Background Note for the 2026 World Development Report

The AI Exposure of Export-Linked Jobs

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Abstract

This paper studies the implications of artificial intelligence (AI) for export-linked jobs. Leveraging data from recent labor force surveys and input-output tables for 26 economies, we estimate comparative advantages across occupations, classified by their exposure to task augmentation and substitution through AI. We find that a larger share of export-linked jobs is at risk of AI substitution in economies with higher GDP per capita, reflecting export specializations in service sectors and more routine-cognitive tasks within goods-producing sectors. However, the substitution and augmentation of export-linked jobs are likely to coincide and to reinforce existing comparative advantages. Our findings suggest limited scope for employment growth in AI-exposed, export-linked jobs in most economies with lower GDP per capita.

Keywords: *Artificial intelligence, tasks, international trade, comparative advantage*

JEL codes: F14, F16, O14, O33

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1. Introduction

With the rise of global value chains (GVCs), countries trade "tasks" rather than finished goods or services (de Vries and Timmer 2025; Grossman and Rossi-Hansberg 2008). In GVCs, production is linked across multiple sectors and countries, with each stage involving distinct tasks performed by workers in different occupations and by machines. Instead of performing all tasks along an entire value chain—such as from research and development to fabrication and support services—countries specialize in particular tasks along GVCs that reflect the comparative advantage of their factor endowments. In other words, even if two countries are characterized by export specializations in the same sector, they often differ in the stage of the value chain they participate in, and thus in their task specialization. For example, in electronics, Mexico's strongest comparative advantage lies in fabrication, while the United States mostly specializes in managerial tasks (Timmer, Miroudot, and de Vries 2019).

How will generative artificial intelligence (AI) affect countries' comparative advantages and export-linked jobs? Existing studies suggest that AI's job implications largely differ across occupations (Bonfiglioli et al. 2025; Gmyrek, Viollaz, and Winkler 2026; Huang et al. 2026; Liu, Wang, and Yu 2026; World Bank 2025). In occupations that mostly comprise critical, interpersonal, and non-routine cognitive tasks—such as medical practitioners, judges, and CEOs—AI has the potential to augment human labor. In contrast, workers who predominantly perform routine-cognitive tasks—such as call center agents, translators, and programmers—are at higher risk of AI substitution. In business process outsourcing (BPO) services, for example, the diffusion of AI has led to a significant decline in job postings (World Bank 2026a).

Open-economy models on the impact of AI suggest the following mechanisms (Grover, Panigrahi, and Winkler 2026; Jakubik, Rotunno, and Saini 2025). Through labor substitution and augmentation, AI reduces the production costs for a given output bundle and raises productivity. The magnitude of this productivity effect increases with the level of AI exposure, which in turn depends on an economy's occupational composition and input-output linkages. An economy with a workforce that is specialized in non-routine manual tasks and with limited spillovers from lower-priced domestic or imported intermediate inputs has less potential to realize productivity and export gains from AI.

Since countries have different task specializations and input-output linkages, the effect of AI on export-linked jobs is likely to differ from one country to another. Against this background, this paper examines the following three research questions. *First*, given countries' current revealed task specialization, to what extent are export-linked jobs exposed to AI augmentation potential and AI substitution risk, and how does the level of exposure differ across countries? *Second*, how much does this AI exposure level vary across sectors? *Finally*, what are the implications of AI for countries' revealed comparative advantage and export-linked employment?

Leveraging data from recent labor force surveys and input-output tables for 26 economies, we estimate comparative advantages across occupations, classified by their exposure to task augmentation and substitution through AI. We find that a larger share of export-linked jobs is at risk of AI substitution in higher-income economies, reflecting export specializations in service sectors and more routine-cognitive tasks within goods-producing sectors. However, the substitution and augmentation of export-linked jobs are likely to coincide and to reinforce existing comparative advantages. Our findings suggest limited scope for employment growth in AI-exposed, export-linked jobs in lower-income economies.

These findings contribute to two emerging strands of literature. *First*, this paper relates to recent research on countries' trade specializations based on occupations/tasks rather than products or sectors. While earlier work has long conceptualized new specialization measures in internationally fragmented production (Baldwin and Robert-Nicoud 2014; Grossman and Rossi-Hansberg 2008; Lall 2000; Lee and Yi 2018), advances in the availability of internationally comparable input-output tables and data on employment by detailed occupations and sectors have only recently enabled empirical studies on global trade in tasks (Coveri, Giammetti, and Zanfei 2025; de Vries and Timmer 2025; Kruse et al. 2025; Timmer, Miroudot, and de Vries 2019). We are the first to apply this approach to study the implications of AI on export-linked jobs. *Second*, this paper also relates to the recent literature on the impacts of AI on services offshoring. While some studies find that AI can increase service offshoring to developing countries through productivity gains (Stapleton and O'Kane 2026), others find either insignificant (Bastos and Nayyar 2026) or negative displacement effects that reduce services offshoring to developing countries (Betai and Chen 2026; World Bank 2026a). While our findings generally align more closely with the latter studies, our framework rationalizes the heterogeneous effects found across studies.

The paper proceeds as follows. Section 2 outlines the methodology for identifying export-linked employment and estimating task specializations using revealed comparative advantages, followed by a discussion of the underlying data. Section 3 presents the empirical findings, while Section 4 offers some concluding remarks.

2. Empirical Methodology

In this section, we outline our empirical methodology. We first describe the measurement of export-linked jobs across detailed occupational groups, classified by their exposure to task augmentation and substitution through AI. This measure is then used to estimate countries' task specializations using revealed comparative advantages (RCAs). Lastly, we describe the data used in our analysis.

2.1. Identifying export-linked jobs

Exports create employment directly within the sector that produces the exported goods or services. They further create employment indirectly in other upstream sectors that provide intermediate inputs to the exporting sector. For example, the export of electronics creates jobs in the electronics

sector, as well as in business services firms that provide services to firms in the electronics sector. Here, the analysis follows the methodology of Kruse et al. (2025) and links trade, intersectoral linkages, and employment data to identify both direct and indirect export-linked employment.

