The Office of the
Chief Economist of
the South Asia Region

OCTOBER 2025

South Asia Development Update

Jobs, AI, and Trade

WORLD BANK GROUP

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UNTIL TUESDAY, OCTOBER 7 AT 11:30 AM IST (6 AM UTC)

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The cutoff date for the data used in the report was September 18, 2025.

AI disclosure statement: AI was used in the classification of occupations in the business services sector in Chapter 2. ChatGPT-4o was used during June and July 2025 to classify occupations. A list of all 4-digit ISCO occupation names, descriptions, and codes was uploaded to the chatbot interface, along with a series of prompts requesting ChatGPT to identify occupations associated with the business services sector based on how occupational descriptions matched with core business services jobs, including IT, software development, and back office functions. All AI-generated outputs were carefully reviewed for accuracy, and substantial revisions were made based on manual reading of the occupation classifications. Further details are available in annex 2.2. NotebookLM powered by Google Gemini 2.5 Pro was used during July and August 2025 to review the full text of academic articles and to identify relevant papers for a meta-analysis. The main prompt used was: "*For the uploaded articles, could you identify which papers estimate the impact of trade liberalization or tariff change on employment, wage, or productivity*?" All AI-generated outputs were carefully reviewed for accuracy, and substantial revisions were made based on manual reading of the paper abstracts. Details are described in annex 3.1.

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South Asia as used in this report includes Bangladesh, Bhutan, India, Maldives, Nepal, and Sri Lanka. The cutoff date for this report was September 18, 2025.

Foreword

There are two distinct economies in South Asia.

Most people work in the traditional economy, as farmers or in small informal businesses. Competition is limited by fragmented markets and high tariff barriers, and productivity by low adoption of modern technology. Workers are often underemployed and poorly paid.

A small but growing number of South Asians work in the modern economy. This economy is cutting-edge and globally competitive. It includes high-tech service hubs and export-oriented factories producing textiles and pharmaceuticals. Jobs here are highly productive and better paid. This economy is well positioned to take advantage of new patterns of global trade, and new technologies like artificial intelligence (AI).

There are two economies in South Asia—a less productive traditional one and a dynamic modern one. Most people work in the first one, but South Asia will better achieve its ambitions if more shift to the second one. Lowering tariffs and leveraging artificial intelligence can help.

These two economies exist side by side in South Asia, but in some ways are worlds apart. The resources needed to fuel the growth of the modern economy are locked within the traditional economy. People are often unable to move to the sectors, firms, and locations where they are best suited. Unlocking this flow is essential for the region's ambitions.

A key obstacle is tariffs. South Asia's high tariffs have protected the least dynamic parts of the labor market, such as agriculture, where employment has fallen. High tariffs have also handicapped manufacturing: the sector faces average tariffs on intermediate inputs that are more than twice those in other emerging market and developing economies (EMDEs).

By contrast, the one-third of jobs in sectors with the lowest tariffs, such as services exports, accounted for three-quarters of job growth during 2013–23, and workers in these jobs have been significantly higher-paid, higher-skilled and younger.

Carefully sequenced tariff cuts, starting with imported inputs, could help both South Asia's manufacturing sector as well as its labor markets. The highest tariffs that protect a large share of the workforce could be lowered more gradually, by legislating a multi-year glide toward a low final level. This would allow the affected workers, firms, and regions time to adjust in response to other opportunities arising elsewhere.

Another obstacle to labor movement in South Asia is the lack of skills and infrastructure needed to take advantage of AI. The traditional economy is unlikely to benefit much from AI, as jobs there tend to be low-skill, agricultural, or manual. However, productivity gains could be substantial for the 15 percent of South Asian workers in the modern economy. These workers tend to be highly educated and experienced, and their jobs have stronger complementarities with AI.

South Asia could strengthen the foundations for maximizing the benefits of AI by raising the share of skilled workers and ensuring reliable electricity as well as consistent and fast internet access. Improving infrastructure and facilitating labor mobility can help maximize AI's benefits while minimizing labor market disruptions.

Pursued in tandem, policy reforms to expand trade and to increase labor market flexibility could be transformative, channeling resources toward successful, productive sectors. Greater public and private investment can build out the transportation, energy, and telecommunications infrastructure underpinning greater trade and use of AI. Firms and workers made more productive by AI and inexpensive foreign inputs can pay taxes that sustain continued public investment and strong social welfare systems.

Unlocking South Asia's potential is urgent. Every year, about 16 million people enter the job market, but only about 10 million can find work. Reforms that allow firms to grow into new markets using new technologies are critical for boosting job creation, investment, and sustained growth.

Johannes C.M. Zutt
Vice President, South Asia Region

Executive Summary

Growth in South Asia is on track to exceed earlier expectations and reach 6.6 percent in 2025, but is expected to slow to 5.8 percent in 2026, in part as a result of higher-than-expected tariffs on India's exports to the United States. While this short-term outlook is subject to downside risks, over the longer term, artificial intelligence (AI) could promote growth by boosting productivity especially among those 15 percent of South Asian workers who are in jobs where AI strongly complements human labor. Such a growth dividend could be amplified by trade reforms. Carefully sequenced tariff cuts, especially in conjunction with broader free trade agreements, would encourage private investment and job creation in trade-related activities, which disproportionately employ South Asia's younger and higher-skilled workers and have accounted for most of South Asia's employment growth over the past decade. This could particularly benefit manufacturing, where elevated tariffs on production inputs currently diminish competitiveness. South Asia's governments can support the adjustment of labor markets to new technologies and trade opportunities by proactively removing obstacles to workers' reallocation to new firms, occupations, and locations. Simultaneously, they could protect vulnerable workers during this period of change by streamlining and strengthening safety nets.

Chapter 1. Progress and Peril. Growth in South Asia is on track to exceed earlier expectations and reach 6.6 percent in 2025, but is expected to slow to 5.8 percent in 2026, in part due to higher-than-expected tariffs on India's exports to the United States. The region is making progress toward addressing vulnerabilities but risks remain. South Asian economies would be affected by spillovers from a persistent global economic slowdown and export market dislocations, labor market disruptions from artificial intelligence (AI), social unrest, or geopolitical tensions. Over the longer term, new technologies such as AI and more open trade regimes could catalyze renewed growth momentum by encouraging private investment and productivity. Policymakers can foster both growth and job creation by enhancing the flexibility of their economies, improving connectivity, encouraging upskilling of the workforce, and providing an appropriate safety net.

