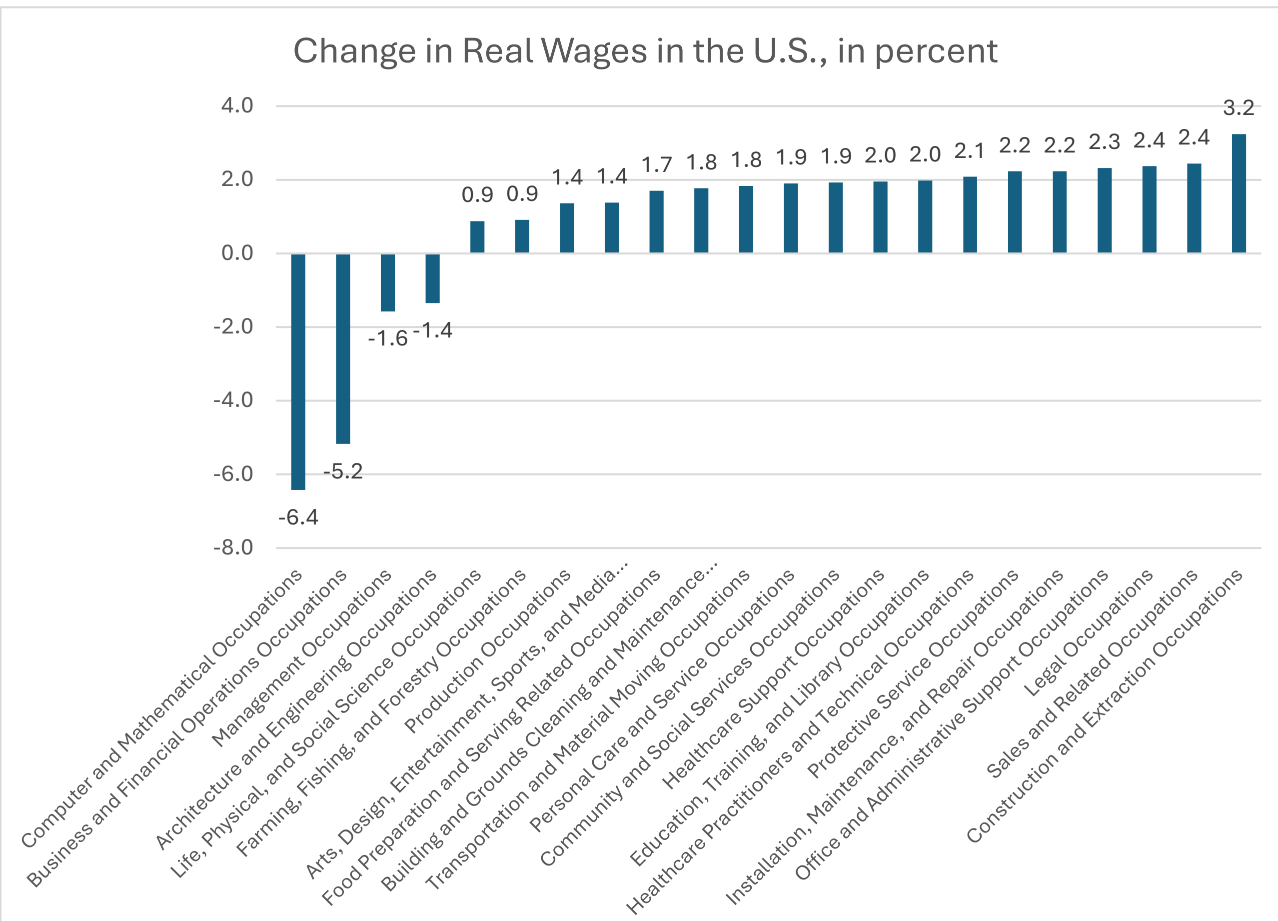
Conversely, AI-enhanced productivity gains lower production costs throughout the U.S. economy, driving increases in total output, real income, and consumption. This results in higher labor demand, particularly in occupations with limited AI exposure and only marginal productivity improvements. Real wages in these roles consequently rise, as indicated in figure 3. The real price of capital in the United States also sees an increase of 1.8 percent.