More specifically, export-linked jobs in different sectors *i* and occupational groups *o*, $l_{i,O}$, are computed in an input-output analysis using the following equation:

$$l_{i,o} = \hat{c}\,(I - A^D)^{-1}e \tag{1}$$

where *e* denotes a country's export vector of dimensions ($i \times 1$) with each element representing exports of a specific sector. A^D is the domestic input coefficient matrix ($i \times i$) and I the identity matrix ($i \times i$), such that $(I - A^D)^{-1}$ is the Leontief inverse, and $\hat{c}$ denotes a diagonal matrix ($i \times i$) with domestic employment over output coefficients. The Leontief inverse ensures that both direct and indirect export-linked employment are included.

2.2. Estimating task specializations

After identifying export-linked jobs, we estimate countries' revealed comparative advantages (RCAs). As introduced in Balassa (1965), RCAs measure the ratio of a country's gross export shares across sectors or products relative to the global average, with values above 1 indicating export specializations. Here, we move beyond the standard measure in two aspects. *First*, we calculate RCAs based on export-linked jobs $l_{i,o}$, instead of gross export values or income. *Second*, we calculate RCAs across occupation-sector pairs, which have been described as a measure of countries' "functional specialization" (Timmer, Miroudot, and de Vries 2019) or "task specialization" (Kruse et al. 2025) in trade. Therefore, we calculate the following equation:

$$RCA_{c,i,o} = \frac{\left(l_{c,i,o} \Big/ \sum_i \sum_{\boldsymbol{o}} l_{c,i,o}\right)}{\sum_c l_{c,i,o} \Big/ \sum_c \sum_i \sum_o l_{c,i,o}} \tag{2}$$

where $RCA_{c,i,o}$ captures the degree of task specialization through revealed comparative advantages in export-linked jobs in country *c*, sector *i*, and occupation *o*.

2.3. Data

Identifying export-related jobs and estimating task specializations by AI exposure requires detailed employment data and input-output tables. We draw employment data from recent labor force surveys, harmonized by the World Bank and the International Labour Organization (ILO). Data on intersectoral linkages, gross output, and exports are from the Asian Development Bank (ADB) Multiregional Input-Output Tables and the Groningen Growth and Development Centre (GGDC) Africa Supply and Use Tables. Recent data from all these sources is available for 26 economies across the entire income spectrum. Annex Table 1 provides additional details on specific data

sources used for each country. All sectoral data are mapped into a consistent set of 20 sectors (see Annex Table 2).

To overlap export-linked jobs and AI exposure, we follow Gmyrek, Viollaz, and Winkler (2026) and apply AI exposure scores from Gmyrek et al. (2025) to 4-digit ISCO occupations, with gradients 1 and 2 indicating "jobs with augmentation potential" and gradients 3 and 4 indicating "jobs at risk of AI substitution." The AI exposure scores from Gmyrek et al. (2025) assess the perceived technical feasibility of automating tasks with generative AI tools across detailed occupations. The scores are highly aligned with existing exposure scores, such as those from Felten et al. (2021, 2023) and Eloundou et al. (2024), and provide the first reliable link to internationally comparable labor force statistics across countries.[1]

3. Empirical results

3.1. Export-linked jobs at risk of AI substitution

Figure 1 shows the share of export-linked jobs at risk of AI substitution across countries.[2] First, there is a large variation across countries, ranging from 1.3 percent of aggregate export-linked jobs at risk of AI substitution in Pakistan to 17.4 percent in Switzerland (Figure 1A). Second, the quadratic polynomial fit shows that a larger share of export-linked jobs is at risk of AI substitution in higher-income countries than in lower-income countries. Notable outliers at their respective income levels are India, which exceeds the trend line by about one-half, and the United Arab Emirates, with less than half the expected share, resulting in an AI substitution risk for between 5 and 6 percent of export-linked jobs in both economies, despite large differences in GDP per capita.[3]

The risk of AI substitution is lower for workers with export-linked jobs in goods-producing sectors (Figure 1B). For all countries in our sample with GDP per capita below US$10,000, including India, less than 2 percent of export-linked workers are at risk of AI substitution in goods-producing sectors. In contrast, workers are more likely to be replaced by AI in service sectors in all countries (Figure 1C). The higher but flatter trend line indicates the larger sectoral difference among workers in countries with lower income, who are more than twice as likely to be replaced in service sectors than goods-producing sectors. This difference is particularly prominent in South Asian economies (Figure 1D).