In addition to regional growth prospects, this edition examines in depth the labor market impact of two major economic shifts: the growing adoption of AI and reforms to increase South Asia's trade openness.

Chapter 2. Artificial Intelligence, Real Impact: Labor Market Implications of AI Adoption in South Asia. South Asia's workforce is only moderately exposed to changes caused by the adoption of AI owing to the predominance of low-skill, agricultural, and manual jobs, which tend to be those least likely to be replaced by AI. But demand for AI skills has grown rapidly, and jobs requiring these skills command a wage premium of nearly 30 percent relative to other white-collar jobs. Productivity gains could be substantial for the 15 percent of South Asian workers who are in jobs with strong complementarities with AI and who tend to be highly educated, experienced workers. Only 7 percent of South Asia's jobs are highly exposed to AI without being complementary to its use, and are thus at risk of automation—well below the 15 percent exposure in other emerging markets. Moderately educated, young workers are the most vulnerable to job displacement. The introduction of Generative AI has already reduced monthly job listings by around 20 percent for the most exposed and most substitutable white-collar occupations. The largest relative job losses have occurred in the business services and information technology sectors, and among upper-middle-skilled and entry-level workers. South Asia could strengthen the foundations for maximizing the benefits of AI by raising the share of skilled workers and ensuring reliable electricity, as well as consistent and fast internet access. Improving infrastructure and facilitating labor mobility can help maximize AI's benefits while minimizing labor market disruptions.

Chapter 3. Trading Protection for Jobs. Carefully sequenced trade reforms could encourage private investment and create jobs for South Asia's growing working-age population.

Historically, both in South Asia and around the world, major trade reforms have typically coincided with periods of significantly faster aggregate employment and output growth. However, higher-skilled and younger workers, and those in manufacturing, have benefited more than others. These patterns would likely be amplified in South Asia if governments decided to lower tariffs now. The one-third of South Asian workers in sectors with the lowest tariffs (mostly services) have accounted for more than three-quarters of aggregate employment growth. Ambitious tariff cuts in South Asia, especially in conjunction with broader free trade agreements, would particularly benefit younger and higher-skilled workers and those in manufacturing, who tend to work in trade-oriented sectors that are currently held back by elevated tariffs on inputs. Removing obstacles to a reallocation of workers across firms, sectors, and locations would help unlock gains for more workers. Governments can support this process through efforts such as improving connectivity, worker skilling, better job matching, the removal of obstacles to firms' growth, and an appropriate social safety net. Past experience suggests that the revenue implications of tariff cuts are manageable.

Box 3.1. Sequencing Trade and Labor Reforms. Ambitious trade reforms in South Asia could deliver substantial gains in exports and incomes, in part as a result of workers reallocating toward more productive firms, sectors, and locations. High switching costs for workers could diminish some of the potential gains. Even modest improvements in labor mobility could substantially increase the income gains from trade reform.

Box 3.2. No Tariffs, No Problem: Managing the Revenue Impact of Tariff Cuts. Most South Asian countries derive 4–19 percent of their government revenues, or 0.7–3.7 percent of GDP, from trade. Past episodes of major tariff cuts were, on average, accompanied by a small decline in trade revenue of less than 0.1 percentage point of GDP. Total tax revenue-to-GDP ratios stayed broadly flat during these reforms, as trade tax revenue losses were offset by gains in other tax revenues, especially from consumption taxes. These tariff reductions rarely involved tax rate increases, and typically relied on base broadening or better tax administration.

Abbreviations

ADB	Asian Development Bank
AE	Advanced Economies
AI	Artificial Intelligence
AIOE	Artificial Intelligence Occupational Exposure
AIPI	AI Preparedness Index
ASPIRE	Atlas of Social Protection Indicators of Resilience and Equity
ATC	World Trade Organization Agreement on Textiles and Clothing
BA	Bachelors Degree
BGD	Bangladesh
BGR	Bulgaria
BIS	Bank for International Settlements
BPM	Business Process Management
BPO	Business Process Outsourcing
BRA	Brazil
BTA	United States-Vietnam Bilateral Trade Agreement
BTN	Bhutan
C-AI	Complementary-adjusted Artificial Intelligence
C-AIOE	Complementary-adjusted Artificial Intelligence Occupational Exposure
CEO	Chief Executive Officer
CEPII	Centre d'Etudes Prospectives et d'Informations Internationales
CHE	Switzerland
CHELEM	Comptes Harmonisés sur les Echanges et L'Economie Mondiale
CIT	Corporate Income Tax
CHN	China
CNY	Chinese Yuan
COL	Colombia
CPI	Consumer Price Index
CRI	Costa Rica
CYP	Cyprus
DD	Difference-in-differences
DOM	Dominican Republic
DZA	Algeria
EAP	East Asia and the Pacific
ECA	Europe and Central Asia
EGY	Egypt
EMDE	Emerging Market and Developing Economies
EPZ	Export Processing Zones
FDI	Foreign Direct Investment
FE	Fixed Effects
FTA	Free Trade Agreements
FY	Fiscal Year
GDP	Gross Domestic Product
GenAI	Generative Artificial Intelligence
GEO	Georgia

Abbreviations (continued)

GGDC	Groningen Growth and Development Centre
GLD	Global Labor Database
GSP	Generalized System of Preference
HS	High-School Degree
ICT	Information and Communication Technologies
IDN	Indonesia
IEA	International Energy Agency
ILO	International Labour Organization
ILO	International Labour Organization
ILOSTAT	International Labour Organization Database on International Labour Statistics
IMF	International Monetary Fund
IND	India
ISCO	International Standard Classification of Occupations
ISIC	International Standard Industrial Classification
ISR	Israel
IT	Information Technology
IV	Instrumental Variable
JAM	Jamaica
JOR	Jordan
JPY	Japanese Yen
JPN	Japan
KPO	Knowledge Process Outsourcing
LAC	Latin America and the Caribbean
LCOE	Levelized Cost of Energy Values
LFPR	Labor Force Participation Rate
LFS	Labor Force Surveys
LHS	Left hand side
LKA	Sri Lanka
LLM	Large Language Model
Mbps	Megabits per second
MCCI	Metropolitan Chamber of Commerce and Industry
MDV	Maldives
MEX	Mexico
MHh	Megawatt hour
ML	Machine Learning
MNA	Middle East and North Africa
MNG	Mongolia
MONA	International Monetary Fund Monitoring of Fund Arrangements
NAFTA	North American Free Trade Area
NBER	National Bureau of Economics Research
NLP	Natural Language Processing
NNs	Neural Networks
NPL	Nepal
O*NET	Occupational Information Network
OECD	Organisation for Economic Co-operation and Development