[8] It has widely been observed that the use of AI in exposed occupations can lead to short-term increases in unemployment. Our model, using a fixed-labor closure, distributes the labor impacts entirely on wages. However, this should not matter much for our primary results. Our primary interest is in changes in international trade patterns, which are driven by productivity-induced labor cost savings across countries, sectors, and occupations. The distribution of these costs savings are similar whether these cost savings are manifest as lower wages or lower employment.

Sales, and office and administrative support occupations—despite having relatively high exposure to AI—experience modest real wage increases. This can be attributed to their classification in our enhanced GTAP framework as low-skilled occupations that are more easily substituted with capital. As capital rents rise across sectors, sectors with higher primary-factor demand can more readily substitute capital with low-skilled workers. As a result, workers in low-skilled occupations can more easily move into sectors where labor demand is stronger. In contrast, high-skilled professions such as computer and mathematics, business and finance, management, and architecture and engineering are less substitutable with capital and face greater challenges transitioning to other sectors, resulting in real wage declines.

Finally, the U.S.-focused simulation results indicate that the U.S. skill premium falls by 3.5 percent due to real wage declines in several high-skilled occupations and rises in many low-skilled ones.

Figure 3: Change in Real Wages in the United States, in percent, relative to the baseline, simulation 1



Changes in Welfare, GDP, Real Income, Output and Cross-Border Trade

With an AI-induced labor productivity gain across the whole U.S. economy, U.S. welfare, measured by equivalent variation (EV), increases by $221.9 billion. U.S. real GDP increases by 1.0 percent, equivalent to $208.9 billion. U.S. household income increases by 1.6 percent.

An AI-driven increase in labor productivity across the U.S. economy results in reduced production costs and increases total U.S. output by 0.9 percent, equivalent to $339.4 billion.[9] The sectors experience the highest output growth in percentage change terms include construction services (2.3 percent), insurance (2.0 percent), computer, electronic and optical products (1.9 percent), other financial services (1.8 percent), and other business services (1.6 percent).[10] These increases amount to $39.8 billion, $24.8 billion, $8.4 billion, $27.0 billion, and $81.8 billion, respectively. These industries employ occupations with the greatest exposure to AI, thereby realizing the most significant improvements in labor productivity and highest output growth.

Regarding cross-border trade, total U.S. exports of goods and services to global markets declines by 2.0 percent, equivalent to a decrease of $44.5 billion. Only a few sectors report growth in exports: other financial services (2.2 percent), other business services (1.5 percent), insurance (1.5 percent), and computer, electronic, and optical products (1.3 percent). In contrast, U.S. imports from the world increases across nearly all sectors, with total imports rising by 2.2 percent, or $66.2 billion. Generative AI primarily enhances labor productivity and output within U.S. service sectors,[11] which tend to employ a higher proportion of AI-exposed occupations. As services are generally much less traded than goods, growth in U.S. real income and consumer demand results in increased total U.S. imports and a decline in overall U.S. exports.