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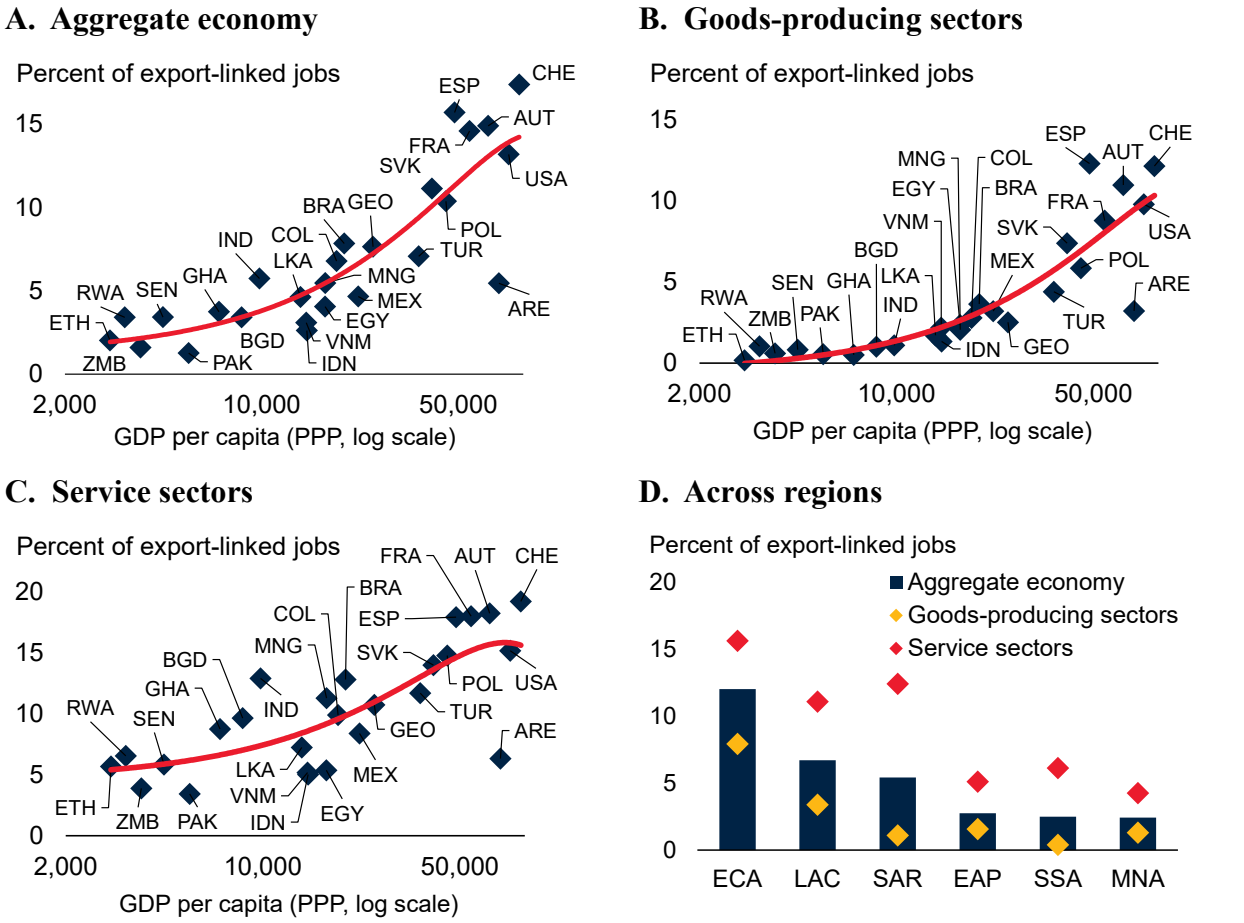
[1] See World Bank (2026b) for a discussion of the existing AI exposure measures.

[2] To highlight countries' specializations within exports, the discussion focuses on AI exposure shares in percent of total export-linked employment. Despite higher-income countries' larger average export shares in GDP, our previous cross-country findings remain robust if we express the share of export-linked jobs in percent of total employment, though, of course, at a lower overall level (Annex Figure 1). Export-linked jobs at risk of AI substitution account for less than 7 percent of total employment across all sample economies, with larger reductions among regions that are relatively closed to international trade, such as South Asia and Sub-Saharan Africa.

[3] For India, the upward deviation is linked to its export specialization in business services, which accounted for about 30 percent of total exports in 2024. For the United Arab Emirates, in contrast, the downward deviation is related to its export specialization in mineral fuels and strong indirect employment linkages to the construction sector, which accounted for about 17 percent of total employment in 2023.

Figure 1. Share of export-linked jobs at risk of AI substitution



Sources: ADB Multiregional Input-Output Tables (database); Africa Supply and Use Tables (database); Global Labor Database; International Labour Organization; World Development Indicators (database); World Bank.

Note: EAP = East Asia and the Pacific; ECA = Europe and Central Asia; LAC = Latin America and the Caribbean; MNA = Middle East, North Africa, Afghanistan, and Pakistan; SAR = South Asia; SSA = Sub-Saharan Africa. For country abbreviations, see International Organization for Standardization (ISO). "Export-linked jobs" represent employment that is directly or indirectly linked to the production of exports and is calculated in an input-output analysis following the methodology of Kruse et al. (2025). AI exposure scores from Gmyrek, Viollaz, and Winkler (2026) are applied to 4-digit ISCO occupations, with gradients 3 and 4 indicating "jobs at risk of AI substitution". Broad sectors are disaggregated following ISIC, revision 4, with "Goods-producing sectors" comprising sections A to F (i.e., agriculture, mining, manufacturing, utilities, and construction) and "service sectors" comprising all other divisions. "Aggregate economy" refers to the sum across all sectors.

A.-C. Red line indicates the quadratic polynomial fit on the underlying data.

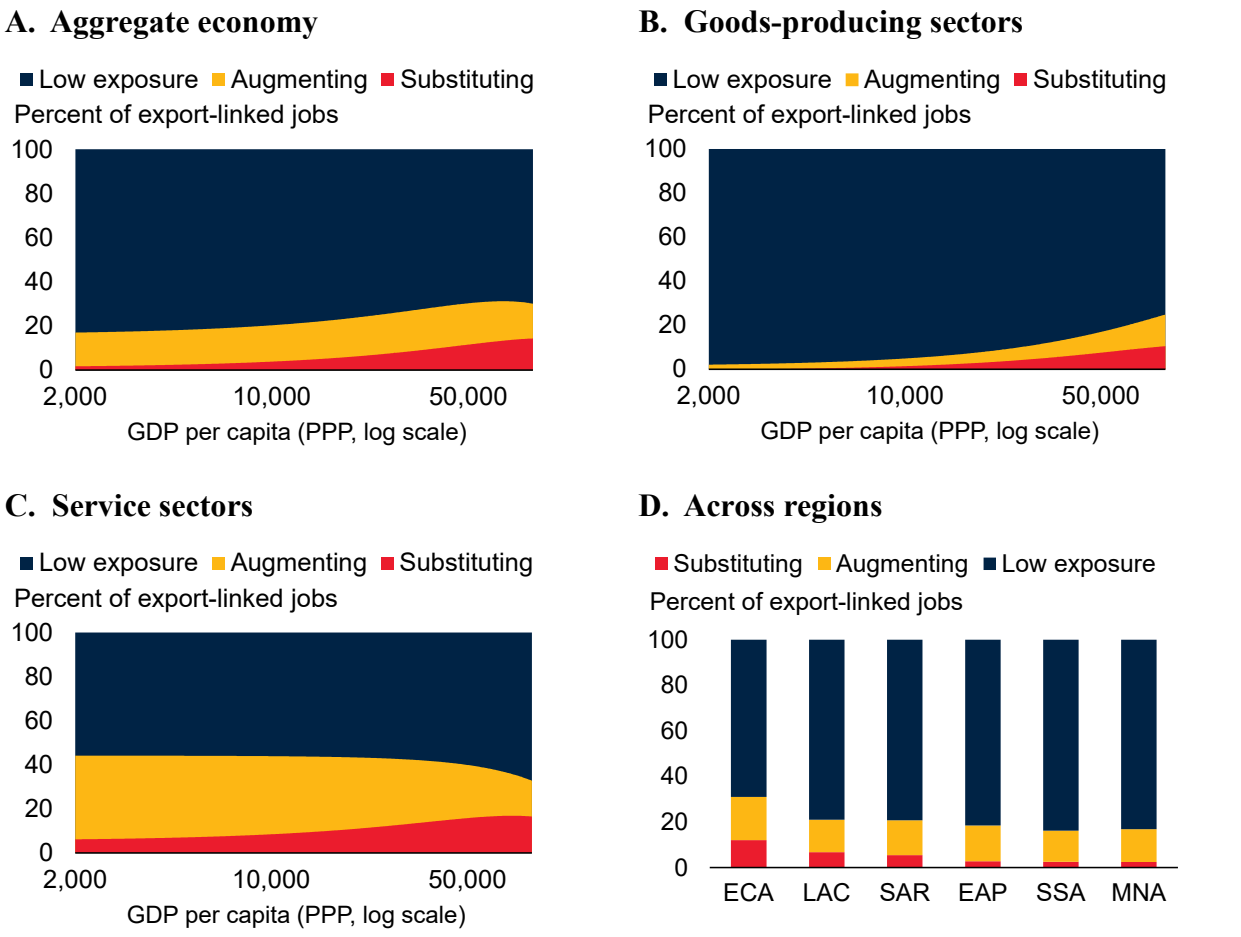
D. Regional aggregates refer to employment-weighted averages.