Abbreviations (continued)

OLS	Ordinary Least Squares
PAK	Pakistan
PHL	Philippines
PIT	Personal Income Tax
PMI	Purchasing Manager Index
PPI	Producer Price Index
R&D	Research and Development
RCEP	Regional Comprehensive Trade Agreement
RePEc	Research Papers in Economics
RHS	Right hand side
ROW	Rest of the World
S&P	Standard & Poor's
SADU	South Asia Development Update
SAR	South Asia Region
SME	Small and Medium-sized Enterprises
SOC	Standard Occupational Classification
SSA	Sub-Saharan Africa
STEM	Science, Technology, Engineering, and Mathematics
TFP	Total Factor Productivity
THA	Thailand
U.S.	United States
UCDP	Uppsala Conflict Data Program
UNESCAP	United Nations Economic and Social Commission for Asia and the Pacific
UNU-WIDER	United Nations University World Institute for Development Economics Research
USA	United States of America
USD	United States Dollar
VAR	Vector Autoregression
VAT	Value-added tax
VC	Venture Capital
WDI	World Development Indicators
WTO	World Trade Organization
y/y	year to year

CHAPTER 1

Progress and Peril

Chapter 1: Progress and Peril

Growth in South Asia is on track to exceed earlier expectations and reach 6.6 percent in 2025, but is expected to slow to 5.8 percent in 2026, in part due to higher-than-expected tariffs on India's exports to the United States. The region is making progress toward addressing vulnerabilities but risks remain. South Asian economies would be affected by spillovers from a persistent global economic slowdown and export market dislocations, labor market disruptions from artificial intelligence (AI), social unrest, or geopolitical tensions. Over the longer term, new technologies such as AI and more open trade regimes could catalyze renewed growth momentum by encouraging private investment and productivity. Policymakers can foster both growth and job creation by enhancing the flexibility of their economies, improving connectivity, encouraging upskilling of the workforce, and providing an appropriate safety net.

Introduction

Growth in South Asia is expected to slow sharply from 6.6 percent in 2025 to 5.8 percent in 2026 (figure 1.1). The forecast for 2025 has been revised up amid higher-than-anticipated public investment in India and a broad-based recovery in Sri Lanka. For 2026, the forecast has been downgraded, as some of these effects unwind and India continues to face higher-than-expected tariffs on goods exports to the United States. Despite this slowdown, growth in the region is expected to remain more robust than in other emerging market and developing economies (EMDEs). Vulnerabilities remain, particularly in terms of high debt levels and low foreign exchange buffers in some countries, but most South Asian countries are making progress toward addressing macroeconomic imbalances such as current account deficits.

Inflation in the region is either within central bank targets or trending toward them. Central banks are generally easing monetary policy, although a growing share of central bank communications has expressed caution about moving too quickly in an environment of elevated uncertainty.

Financial markets around the world, including in South Asia, appear to be placing little weight on downside risks. Stock market valuations in major markets dipped temporarily earlier this year in response to new tariff announcements but have more than recovered in recent months. Borrowing costs for both sovereigns and corporates remain above their pre-pandemic average but spreads over U.S. Treasury yields have remained narrow. Credit ratings for EMDE sovereigns have generally been improving.

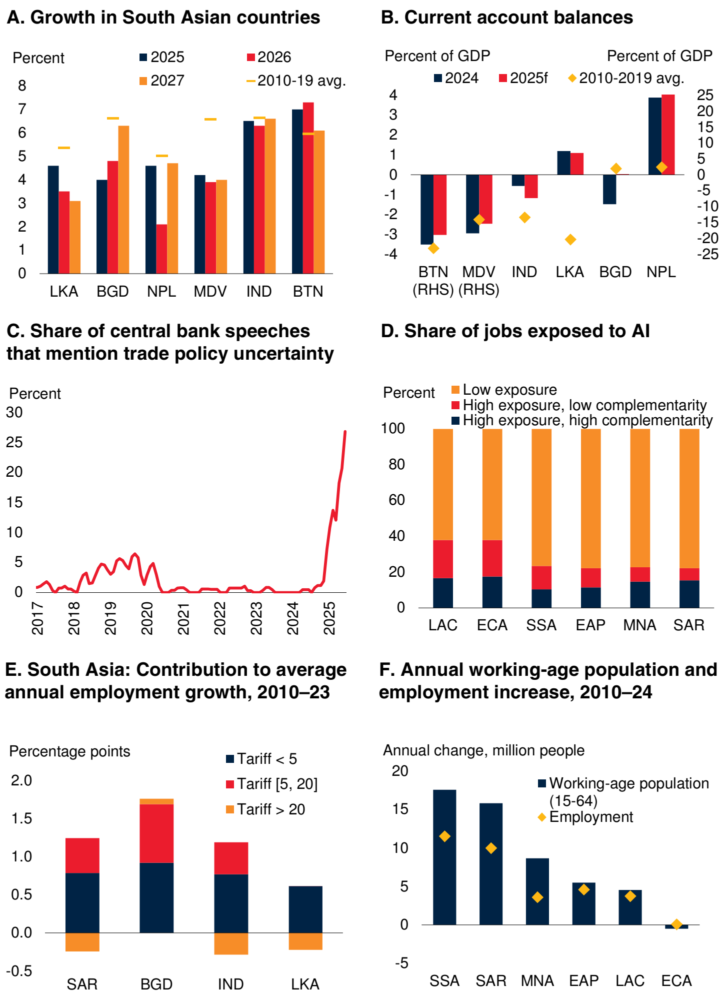
South Asia's growth prospects could be derailed in a variety of ways. The region has faced several public uprisings, such as those that led to the collapse of the government in Nepal in September, in Bangladesh in 2024, and in Sri Lanka in 2022. With continued trade tensions, weak global trade and investment could lead to a period of slow global growth, which could spill over to South Asia. High debt makes several South Asian countries' fiscal positions vulnerable to an increase in interest rates or a decline in growth rates, with any stresses quickly transmitted to the financial system because of banks' sovereign debt holdings. Artificial intelligence (AI) could boost productivity, but also has the potential to disrupt labor markets. Rising tariffs in major export markets may undermine efforts to improve manufacturing. Mounting geopolitical pressures might raise energy costs and weaken energy security.

