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

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Outline

- Background and Motivation
- Model Development: Labor Occupation Data and Capital-Skill Complementarity
- Calibration of AI-Induced Labor Productivity Shocks
- Simulation and Results

Background and Motivation

- There has been rapid development in generative AI in recent years, and the technology is increasingly being used across a wide range of occupations.

- Much of the existing literature on the impact of generative AI has focused on measuring AI exposure by occupation and on estimating how generative AI affects labor demand and labor productivity.

- To date there is little research about how generative AI diffusion alters cross-border trade patterns or shifts wage gaps within and between countries.

- This paper fills this gap using an **enhanced CGE GTAP model** with **22 U.S. occupations.**

Our Paper's Contributions

- expands GTAP model labor data, with a 2019 baseline, into 22 occupational groups using Demirkaya et al. (2025)
- incorporates capital–skill complementarity
- analyzes the effects of generative AI diffusion on global trade patterns and wage disparities within and between countries

Model Development: Incorporating labor occupation data into the GTAP model

- Standard GTAP has five labor categories
  - technicians/professionals
  - officials and managers
  - clerks
  - service workers
  - agricultural and other unskilled workers.

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- The labor extension of the GTAP model we developed has **22 occupations** grouped into two bundles according to wage levels.

Other assumptions:
- 2019 baseline;
- 7 regions: USA, Canada, Mexico, UK, EU27, China, Rest of the World (ROW);
- 65 sectors.

Two labor groupings 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	

Model development: incorporating capital-skill complementarity

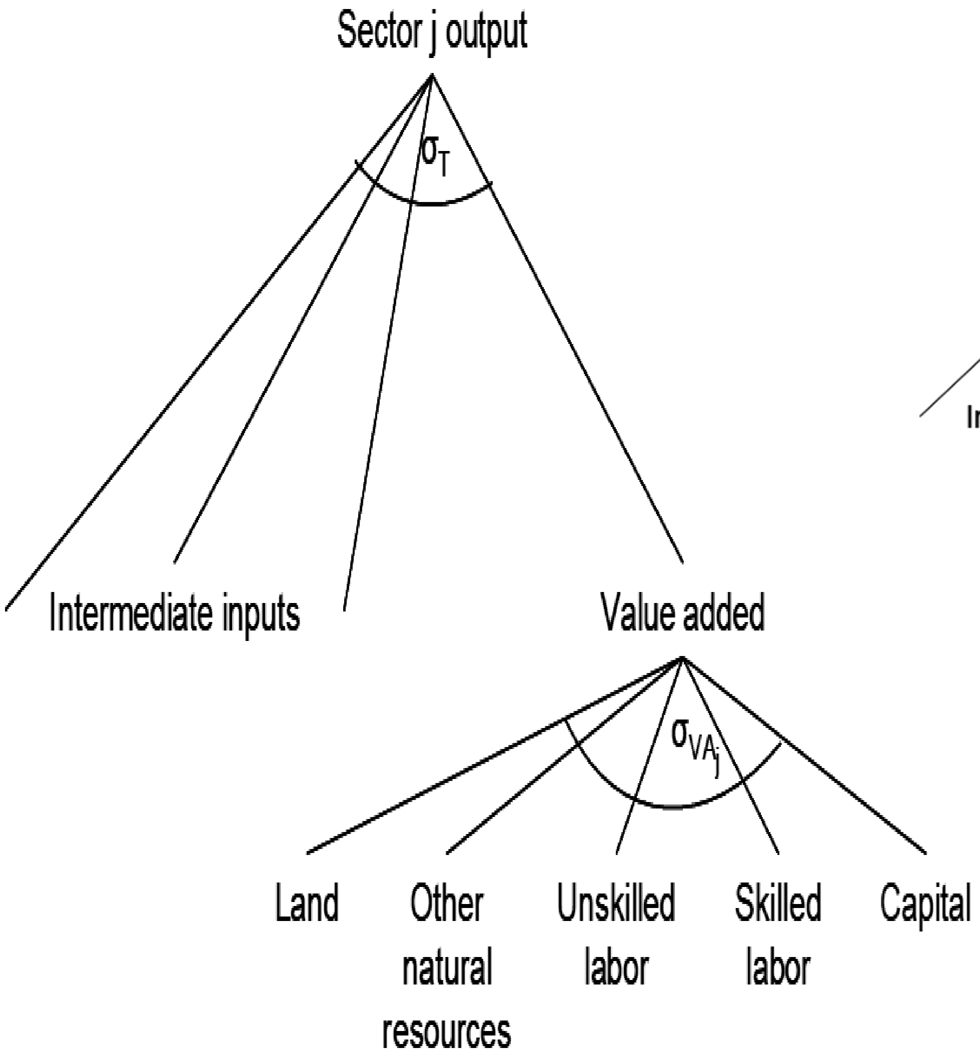
- The dramatic rise in the U.S. skill premium that began around the 1980s prompted scholars to investigate its underlying drivers.