3.2. Export-linked jobs by AI exposure type

Figure 2 shows the composition of export-linked jobs by AI exposure types over countries' GDP per capita levels. The red area represents jobs at risk of AI substitution (as captured in Figure 1), and the yellow area shows jobs with AI augmentation potential. The results suggest that most workers in export-linked jobs are not (or only partially) exposed to AI, and thus neither at risk of

AI substitution nor likely to leverage AI to boost their productivity. Across countries at all levels of GDP per capita and regions, export-linked jobs with AI augmentation potential account for a relatively constant share of about 15 percent of all export-linked jobs (Figure 2A, D).

Figure 2. Export-linked jobs by AI exposure type



Sources: ADB Multiregional Input-Output Tables (database); Africa Supply and Use Tables (database); Global Labor Database; International Labour Organization; World Development Indicators (database); World Bank.

Note: EAP = East Asia and the Pacific; ECA = Europe and Central Asia; LAC = Latin America and the Caribbean; MNA = Middle East, North Africa, Afghanistan, and Pakistan; SAR = South Asia; SSA = Sub-Saharan Africa. "Export-linked jobs" represent employment that is directly or indirectly linked to the production of exports and is calculated in an input-output analysis following the methodology of Kruse et al. (2025). AI exposure scores from Gmyrek, Viollaz, and Winkler (2026) are applied to 4-digit ISCO occupations, with gradients 1 and 2 indicating "jobs with augmentation potential" and gradients 3 and 4 indicating "jobs at risk of AI substitution". Broad sectors are disaggregated following ISIC, revision 4, with "Goods-producing sectors" comprising sections A to F (i.e., agriculture, mining, manufacturing, utilities, and construction) and "service sectors" comprising all other divisions. "Aggregate economy" refers to the sum across all sectors.

A.-C. Outlines of the three AI exposure areas indicate the quadratic polynomial fit on the underlying data.

D. Regional aggregates refer to employment-weighted averages.

The relatively stable share of export-linked jobs with AI augmentation potential masks a striking sectoral difference. Despite lower overall levels, the AI augmentation potential of export-linked jobs in goods-producing sectors increases with GDP per capita (Figure 2B). This is consistent with the introductory example of higher-income countries upgrading the tasks they perform in manufacturing value chains (Timmer, Miroudot, and de Vries 2019). In contrast, the AI augmentation potential of export-linked jobs in service sectors is lower at higher levels of GDP per capita (Figure 2C). This pattern is consistent with advanced stages of automation in higher-income countries, where services are increasingly dominated by manual, non-routine jobs, such as mechanics and machine operators in the transportation and storage sector. The larger risk of AI substitution in more advanced economies, therefore, reflects export specializations in sectors and occupations that are more AI-exposed.