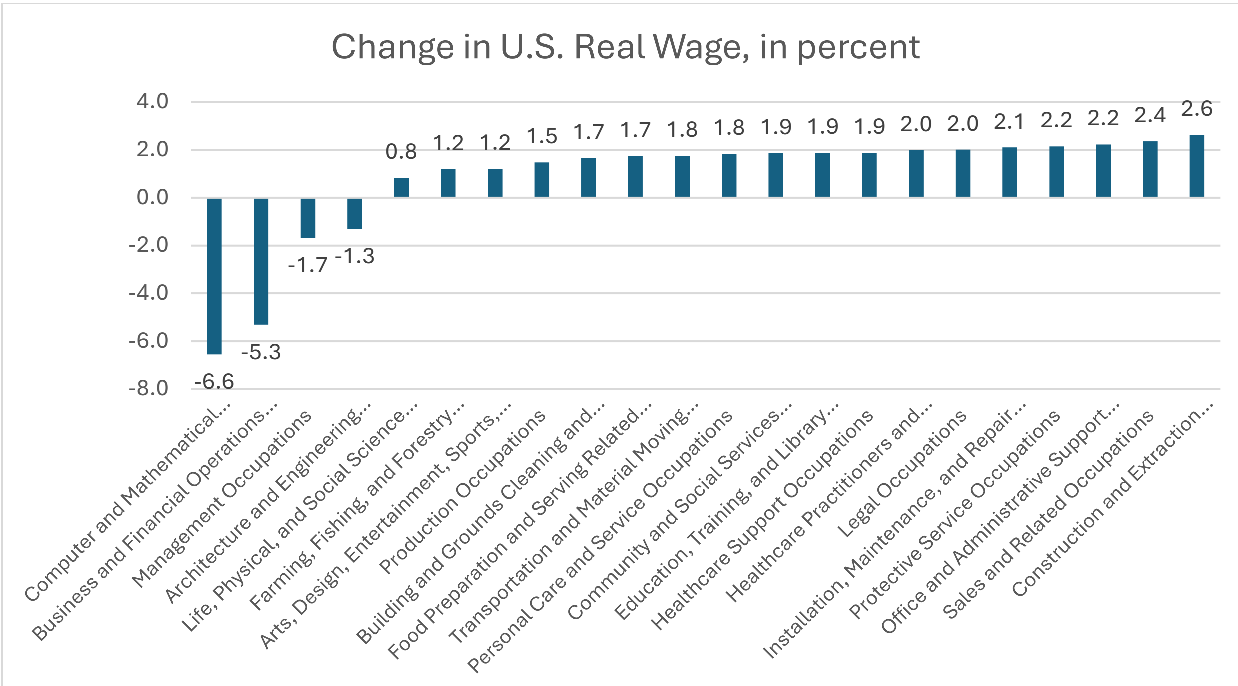
2) **Global Simulation Implementing Labor Productivity Shocks in China, Mexico, EU27, Canada, the United Kingdom, and the Rest of the World, Alongside U.S. Occupation-level Productivity Shocks**

In the second global simulation, the patterns of change in U.S. real wages by occupation closely resemble those from the U.S.-focused simulation. Real wages in the United States fall most sharply in occupations with high AI exposure: computer and mathematical roles drop by 6.6 percent, business and finance professionals decrease by 5.3 percent, managers by 1.7 percent, and architects and engineers by 1.3 percent (figure 4). In

[9] The dollar value is calculated using the pre-simulation baseline price levels.
[10] Construction services includes construction design, and therefore employ many architects and engineers, and managers.
[11] And a few knowledge-intensive goods, such as computer, electronic, and optical products.