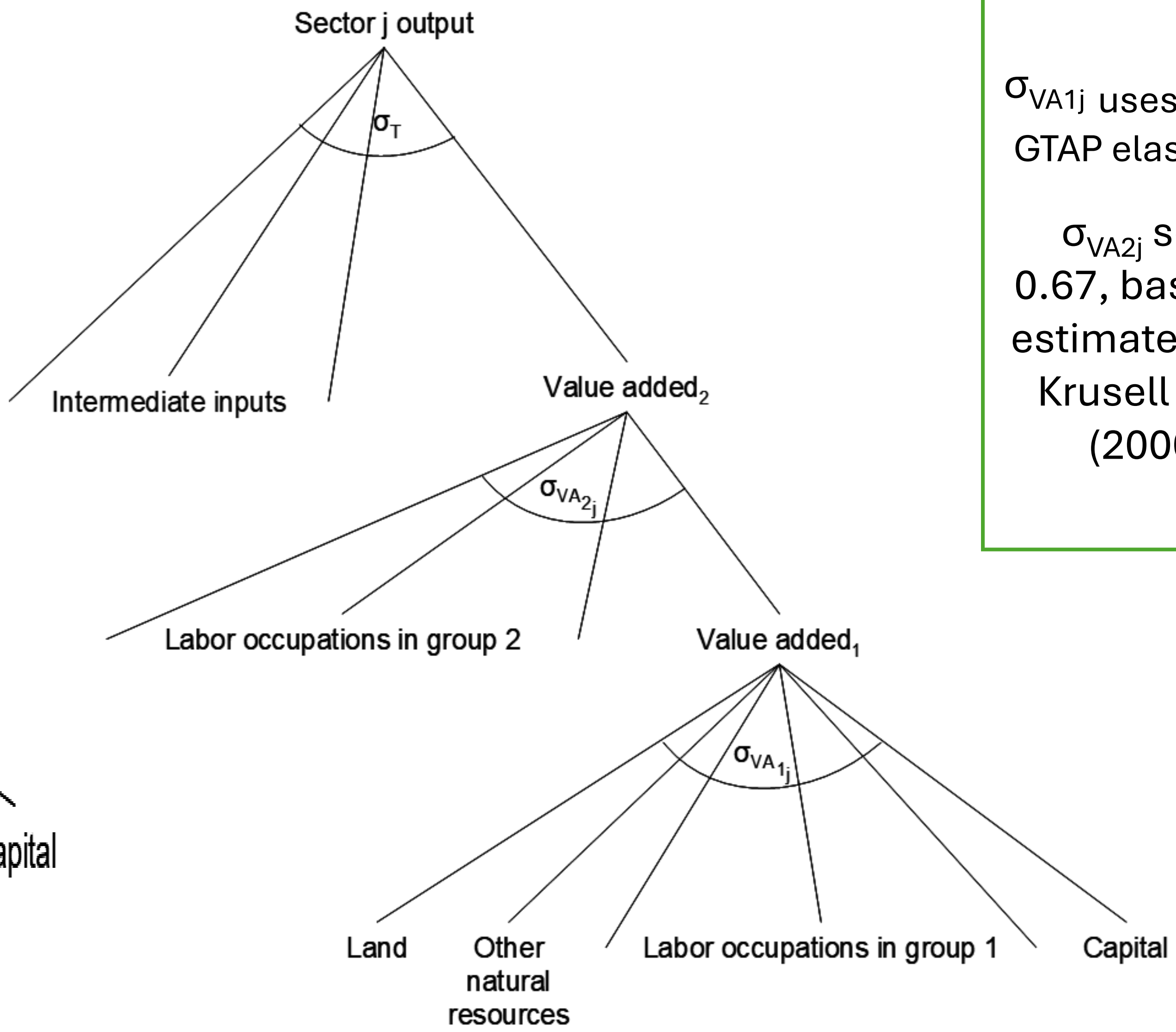
- Krusell et al. (2000), Maliar et al. (2022), and Ohanian et al. (2023) demonstrated empirically that **capital is less substitutable with skilled labor than with unskilled labor.** Consequently, the decline in the relative price of capital leads to an increase in the relative demand for skilled labor, driving up their wages.