3.3. AI exposure of export-linked jobs by sector

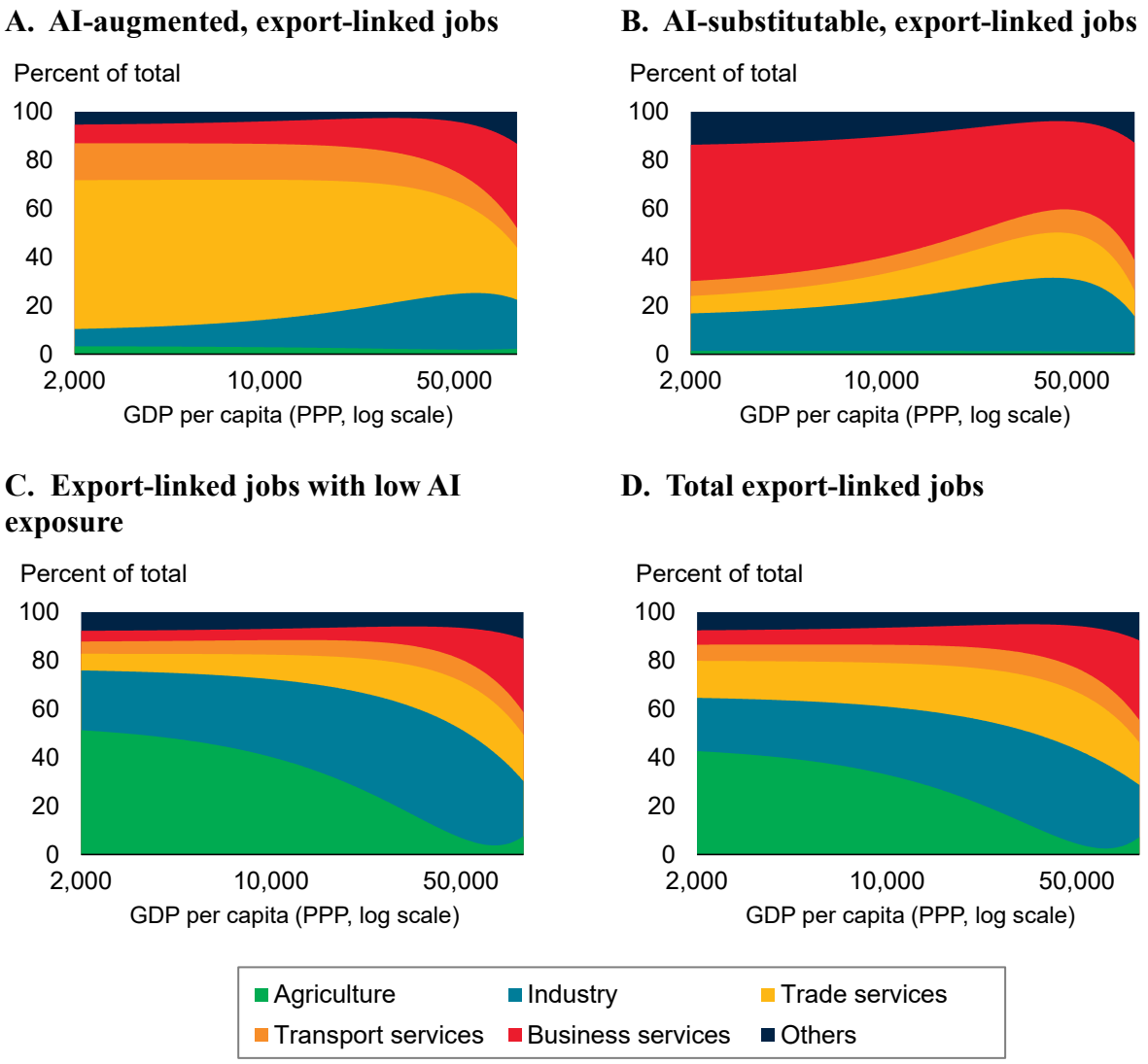
Are the export-linked jobs that are exposed to AI concentrated in the same sectors across countries? Figure 3 compares the sectoral composition of export-linked jobs across AI exposure types at different levels of GDP per capita. To gain a deeper understanding of countries' sectoral specializations within goods and services, it provides more disaggregated employment shares across six sectors.

Most export-linked jobs with AI augmentation potential in lower-income economies are in trade services, comprising wholesale and retail trade as well as hotel and restaurant services (Figure 3A). For example, a shopkeeper can use AI for budgeting and advise on product ranges, prices, deliveries, and warranties. But a shopkeeper also performs manual and non-routine tasks, such as stacking and displaying goods for sale or examining returned goods.[4] More than half of AI-augmented jobs are in trade services at GDP per capita levels below US$25,000. Yet, its share declines toward higher income levels. At a GDP per capita of around US$60,000, jobs in industry and business services respectively account for more than one-fifth of AI-augmented jobs. For example, industry in advanced economies employs electrical engineers, who can use AI for initial designs and calculating material requirements, but require significant human expertise and physical presence to ensure correct installation and troubleshooting on-site.

The business service sector employs the largest share of export-linked workers at risk of AI substitution across all income levels, from more than half at GDP per capita levels below US$10,000 to around 40 percent in higher-income countries (Figure 3B). Across all income levels, business services employ clerical support workers, who predominantly perform routine-cognitive tasks, such as transferring data between different computer programs, transcribing information, or proofreading and correcting manuscripts. These jobs are at risk of AI substitution across all countries. In contrast to AI-augmented jobs, a larger share of AI-substitutable export-linked jobs is in trade services at higher income levels. These, for example, relate to tasks, such as updating marketing databases or advising customers on product use.

[4] Examples are from the AI exposure codebook of tasks by occupation from Gmyrek, Viollaz, and Winkler (2026).

Figure 3. Sectoral shares of export-linked jobs by AI exposure type



Sources: ADB Multiregional Input-Output Tables (database); Africa Supply and Use Tables (database); Global Labor Database; International Labour Organization; World Development Indicators (database); World Bank.

Note: "Export-linked jobs" represent employment that is directly or indirectly linked to the production of exports and is calculated in an input-output analysis following the methodology of Kruse et al. (2025). AI exposure scores from Gmyrek, Viollaz, and Winkler (2026) are applied to 4-digit ISCO occupations, with gradients 1 and 2 indicating "jobs with augmentation potential" and gradients 3 and 4 indicating "jobs at risk of AI substitution". sectors are disaggregated following ISIC, revision 4, with "Agriculture" comprising section A; "Industry" comprising sections B to F; "Trade services" comprising sections G and I; "Transport services" comprising section I; "Business services" comprising sections J to N; and "Others" comprising sections O to U. Outlines of the six sectoral areas indicate the quadratic polynomial fit on the underlying data.

Among lower-income countries, the largest share of export-linked jobs with low overall exposure to AI is in agriculture (Figure 3C). Yet, amid structural transformation, that share is declining with rising GDP per capita levels, and above US$14,000 industry accounts for a larger share of export-linked jobs with low AI exposure. Both goods-producing sectors (agriculture and

industry)—in line with Figure 2B—employ a larger share of workers performing manual tasks, especially in lower-income countries. More than half of export-linked jobs with low AI exposure are in service sectors at GDP per capita levels above US$53,000. For example, such business services employ physical and engineering science technicians, who collect samples and prepare materials and equipment for experiments, tests, and analyses for a specialized laboratory. Consistent with most export-linked jobs having a low overall exposure to AI augmentation or substitution (Figure 2D), the sectoral patterns for this group are closest to the aggregate sectoral distribution of export-linked jobs (Figure 3D).