While some of these forces create short-term risks, they could also accelerate longer-term growth. Carefully sequenced reductions in tariffs—ideally in the context of broader free trade agreements—could especially benefit the sectors whose outputs have the lowest tariff protections but face higher tariffs on intermediate inputs than in other EMDEs. Effective, sustained public investment can crowd in private investment, which has been

Note: This chapter was prepared by Patrick Kirby.

FIGURE 1.1 Overview

Growth is expected to decelerate in South Asia in 2026. The region remains vulnerable to social unrest and macroeconomic disruptions, even as most countries have reined in current account deficits from pre-pandemic highs. Inflation is generally contained, both globally and in South Asia, but central banks are moving cautiously because of high trade policy uncertainty. South Asia may be well placed to benefit from artificial intelligence, because a larger share of exposed jobs could improve productivity rather than be replaced. The most job-creating sectors have been those least protected by tariffs, but aggregate job creation has been slower than needed to absorb the growing working-age population.



Sources: Bank for International Settlements (BIS); Global Labor Database; International Labour Organization; International Monetary Fund; Lightcast (database); Penn World Table (database); Pizzinelli et al. (2023); United Nations World Population Prospects (database); World Bank Macro Poverty Outlook; World Development Indicators (database); World Trade Organization Analytical Database; World Bank.

Note: BGD = Bangladesh; BTN = Bhutan; EAP = East Asia and the Pacific; ECA = Europe and Central Asia; IND = India; LAC = Latin America and the Caribbean; LKA = Sri Lanka; MDV = Maldives; MNA = Middle East and North Africa; NPL = Nepal; RHS = right-hand side; SAR = South Asia; SSA = Sub-Saharan Africa.

A. For India, "2025", "2026", and "2027" refer to FY25/26, FY26/27, and FY27/28. For other countries that use fiscal rather than calendar years, "2025", "2026" and "2027" represent FY24/25, FY25/26 and FY26/27.

B. Chart shows current account balances as a share of GDP.

C. Chart shows the share of central bank speeches at https://www.bis.org/cbspeeches that reference trade policy uncertainty. A speech refers to trade policy uncertainty if it contains at least one trade-policy-related term (such as tariff, trade agreement, and import duty) within 10 words of an uncertainty-related term (such as risk, uncertainty and concern). The full list of search terms and proximity rules follows Caldara et al. (2020). Last observation is September 18th 2025.

D. Bars show the percentage of occupations exposed to artificial intelligence across EMDE regions. See chapter 2 for more details.

E. See chapter 3 for more details.

F. Working age population defined as individuals between the ages of 15 and 64.

sluggish for several years (World 2024b). Private investment could generate productivity gains through the adoption of new technologies. For example, the rapid adoption of AI—in which computers perform activities generally associated with human intelligence—could significantly boost productivity in the long term, though it may lower demand for some types of tasks and occupations (chapter 2).

Pursued in tandem, these policy reforms could be transformative. Trade openness and labor market flexibility can support successful, productive sectors like business services. Greater public and private investment can put in place the transportation, energy, and telecommunications infrastructure underpinning greater trade and use of AI. Firms and workers made more productive by AI and inexpensive foreign inputs can pay taxes that sustain continued public investment and strong social welfare systems. Progress along multiple fronts can help South Asia sustain its record of strong growth and boost the pace of job creation, which has been slower than needed to absorb the growing working-age population.

Global developments and outlook

Global growth is showing early signs of being damaged by rising uncertainty over tariffs and trade policy (figure 1.2). Forecasts for 2025 growth rates of major economies dipped in April after major economies announced new tariffs. Except for the United States, the forecasts recovered after tariff implementation was delayed and moderated.

Global trade policy uncertainty has retreated from its April highs but remains elevated by historical standards. This largely reflects changing U.S. import tariffs, which have been introduced, delayed, and adjusted frequently in recent months. The net effect has been that U.S. tariffs have risen to their highest level in nearly a century, from 2.4 percent in 2024 to 17.4 percent in September 2025.

The effects of changing trade policy are apparent in some categories of trade. Bilateral merchandise trade between the United States and China, for example, has been subjected to significant tariff increases, and U.S. imports from China being down by about one-quarter since April. Aggregate global trade volumes have remained resilient so far, growing 3.6 percent in the 12 months ending in June, as companies increased and stockpiled imports prior to the imposition of new tariffs.

Financial markets appear to be placing little weight on downside risks. Stock market valuations in major markets dipped in response to new tariff announcements in April, but have generally rebounded since then (figure 1.3). U.S. technology stocks have been especially buoyant. Borrowing costs for both sovereigns and corporates remain above their pre-pandemic average, even as spreads over U.S. Treasury yields have generally been small. Credit ratings for EMDE sovereigns have been improving.

Inflation remains close to central bank targets in most countries but has been trending up in 2025. Import prices are being pushed up in some countries by tariffs, and pushed down in others by the falling price of goods coming from China and currency appreciation against the U.S. dollar. Commodity prices have been volatile without a clear trend.

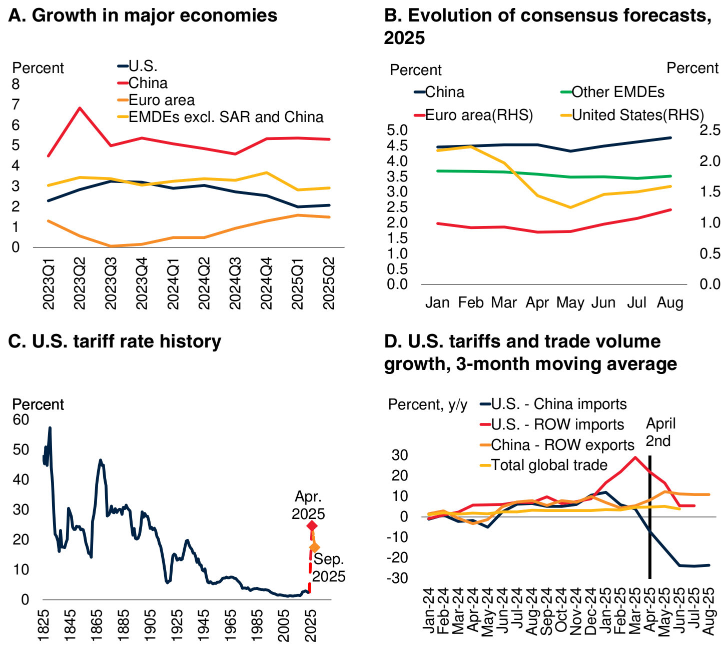
Central bank decisions around the world have been highly synchronized since the pandemic but are now becoming more varied as inflation dynamics become more country specific. In countries imposing tariffs, central banks must balance the risk that tariffs trigger persistent price increases against any need to support demand. The majority of central banks are still easing policy, often at a very gradual pace. Central bank communications are increasingly expressing caution about moving too quickly in an environment of elevated uncertainty.