- Dix Carneiro et al. (2023) incorporated this mechanism into their structural GE model with labor extensions, which includes two labor categories: unskilled and skilled labor.

- We change the production function and incorporate a similar mechanism in our enhanced version of the GTAP model.

Model development: Incorporating capital-skill complementarity





σ_{VA1j} uses default GTAP elasticities

σ_{VA2j} set at 0.67, based on estimates from Krusell et al. (2000).

Simulation

Global simulation using the enhanced GTAP model framework:

- Generative AI-induced labor productivity shocks to the 22 different occupations across the United States, and to skilled and unskilled labor in all other countries/regions.

Calibration of AI-Induced Labor Productivity Shocks

- Bick et al. (2025) estimate that generative AI raised average U.S. labor productivity **by 1.4 percent** across all workers.

- 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.
  - Ei denote the AI exposure score for occupation i
  - Si denote each occupation's employment share
  - The occupation-level labor productivity shock is gi = kEi (k is a scaling factor)
  - Employment weighted average of gi equals to the aggregate AI-driven labor productivity gain of 1.4 percent: ∑Si*gi=0.014
  - K=0.014/(∑Si*Ei)

AI Exposure Score and Occupation-Specific Labor Productivity Shock for the U.S.

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

Labor productivity shock implemented for the U.S. in the simulation

Calculate the generative AI-induced labor productivity shock to skilled and unskilled labor in other regions

Labor Productivity Shock implemented for other regions

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

- Generative AI boosts labor productivity **by 2.4 percent for skilled labor and by 1.0 percent for unskilled labor** in the United States

	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

Key takeaways from the Simulation

With an AI-induced global increase in labor productivity, **all countries and regions experience gains in welfare and real GDP.** The largest percentage increases in real GDP occur in advanced economies. **Although output rises everywhere, the pattern of growth differs across regions**: for example, China's largest output gains occur in highly tradable manufacturing sectors, whereas in the United States the biggest increases are in non-traded service sectors. These differing output patterns reshape international trade flows. The labor market impact on wages directly reflects the capital-skill complementarity mechanism implemented in our model.

With an AI-induced labor productivity gain globally, all countries and regions experience an increase in welfare and real GDP. The biggest gains in real GDP, in percentage change terms, are in advanced economies compared to emerging and developing economies.

Change in Welfare	**in billion dollars**
China	52.2
Canada	22.2
Mexico	3.5
USA	219.4
UK	28.0
EU27	132.5
ROW	116.6

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

A global increase in labor productivity driven by AI has varying output effects across regions. The sectors with the largest output increases in China are highly tradable manufacturing sectors, whereas in the U.S. the largest gains occur in non-traded service sectors.

Sectors with the Highest Output Increase in China	in percent	in billion dollars
Education	1.0	6.6
Computer, electronic, and optical products	0.9	8.7
Leather	0.9	1.7
Chemicals	0.9	8.3
Textiles	0.9	6.3
Fiber crops	0.8	0.5
Other Manufacturing	0.8	3.2
Air transport	0.8	0.9
Non-ferrous metal	0.7	4.9
Pharmaceuticals	0.7	5.6
Apparel	0.7	3.3
Rubber and Plastic	0.7	3.7
Electrical equipment	0.7	11.9