3.4. AI exposure and revealed comparative advantages

How are countries' trade specializations affected by the diffusion of AI? Table 1 presents the revealed comparative advantages (RCAs) calculated based on export-linked jobs and their AI exposure across four quadrants.[5] Upper quadrants indicate countries with export specializations in tasks that are at risk of AI substitution, that is, countries with a higher share of AI-substitutable export-linked jobs than the employment-weighted average observed in our sample. Right-hand side quadrants show countries with export specializations in AI-augmented tasks. Per definition, countries that have a task specialization with low exposure to AI are reported in the lower-left quadrant.

Open-economy models suggest that gains in productivity and comparative advantage increase in the overall level of AI exposure (Grover, Panigrahi, and Winkler 2026; Jakubik, Rotunno, and Saini 2025). The implications of AI for export-linked jobs therefore depend on the interaction between augmentation potential and substitution risks. In the short run, AI substitution negatively impacts employment, whereas high relative exposure to AI augmentation implies employment gains from increased productivity and improved comparative advantage. AI substitution itself also implies increased export productivity[6], yet without a comparable employment expansion. Annex Figure 3 provides a stylized summary of the net effects implied for productivity and employment. Export productivity and comparative advantage are likely to improve most in the upper-right quadrant, least in the lower-left quadrant, and at a medium level in the two off-diagonal quadrants. Consequently, the net impact on export-linked employment is likely to be most strongly negative in the upper-left quadrant, and most likely to be positive in the lower-right quadrant, while countries in the diagonal quadrants are likely to see a more modest employment impact from AI.

Panel A of Table 1 shows task specializations across all export-linked jobs. Most countries that fall into the upper-right quadrant, with the likely most significant improvements in comparative advantage but modest job displacement due to AI, are higher-income countries. The countries with the lowest GDP per capita levels within this group are Brazil and Colombia. The sum of RCAs in AI-augmented and AI-substitutable tasks is largest for Switzerland, Spain, and France within our sample.

[5] Table 1 is a parsimonious summary of these revealed comparative advantages for the purpose of comparing country groups. Annex Figure 2 also documents variation across countries within each quadrant.

[6] AI substitution does not imply an increase in individual workers' productivity, which is limited to AI augmentation. But it improves broader measures of sectoral productivity, such as export income or value added per worker.

Most countries that fall into the lower-left quadrant, with the likely weakest productivity boost from AI but also only modest job displacement[7], are "early industrializers". These economies have above-average shares of export-linked employment in either agriculture, such as Ethiopia and Zambia, or industry, such as Bangladesh, Mexico, and Viet Nam. Most countries that fall into the lower-right quadrant, which are most likely to see a positive employment impact amid a moderate export expansion, are "early de-industrializers".[8] These economies are characterized by low shares of export-linked employment in industry and predominantly shifted from agriculture directly into services, with many workers in trade services, such as hotels and restaurants, as well as wholesale and retail. Austria, the only economy that falls into the upper-left quadrant, is—among the countries within our sample—likely to experience the strongest negative impact on export-linked employment.

Table 1. Revealed comparative advantages by the AI exposure of export-linked jobs

A. Task specialization in exports: **All sectors**		*AI-augmented jobs*	
		RCA < 1	RCA > 1
AI-substitutable jobs	RCA > 1	AUT	BRA, CHE, COL, ESP, FRA, GEO, POL, SVK, TUR, USA
	RCA < 1	BGD, ETH, IND, MEX, MNG, PAK, RWA, VNM, ZMB	ARE, EGY, GHA, IDN, LKA, SEN

B. Task specialization in exports: **Business services**		*AI-augmented jobs*	
		RCA < 1	RCA > 1
AI-substitutable jobs	RCA > 1	IND	AUT, BRA, CHE, COL, ESP, FRA, POL, SVK, USA
	RCA < 1	EGY, ETH, IDN, GEO, GHA, MEX, MNG, PAK, RWA, SEN, TUR, VNM, ZMB	ARE, BGD, LKA

Sources: ADB Multiregional Input-Output Tables (database); Africa Supply and Use Tables (database); Global Labor Database; International Labour Organization; World Development Indicators (database); World Bank.
Note: RCA = "Revealed comparative advantage", as introduced in Balassa (1965), with two modifications: (1) based on export-linked jobs, not export value or income; (2) across occupation-sector pairs. Values above 1 indicate countries' export specializations. For country abbreviations, see International Organization for Standardization (ISO). AI exposure classification from Gmyrek, Viollaz, and Winkler (2026), with "AI-augmented jobs" comprising exposure gradients 1 and 2 and "AI-substitutable jobs" comprising exposure gradients 3 and 4. Refer to annex figure 2 for the full scatter plot and to annex table 2 for the sectoral definition of "business services".

[7] Per definition, countries in the lower-left quadrant are likely to also experience a strengthening in their current export specialization in tasks with low AI exposure. Yet, this does not necessarily imply a positive employment impact, given the lack of productivity improvements from AI.

[8] In reference to what Rodrik (2016) describes more comprehensively as "premature deindustrialization".

The concentration of countries in the top-right and bottom-left quadrants suggests that the substitution and augmentation of export-linked jobs through AI are likely to coincide and reinforce existing comparative advantages. Differences in countries' task specializations between panels A and B of Table 1 document that AI exposure can differ substantially across sectors. India, for example, is characterized by a relatively low level of AI exposure to its export-linked jobs in the aggregate economy, due to a large share of employment in agriculture. Yet, a relatively large share of its export-linked jobs in the business services sector is at risk of AI substitution. In other words, India has specialized in exporting business services that can be automated by AI, implying negative within-sector, but only moderate aggregate, employment impacts, while exports might continue to grow (World Bank 2026a).

4. Concluding remarks

This paper seeks to add insight into the implications of AI for countries' comparative advantages and export-linked jobs. It leverages data from recent labor force surveys and input-output tables for 26 economies to estimate comparative advantages in tasks, classified by their exposure to AI-driven augmentation and substitution. While most export-linked jobs across countries are not (or only partially) exposed to AI, and thus not at risk of AI substitution or likely to experience productivity gains from AI, we find that a larger share of export-linked jobs is at risk of AI substitution in higher-income economies. Yet, the substitution and augmentation of export-linked jobs are likely to coincide and to reinforce existing comparative advantages. Our findings suggest limited scope for employment growth in AI-exposed, export-linked jobs in most lower-income economies.