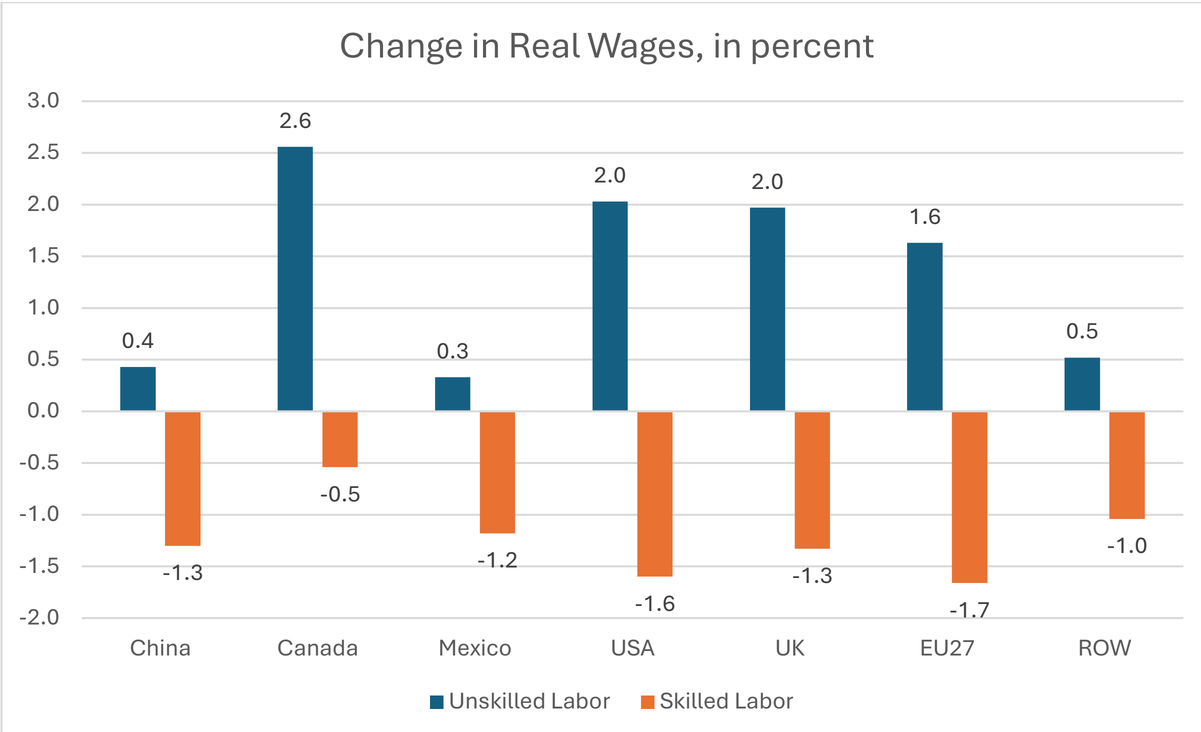
contrast, many low-skilled occupations—such as construction and extraction workers, protective services personnel, and installation and repair workers—see an increase in real wages since these roles face less impact from AI. Overall, the skill premium in the U.S. decreases by 3.6 percent.

Figure 4: Change in U.S. Real Wages, in percent, relative to the baseline, simulation 2



Regarding changes in real wages across various regions, all countries and regions experience a decrease in real wages for skilled labor and an increase in real wages for unskilled labor (Figure 5 below). Advanced economies such as Canada, the United States, the UK, and the EU27, which benefit from a larger generative AI-driven positive labor productivity shock compared to developing regions, see a greater rise in real wages for unskilled labor than emerging and developing economies like China and Mexico. The labor productivity improvements attributed to generative AI contribute to a reduction in skill premium globally; however, the magnitude of this decline is more pronounced in advanced economies than in emerging and developing economies. Skill premium in the United States, Canada, UK, the EU27 declines by 3.6 percent, 3.1 percent, 3.3 percent and 3.3 percent, respectively, while skill premium in China and Mexico declines by only 1.7 percent and 1.5 percent, respectively. A worldwide decrease in skill premium shows that wage gaps between skilled and unskilled labor within each individual country is shrinking. Nevertheless, because advanced economies are more exposed to AI, wages for unskilled workers rise faster there than in developing economies. This trend leads to a growing wage gap between advanced and developing economies (see figures 4 and 5).

Figure 5: Change in Real Wages Across Regions, in percent, relative to the baseline, simulation 2



Note: U.S. results are the weighted-average of changes in real wages of the 9 high-skilled occupations and 11 low-skilled occupations.

Change in Welfare, Real GDP, Real Household Income and Cross-Border Trade

With an AI-induced labor productivity gain globally, all countries and regions experience an increase in welfare and real GDP (see table 5 and 6). 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 6 below).[12] Meanwhile, advanced economies—including the United States, Canada, the UK, and EU27 countries—experience increases in real household income of 1.0 percent, 0.9 percent, 0.6 percent, and 0.2 percent, respectively. In contrast, emerging and developing economies see declines: real household income falls by 0.5 percent in Mexico and by 0.7 percent in China.

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[12] The country grouping is based on the IMF country classifications: https://www.imf.org/en/publications/weo/weo-database/2023/april/groups-and-aggregates (accessed April 9, 2026).