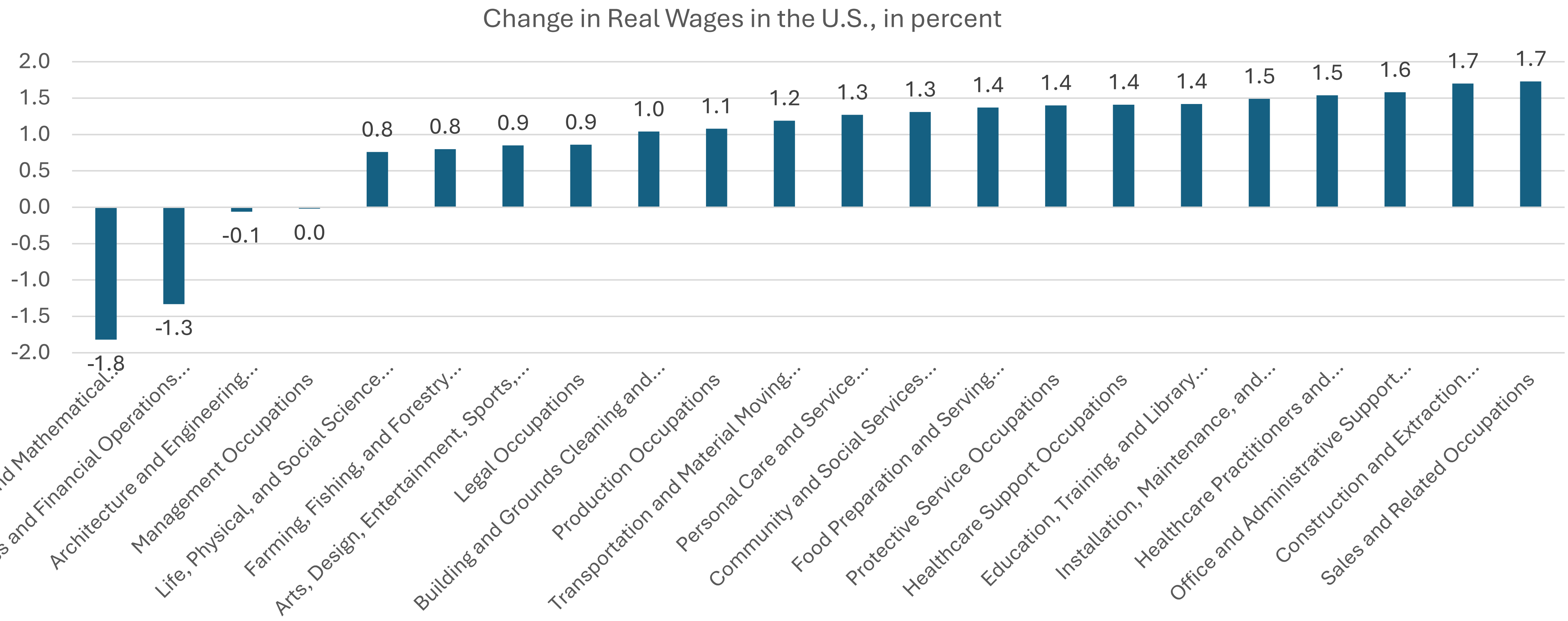
Sectors with the Highest Output Increase in the U.S.	In percent	In billion dollars
Computer, electronic, and optical products	2.0	8.7
Insurance	1.8	21.6
Apparel	1.8	0.4
Other financial services	1.6	24.3
Other services (Government)	1.5	31.3
Information and communication	1.4	20.8
Other transport Equipment	1.3	3.2
Construction Services	1.3	22.5
Other business services	1.3	64.0
Recreation	1.2	11.4
Wholesale and Retail	1.1	39.0

A global increase in labor productivity driven by AI reshapes international trade patterns -- Stronger real GDP growth in advanced economies boosts their domestic demand and consumption, resulting in a larger increase in imports compared to developing countries.