United States. U.S. activity in the first half of the year showed significant swings in trade and inventories as businesses adjusted purchases to accelerate imports in advance of tariff increases. Domestic consumption has slowed as labor markets have cooled. Investment has been supported by strong AI-related investment, but has otherwise weakened.

The fiscal deficit is expected to average 5.8 percent of GDP over the next decade, well above the

FIGURE 1.2 Global economic activity

Expectations for growth in major economies dipped after trade policy uncertainty spiked in April before rebounding. Trade uncertainty remains extremely elevated as the number of tariffs grows, particularly in the United States. Some categories of trade have fallen, but broader impacts from the increase in tariffs are not yet apparent.



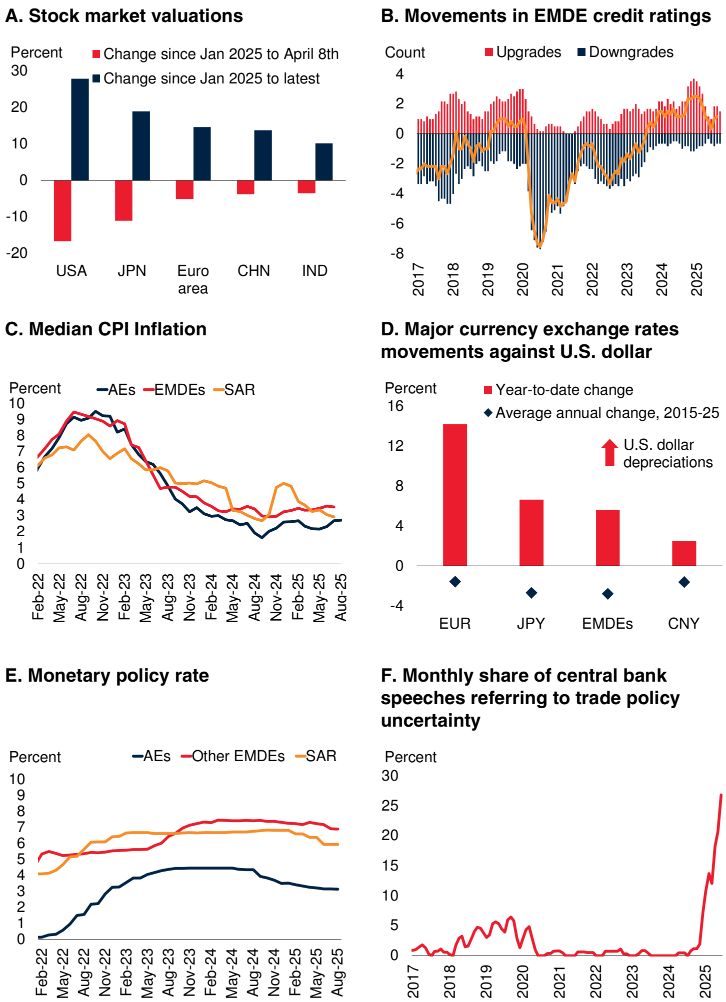
Sources: Budget Lab at Yale; Consensus Economics; Haver Analytics; Tax Foundation; UN Comtrade; World Bank Macro Poverty Outlook; World Bank.
Note: EMDEs = emerging market and developing economies; RHS = right-hand side; ROW = Rest of the World; SAR = South Asia; U.S. = United States; y/y = year to year.
A. Year-on-year growth. "EMDEs excluding SAR and China" is the average growth of 25 countries, weighted by real GDP.
B. "Other EMDEs" includes 45 economies. The horizontal axis shows the month of 2025 in which the forecast was prepared.
C. Values prior to 2025 from Tax Foundation. 2025 values are average effective tariff rates estimated by the Budget Lab at Yale.
D. U.S. and China lines show growth in nominal trade values, while the global line reflects growth in the trade volume index.

average of 4.8 percent of GDP in the decade before the pandemic, as recent tax cuts and increased interest expenditures outweigh the revenues from tariffs (CBO 2025). Inflation expectations have jumped and inflation itself has been trending up as tariffs and a weakening U.S. dollar push up import prices.

Euro area. Growth was more robust than expected in the first half of the year. Consumption growth has been supported by a strong labor market. Wage growth has been robust, and in July unemployment declined to 6.2 percent, its lowest point since the introduction of the euro in 1999. Going forward, tariffs, trade policy uncertainty, and the appreciation of the euro are expected to weigh on exports and investment.

FIGURE 1.3 Financial markets, inflation, and monetary policy

Stock market valuations in major markets dipped in response to new tariff announcements in April but have since generally rebounded. Financial conditions have been easing as credit ratings of EMDEs continue to improve. Inflation has stabilized, and the appreciation of many EMDE currencies may give central banks room to continue easing. Central bank communications suggest a high degree of caution amid elevated uncertainty.



Sources: Bank for International Settlements (BIS); Federal Reserve economic database (FRED); Fitch; Haver Analytics; Moody's; S&P; World Development Indicators (database); World Bank.

Note: AEs = advanced economies; CHN = China; CNY = Chinese yuan; CPI = consumer price index; EMDEs = emerging market and developing economies; EUR = Euro; IND = India; JPN = Japan; JPY = Japanese yen; SAR = South Asia; U.S. = United States.

A. January 2025 value is the monthly average of national stock market benchmarks. Last observation is September 18th, 2025.

B. Chart shows 6-month moving average of sovereign credit rating changes across 104 EMDEs, using average of available Moody's, S&P, and Fitch ratings. Last observation is September 18th, 2025.

C. Inflation calculated as the median rate across 116 EMDEs, 30 AEs, and 6 South Asian countries.

D. "EMDEs" is the Nominal Emerging Market Economies U.S. Dollar Index calculated by the U.S. Federal Reserve Board. Last observation is September 18th, 2025.

E. Monetary policy rate for each region is a weighted average, using 2023 real GDP in U.S. dollars as weights. Sample includes 20 EMDEs, 34 AEs, and 4 South Asian countries—India, Bangladesh, Nepal, and Sri Lanka.

F. Chart shows the share of central bank speeches at https://www.bis.org/cbspeeches that reference trade policy uncertainty. A speech refers to trade policy uncertainty if it contains at least one trade-policy-related term (such as tariff, trade agreement, and import duty) within 10 words of an uncertainty-related term (such as risk, uncertainty and concern). The full list of search terms and proximity rules follows the methodology in Caldara et al. (2020). Last observation is September 18th, 2025.