The analysis of this paper represents a simple empirical exploration. It uses a common input-output framework to link exports, intersectoral linkages, and employment data to identify both direct and indirect export-linked employment. It then maps these jobs into three common AI exposure groups and compares their shares across countries using revealed comparative advantages. Our analysis provides a static, short-term snapshot of the potential AI exposure in export-linked jobs, and, thus, our discussion of these results should not be viewed as causal interpretations. Furthermore, we do not present the mechanisms of our discussion in a general equilibrium model. Both the causal identification of productivity and employment effects as well as analyzing the implications of AI in an open-economy Roy model with input-output linkages and workers sorting across occupations and sectors (as in Lee and Yi 2018) are promising avenues for future research.

One early result emerging from employing open-economy models to AI shocks is an important role of international spillovers (Grover, Panigrahi, and Winkler 2026; Jakubik, Rotunno, and Saini 2025). Countries with strong backward linkages gain from foreign productivity increases through lower prices on imported intermediate inputs, especially if main trade partners are strongly exposed to AI diffusion. In a future edition of this paper, we aim to incorporate this "supply-chain exposure" channel by adding foreign employment embodied in exports into our measure for overall AI exposure.

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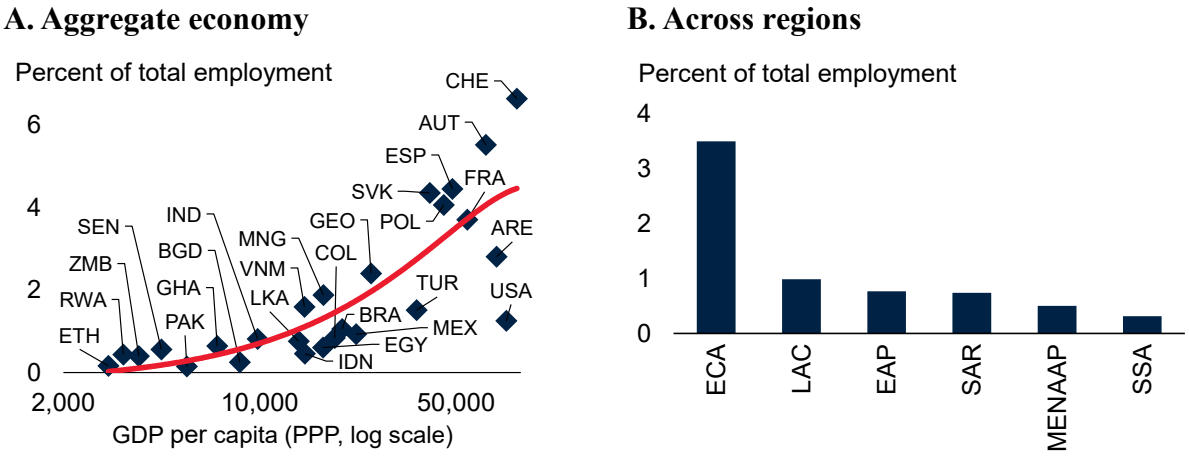
Annex Figure 1. Share of export-linked jobs at risk of AI substitution



Sources: ADB Multiregional Input-Output Tables (database); Africa Supply and Use Tables (database); Global Labor Database; International Labour Organization; World Development Indicators (database); World Bank.

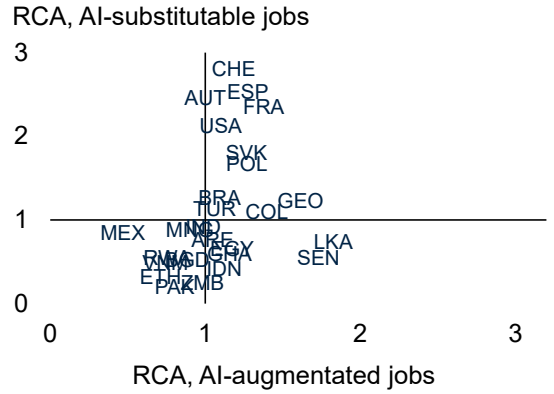
Note: EAP = East Asia and the Pacific; ECA = Europe and Central Asia; LAC = Latin America and the Caribbean; MENAAP = Middle East, North Africa, Afghanistan, and Pakistan; SAR = South Asia; SSA = Sub-Saharan Africa. For country abbreviations, see International Organization for Standardization (ISO). "Export-linked jobs" represent employment that is directly or indirectly linked to the production of exports and is calculated in an input-output analysis following the methodology of Kruse et al. (2025). AI exposure scores from Gmyrek, Viollaz, and Winkler (2026) are applied to 4-digit ISCO occupations, with gradients 3 and 4 indicating "jobs at risk of AI substitution". Broad sectors are disaggregated following ISIC, revision 4, with "Goods-producing sectors" comprising sections A to F (i.e., agriculture, mining, manufacturing, utilities, and construction) and "service sectors" comprising all other divisions. "Aggregate economy" refers to the sum across all sectors.

A. Red line indicates the quadratic polynomial fit on the underlying data.

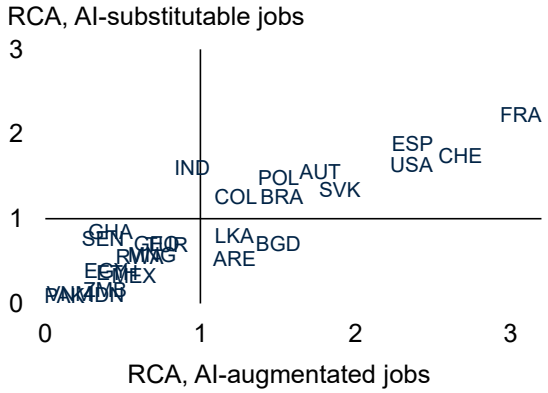
B. Regional aggregates refer to employment-weighted averages.