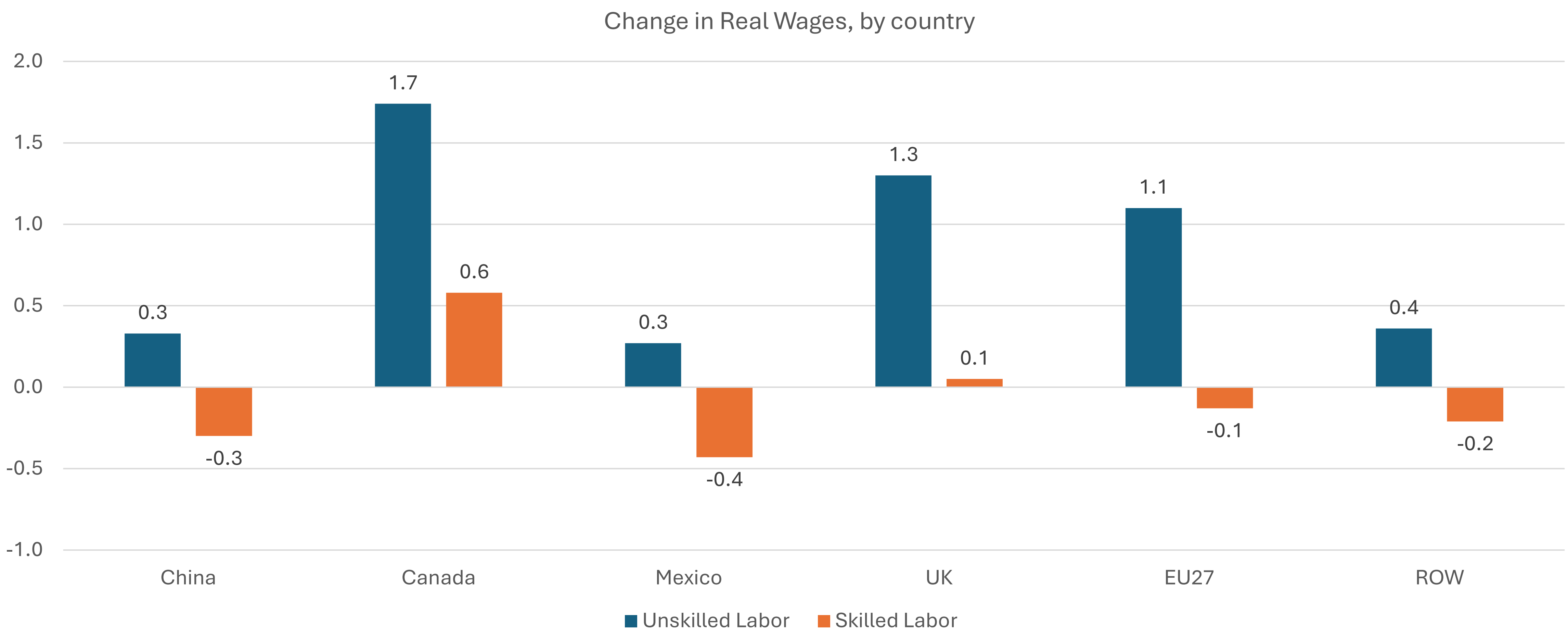
Change in Total Exports	in percent	in billion dollars
China	1.2	32.4
Canada	-0.2	-1.0
Mexico	0.7	3.3
USA	-0.1	-3.3
UK	0.6	4.7
EU27	0.7	46.7
ROW	0.6	49.4

Change in Total Imports	in percent	in billion dollars
China	0.1	2.0
Canada	1.2	6.3
Mexico	0.3	1.1
USA	1.4	41.0
UK	1.0	9.4
EU27	0.8	51.4
ROW	0.3	20.9

U.S. real wages rise for most occupations; however, they decline for a few high-skilled occupations with high AI exposure. This occurs because, as the price of capital increases, demand for skilled labor falls relative to unskilled labor under capital–skill complementarity. U.S. skill premium declines by 1.4 percent.



All countries experience an increase in real wages for unskilled labor, and either a smaller increase or a decline in real wages for skilled labor. This pattern reflects the capital–skill complementarity mechanism: as the price of capital rises, the demand for skilled labor falls relative to unskilled labor. Skill premium declines for all countries.



Future Work

1) Other papers use different methods to compare U.S. occupations by AI intensity.

   - Handa et al. (2025) analyze millions of Claude.ai conversations to identify AI usage patterns across the United States by occupation.

- One possible next step 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.

2) Within the 22 occupations in our enhanced GTAP model, there are differences in tasks and skill levels.

   - An experienced 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.

- Another possible next step, if micro-level data is available, is to take the simulated wage changes by occupation and conduct post-model calculations to examine how those wage effects differ for experienced workers versus entry-level workers within each of the 22 occupations.