China. In China, growth in the first half of 2025 averaged just above 5 percent, a modest acceleration from 2024. Exports have contributed an unusually large proportion of growth. This reflects both an acceleration of shipments before tariff increases and lower import prices, themselves the result of the yuan's real depreciation and falling manufactured goods prices. The economy is benefiting from fiscal support and the bottoming out of its property market after three years of substantial contraction.

Growth in other EMDEs has been decelerating, particularly in countries with greater trade openness. Domestic demand across countries remains generally robust, supported by easing financial conditions and rising real incomes.

Developments in South Asia

Growth remained robust in the region in the first half of 2025. Recent GDP data from South Asian countries met or exceeded market expectations, and growth has continued to outpace that in other EMDEs (figure 1.4). Stock markets in the region have responded with broad-based increases, although these increases have mostly been more moderate than in the average EMDE.

U.S. tariffs on South Asia were announced on April 2, then delayed and adjusted, and finally implemented in August. These additional tariffs, as of the date of publication, are 50 percent on India, 20 percent on Bangladesh and Sri Lanka, and 10 percent on Nepal, Bhutan, and Maldives. As a result of these increases, most goods exported from Bangladesh to the United States face a tariff totaling 35 percent; from Sri Lanka, 30 percent; and from India, 52 percent. Some categories of goods are subject to product-specific tariffs that are currently generally lower than the country-specific tariffs, but may increase in the future. These goods include generic pharmaceuticals and electronics, both of which make up an important part of U.S. imports from India.

For all three countries, the United States is the single largest export market. Some weakness in manufacturing purchasing manager indexes in the region may be linked to uncertainties surrounding U.S. trade policy and the prospects for global trade. Incoming trade data so far do not show a substantial negative impact on South Asian exports, although the underlying situation may be obscured by data lags and by importers accelerating purchases in anticipation of higher tariffs.

Inflation in most of the region is either within central bank targets or trending toward them. Inflation in Bangladesh remains elevated but has slowed since peaking last year. Sri Lanka has recently emerged from deflation, which was largely driven by reductions in administered energy prices.

As in the rest of the world, central banks in South Asia are generally cautiously easing, with the notable exception of Bangladesh Bank. Currencies in the region have been less volatile than in other EMDEs, possibly because they are relatively closed to trade.

Fiscal balances are improving in most countries in the region, even if debt levels and interest payments remain elevated in some cases. Current account positions continue to narrow from the large deficits in the years following the pandemic.

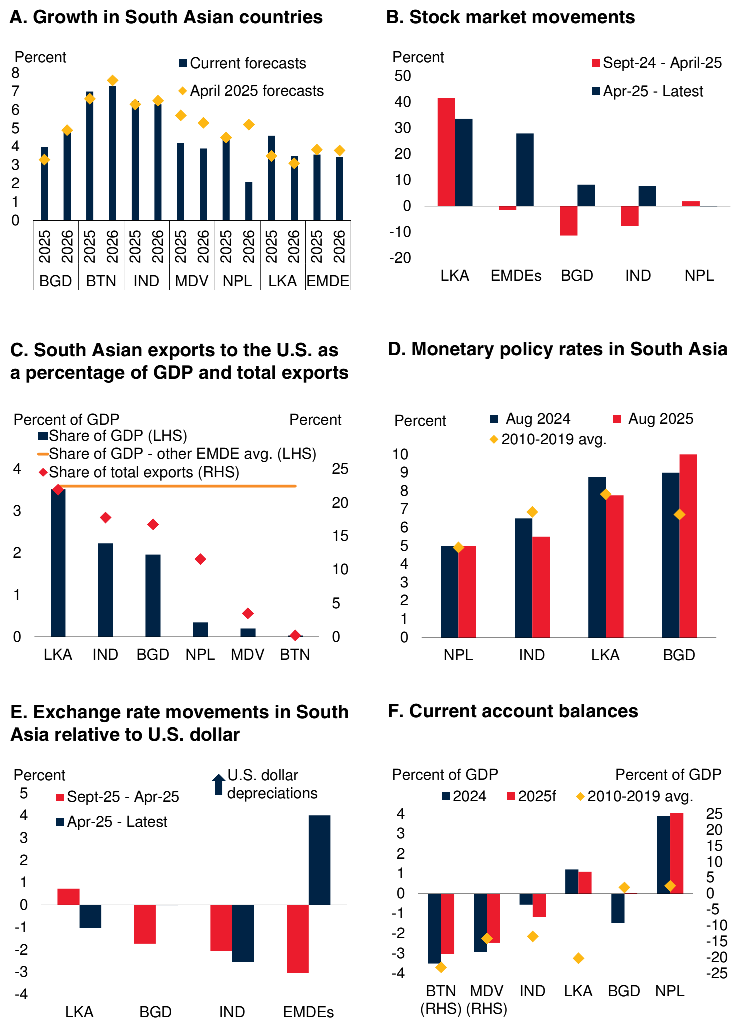
Country developments

In **Bangladesh**, growth bottomed out at around 2 percent in mid-2024, after a public uprising against the government disrupted activity. In the first quarter of 2025, growth rebounded to 4.9 percent year-on-year—the fastest pace in nearly two years, although still well below the country's pre-pandemic rate. Inflation, which peaked above 11 percent in the second half of 2024, has steadily declined to 8.3 percent in August 2025. The central bank tightened monetary policy repeatedly in the second half of 2024 and has held rates steady since. It has indicated that it will begin easing once the real interest rate reaches 3 percent.

Economic weakness is primarily the result of weak investment, as the country faces elevated political uncertainty, law and order challenges, and a high cost of doing business. The financial sector is also burdened with a high level of non-performing loans and is struggling to meet the private sector's demand for credit. Healthy remittance inflows have kept consumption resilient in the face of rising unemployment and falling real wages. Export growth has been solid, and the exchange rate has remained stable since the adoption of a flexible regime in May 2025 (figure 1.5).

FIGURE 1.4 Regional economic activity

Growth in South Asia remains strong. Stock markets in the region have rebounded from tariff-related losses despite substantial increases in U.S. tariffs. Central banks in the region are generally easing monetary policy, except in Bangladesh, and exchange rates in the region have been less volatile than in other EMDEs. Current account positions are moving away from the large deficits of recent years.