Annex Figure 2. Task specializations by the AI exposure of export-linked jobs

A. Aggregate economy



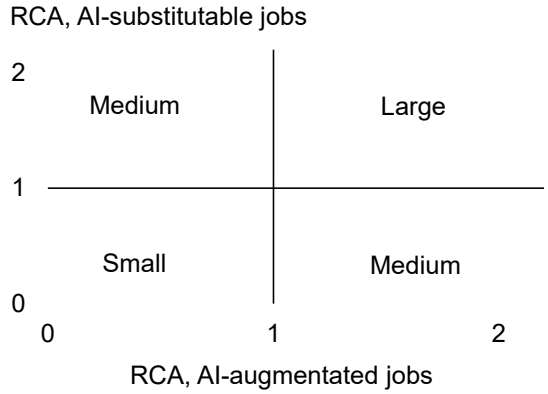
B. Business services



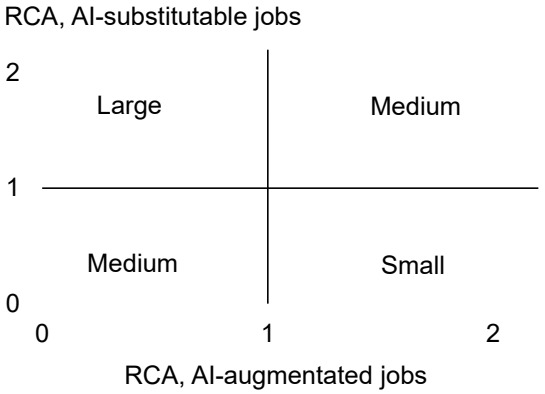
Sources: ADB Multiregional Input-Output Tables (database); Africa Supply and Use Tables (database); Global Labor Database; International Labour Organization; World Development Indicators (database); World Bank.
Note: RCA = "Revealed comparative advantage", as introduced in Balassa (1965), with two modifications: (1) based on export-linked jobs, not export value or income; (2) across occupation-sector pairs. Values above 1 indicate countries' export specializations. For country abbreviations, see International Organization for Standardization (ISO). AI exposure classification from Gmyrek, Viollaz, and Winkler (2026), with "AI-augmented jobs" comprising exposure gradients 1 and 2 and "AI-substitutable jobs" comprising exposure gradients 3 and 4. Refer to annex table 2 for sectoral definition of "business services".

Annex Figure 3. AI impacts across the task space of export-linked jobs

A. Productivity gains



B. Net employment impact



Note: Authors' stylized summary of the net effects of AI on productivity and employment across countries with different export specializations, based on the discussion in section 3.4.

Annex table 1. List of countries and data sources

Code	*Country*	*Employment*	*Input-Output Table*
ARE	United Arab Emirates	2023 Labor Force Survey	2024 ADB MRIOT
AUT	Austria	2024 Labor Force Survey	2024 ADB MRIOT
BGD	Bangladesh	2022, 2024 Labor Force Surveys	2024 ADB MRIOT
BRA	Brazil	2022 PNADC	2024 ADB MRIOT
CHE	Switzerland	2023 Labor Force Survey	2024 ADB MRIOT
COL	Colombia	2024 GEIH	2024 ADB MRIOT
EGY	Egypt, Arab Rep.	2024 Labor Force Survey	2024 ADB MRIOT
ESP	Spain	2023 PIAAC	2024 ADB MRIOT
ETH	Ethiopia	2021 Labor Force Survey	2019 GGDC ASUT
FRA	France	2023 PIAAC	2024 ADB MRIOT
GEO	Georgia	2023 Labor Force Survey	2024 ADB MRIOT
GHA	Ghana	2024 AHIES	2019 GGDC ASUT
IDN	Indonesia	2023 Labor Force Survey	2024 ADB MRIOT
IND	India	2022 Labor Force Survey	2024 ADB MRIOT
LKA	Sri Lanka	2021, 2023 Labor Force Surveys	2024 ADB MRIOT
MEX	Mexico	2023, 2025 Labor Force Surveys	2024 ADB MRIOT
MNG	Mongolia	2022 Labor Force Survey	2024 ADB MRIOT
PAK	Pakistan	2021 Labor Force Survey	2024 ADB MRIOT
POL	Poland	2023 PIAAC	2024 ADB MRIOT
RWA	Rwanda	2021, 2024 Labor Force Surveys	2019 GGDC ASUT
SEN	Senegal	2021 WAEMU	2019 GGDC ASUT
SVK	Slovak Republic	2023 PIAAC	2024 ADB MRIOT
TUR	Türkiye	2019 Labor Force Survey	2024 ADB MRIOT
USA	United States	2019 PIAAC, 2024 CPS	2024 ADB MRIOT
VNM	Viet Nam	2024 Labor Force Survey	2024 ADB MRIOT
ZMB	Zambia	2022 Labor Force Survey	2019 GGDC ASUT

Note: For countries with two years in the "Employment" column, the earlier year indicates the source for within-industry occupation shares from Gmyrek, Viollaz, and Winkler (2026), while the more recent years indicates the source for industry employment levels from the ILO.

Annex table 2. List of sectors

Sector	*ISIC 4, rev. 4*	*Description*
1	01–03	Agriculture, forestry and fishing
2	05–09	Mining and quarrying
3	10–12	Manufacture of food products, beverages, and tobacco products
4	13–15	Manufacture of textiles, wearing apparel, and leather products
5	16–18	Manufacture of wood and paper products, except furniture
6	19–22	Manufacture of fuels and chemical products, including pharmaceuticals
7	23–25	Manufacture of metal and mineral products
8	26–27	Manufacture of computer, electronic and optical products
9	28	Manufacture of machinery and equipment
10	29–30	Manufacture of transport equipment
11	31–34	Other manufacturing
12	35–39	Utilities
13	40–44	Construction
14	45–48, 55–57	Trade services, including accommodation and food services
15	49–54	Transportation and storage
16	58–63, 69–83	Business services
17	64–67	Financial and insurance activities
18	68	Real estate activities
19	84–89	Public administration, education, health, and social services
20	90–99	Other services

Note: ADB Multiregional Input-Output Tables for non-SSA countries report 35 sectors, which are subsequently mapped into these 20 sectors, to ensure consistency with the results for SSA.