Table 5: Change in Welfare Across Regions

	Change in Welfare, in billion dollars
China	47.8
Canada	22.8
Mexico	3.2
USA	218.6
UK	28.3
EU27	132.8
ROW	113.2

Table 6: Change in Real GDP Across Regions

	Change in Real GDP, in percent	in billion dollars
China	0.4	58.2
Canada	1.2	20.9
Mexico	0.3	3.8
USA	1.0	211.1
UK	1.0	28.1
EU27	0.9	134.6
ROW	0.4	110.0

A global increase in labor productivity driven by AI reshapes international trade patterns. As indicated in Table 7 below, total exports from the United States and Canada decline by 0.7 percent and 0.9 percent, respectively, equivalent to $16.5 billion and $4.4 billion. In contrast, total exports from China, Mexico, EU27, the UK, and the Rest of the World increase, with China's exports experiencing the largest growth—a rise of 1.7 percent or $43.5 billion. Regarding imports, advanced economies demonstrate significantly higher percentage increases compared to developing countries. Total imports from the United States, Canada, the UK, and EU27 rise by 1.7 percent, 1.2 percent, 1.1 percent, and 0.8 percent, respectively, whereas developing countries experience only a slight increase—0.1 percent for Mexico—or even a decline of 0.1 percent for China (table 8). These differences primarily stem from greater real GDP growth and real income gains in advanced economies relative to developing countries, resulting in increased domestic demand and consumption in the former but not the latter.

Table 7: Change in Total Exports, by Country, in percent and in billion dollars

Region	in percent	in billion dollars
China	1.7	43.5
Canada	-0.9	-4.4
Mexico	0.9	4.5
USA	-0.7	-16.5
UK	0.4	3.3
EU27	0.6	38.3
Rest of the World	0.7	62.2

Table 8: Change in Total Imports, by Country, in percent and in billion dollars

Change in Total Imports	in percent	in billion dollars
China	-0.1	-2.4
Canada	1.2	6.5
Mexico	0.1	0.6
USA	1.7	51.4
UK	1.1	10.1
EU27	0.8	52.3
Rest of the World	0.2	12.4

Broadly, AI reduces wage gaps between unskilled and skilled labor within countries but increases wage gaps between countries. It reduces wage gaps within countries because AI reduces the demand for high-income labor and increases the relative demand for low-income labor. It increases wage gaps between countries since high-income countries have a comparative advantage in services, and this advantage increases with AI.

CONCLUSION

The results of this paper represent an experiment in which AI-induced productivity increases take place in isolation. The effects of future technologies on trade are more broad-reaching than those discussed here. Automation, for instance, tends to exhibit interaction effects with AI, as the use of AI can accelerate innovation in automation.

A phenomenon not captured in this paper is the possibility that some workers are able to personally capture the productivity gains from AI and increase their wages. This is especially true if those workers possess skills which are complementary to AI.[13] This

[13] Mäkelä and Stephany (2025), examining 12 million U.S. online job vacancies from 2018-2023, identify examples of both substitution and complementarity with AI across sectors, occupations and regions. Skills that are complementary with AI include resilience, agility, analytical capability, and ethics. These skills

relates to the fact that within the 22 occupations in our model, there are differences in tasks and skill levels. A chief accountant may use AI to enhance her ability to do deep analytics and experience higher wages, while a bookkeeper, whose tasks are more substitutable with AI, may experience downward pressure on wages. The enhanced GTAP model framework used in our paper also does not explicitly account for unemployment. It is widely observed that AI adoption in exposed occupations can cause short-term increases in unemployment. Our model assumes full employment and therefore channels all labor-market effects through wages. This simplification should not, however, materially affect our results on changes in international trade patterns. Our primary focus is on how productivity-driven labor cost savings reshape international trade across countries and sectors. These cost savings influence trade patterns in similar ways whether they appear as lower wages or reduced employment.

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command wage premia of 5-10%. Comparable results are obtained for the United Kingdom and Australia. Acemoglu et al. (2026) argue that pro-worker AI can increase the value of human skills and expertise by expanding human capabilities, suggesting that AI may complement certain types of work. Autor et al. (2025) develop a framework for analyzing the effects of task automation and show that technological innovation can automate the expert tasks of one job, making worker skills redundant, while automating routine tasks in another job, increasing the value of worker expertise by freeing workers to focus on higher value-added activities.

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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.