Sources: CEPII, Database for International Trade Analysis (BACI); Federal Reserve economic database; Haver Analytics; Morgan Stanley; World Bank Macro Poverty Outlook; World Trade Organization (WTO), tariff analysis facility; World Bank.

Note: avg. = average; BGD = Bangladesh; BTN = Bhutan; EMDEs = emerging market and developing economies; IND = India; LHS = left-hand side; LKA = Sri Lanka; NPL = Nepal; MDV = Maldives; RHS = right-hand side.

A. For India, "2025" and "2026" refer to FY25/26, FY26/27. For other countries that use fiscal rather than calendar years, "2025" and "2026" represent FY24/25 and FY25/26. EMDE average includes 141 economies.

B. Listed dates are monthly averages of stock indices. "EMDEs" is the Morgan Stanley Capital International Emerging Markets Index. Last observation is September 18th, 2025.

C. Chart shows 2023 values. EMDE average calculated using total nominal exports and total GDP of 153 EMDEs.

D. Rate in Nepal is the overnight repo rate. Rate in Sri Lanka is the standing lending facility rate.

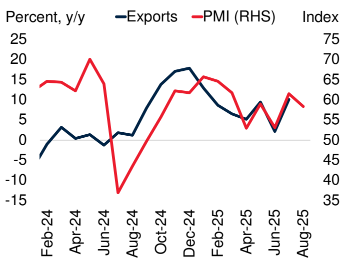
E. Listed dates are monthly averages of currency valuations. "EMDEs" is the Nominal Emerging Market Economies U.S. Dollar Index calculated by the U.S. Federal Reserve Board. Last observation is September 18th, 2025.

F. Chart shows the current account balance as a share of GDP.

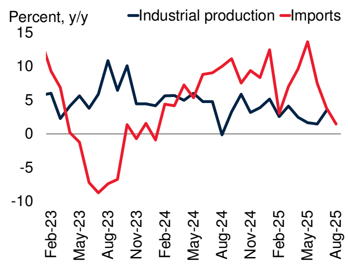
FIGURE 1.5 Country developments

Exports in Bangladesh remain resilient. Domestic demand in India shows signs of continued momentum. The central bank has loosened monetary policy as inflation has slowed. Fiscal and current account deficits in Maldives remain sizable. Activity in Nepal has been supported by hydropower production. Prices in Sri Lanka have only recently emerged from deflation.

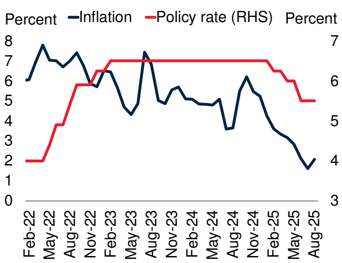
A. Export growth and PMI in Bangladesh



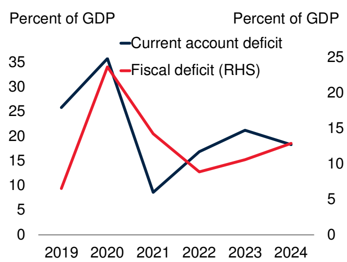
B. Industrial production and imports in India



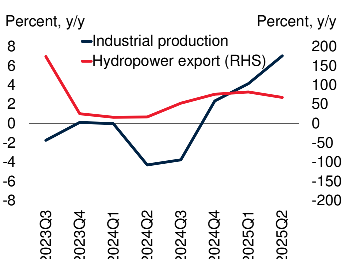
C. Inflation and monetary policy in India



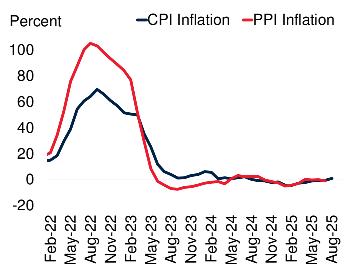
D. Fiscal and current account deficits in Maldives



E. Industrial production and hydropower export growth in Nepal



F. Inflation in Sri Lanka



Sources: Haver Analytics; Metropolitan Chamber of Commerce and Industry, Dhaka (MCCI); World Bank Macro Poverty Outlook; World Development Indicators (database); World Bank.

Note: avg = average; CPI = consumer price index; PPI = producer price index; PMI = Purchase Manager Index; RHS = right-hand side; y/y = year-to-year.

A. Export growth is 3-month moving average of export growth in nominal U.S. dollars. PMI from MCCI, Dhaka.

B. Figure shows 3-month moving averages of imports.

E. Electricity exports are nominal 4-quarter moving average.

F. Figure shows year-on-year Colombo CPI and PPI inflation in Sri Lanka.

In **Bhutan**, electricity production and exports were stronger than expected in the first half of 2025 thanks to high water levels. Hydro construction projects are contributing significantly to growth.

In **India**, real GDP growth exceeded expectations in the April-to-June quarter of 2025, accelerating to 7.8 percent (year-on-year). Growth was supported by strong private consumption and investment and boosted by lower-than-expected prices. Investment growth remains robust, supported by public infrastructure projects, strong credit growth, and loosening monetary policy. Strong rural wage growth has offset slowdowns in urban consumption, as seen in weakness in car sales and personal credit. Industrial production and imports have largely maintained their strong momentum.

Inflation was 2.1 percent in August, within the central bank's 2–6 percent range. After holding its policy rate steady at 6.5 percent since early 2023, the central bank has cut it by a full percentage point since the beginning of 2025.

Stock market valuations struggled at the beginning of the year but have rebounded more recently. Net foreign portfolio investment into India turned negative in June amid rate cuts and geopolitical uncertainty.

In **Maldives**, increasing tourist arrivals continue to fuel growth in 2025, as was the case in 2024. Inflation surged in late 2024, rising from about 1 percent to a peak of 5.9 percent in April 2025. Although the country maintains a fixed exchange rate, import prices have surged due to limited access to foreign currency and depreciation in the parallel market. The fiscal deficit in 2024 was 12.9 percent of GDP, with particularly large expenditures on widespread subsidies, capital expenditures, and interest payments. The current account deficit was 18.3 percent of GDP in 2024, putting pressure on scarce foreign exchange reserves. Domestic banks have helped finance these deficits to some extent, increasing their exposure to sovereign debt.

Nepal experienced its worst unrest in decades in September. A social media ban triggered protests against corruption, followed by widespread unrest causing significant human and economic losses. The damage to public and private infrastructure is still being assessed. An interim prime minister was appointed in September with the objective of organizing elections in March 2026.

The protests reflected frustration with governance and deeper discontent over the lack of economic opportunities for Nepal's youth. This lack of opportunity stems from structural weaknesses holding back private enterprise, including a complex and uncertain business environment, corruption, high trade and transport costs, and inadequate infrastructure. As a result, growth has been slower than peers—averaging 4.3 percent over FY12–24—and job creation has been limited. Youth unemployment reached nearly 22.7 percent in FY23, one of the highest levels in South Asia. Labor migration has become a dominant livelihood strategy and remittances—which average nearly one-quarter of GDP—have sustained basic consumption.

Prior to these developments, economic growth had increased to 4.6 percent in FY25, up from 3.7 percent in FY24. Activity was supported by robust hydropower production, a rebound in industrial output, and a pickup in agricultural activity.

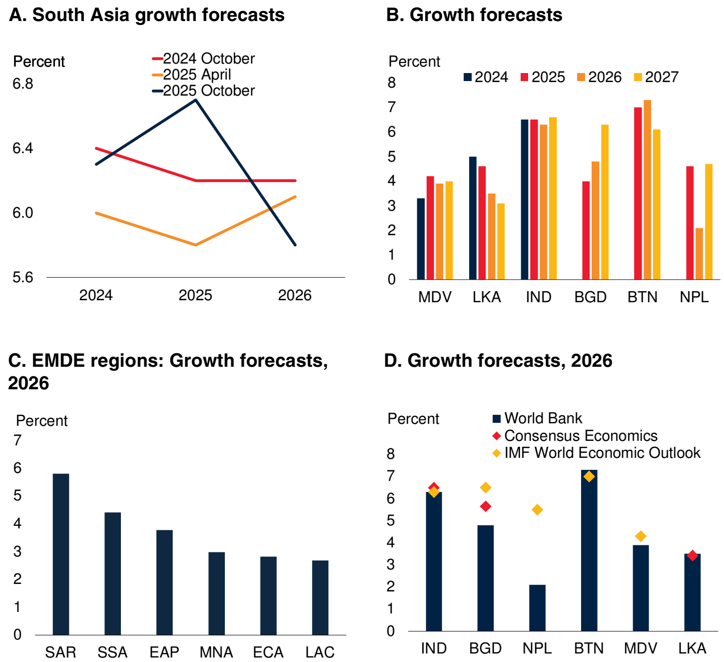
Sri Lanka continues to recover from the economic crisis of 2022–23, which featured a sovereign debt default and the country's worst recession since independence in 1948. The economy grew 4.9 percent in 2025Q2, maintaining essentially the same pace since 2023Q4. Prices declined between September 2024 and July 2025, driven by downward adjustments in energy prices, currency appreciation, and subdued household demand. Prices have increased since August but inflation remains low. The central bank is easing monetary policy, which has improved profitability and capital adequacy in the financial sector. Healthy corporate earnings have helped push Sri Lanka's domestic stock market to an all-time high. Revenue overperformance, structural reforms, and consistent growth—particularly of services exports—have improved current account and fiscal positions.

Outlook for South Asia

Growth in South Asia is expected to slow sharply from 6.6 percent in 2025 to 5.8 percent in 2026 (table 1.1). Despite this deceleration, growth will remain stronger than in other EMDE regions (figure 1.6). Inflation is expected to continue within or trend toward central bank targets.

FIGURE 1.6 Outlook

Growth forecasts for South Asia have been upgraded slightly relative to April and have largely evolved as expected in recent years. Countries in the region generally are growing briskly, and the region's economy is expected to remain stronger than other EMDE regions.



Sources: Consensus Economics; IMF World Economic Outlook (database); World Bank Macro Poverty Outlook; South Asia Development Update; World Bank.

Note: BGD = Bangladesh; BTN = Bhutan; EAP = East Asia and Pacific; ECA = Europe and Central Asia; EMDEs = emerging market and developing economies; IND = India; LAC = Latin America and the Caribbean; LKA = Sri Lanka; MDV = Maldives; MNA = Middle East and North Africa; NPL = Nepal; SAR = South Asia; SSA = Sub-Saharan Africa.

A. Lines show the vintages of World Bank growth forecasts between 2024 and 2025.

B. For India, 2024, 2025, 2026 and 2027 refer to FY24/25, FY25/26, FY26/27 and FY27/28, respectively. For Bangladesh, Bhutan and Nepal 2025, 2026 and 2027 refer to FY24/25, FY 25/26, and FY26/27, respectively.

C. EAP includes 23 economies, ECA 21, LAC 28, MNA 22, SAR 4, and SSA 47.

D. IMF forecasts from April 2025. Consensus forecasts from September 2025.

Growth forecasts for 2026 have been downgraded for India, Maldives, and Nepal, driven by weaker export prospects, growing foreign exchange pressures, and social unrest, respectively. The forecasts for Bangladesh and Sri Lanka have been upgraded as crises in these countries recede, and current account and fiscal balances improve, putting future growth on a stronger footing.

In the baseline forecast, the increase in U.S. tariffs has a manageable adverse impact on activity. Expectations for U.S. tariffs are essentially

TABLE 1.1 Growth in South Asia

	Country fiscal year	Real GDP growth at constant market prices (Percent)				Revision to forecast (Percentage points)	
Calendar year basis		**2024**	**2025(e)**	**2026(f)**	**2027(f)**	**2025(e)**	**2026(f)**
South Asia region		**6.4**	**6.6**	**5.8**	**6.5**	**+0.5**	**-0.6**
South Asia region, excluding India		**4.2**	**4.4**	**5.1**	**5.7**	**+0.3**	**+0.1**
Maldives	January to December	3.3	4.2	3.9	4.0	-1.5	-1.4
Sri Lanka	January to December	5.0	4.6	3.5	3.1	+1.1	+0.4
Fiscal year basis		**23/24**	**24/25(e)**	**25/26(f)**	**26/27(f)**	**25/26(e)**	**26/27(f)**
Bangladesh	July to June	4.2	4.0	4.8	6.3	-0.1	+0.6
Bhutan	July to June	6.1	7.0	7.3	6.1	-0.3	+0.8
India	April to March	9.2	6.5	6.5	6.3	+0.2	-0.2
Nepal	July to June	3.7	4.6	2.1	4.7	-3.1	-0.8

Sources: World Bank, Macro Poverty Outlook, and staff calculations.
Note: (e) = estimate; (f) = forecast. As of July 1st, 2025, Afghanistan and Pakistan have been made part of the Middle East and North Africa (MENA) region, and are no longer grouped in the World Bank's South Asia region. GDP is measured in average 2010–19 prices and market exchange rates. Because quarterly GDP forecasts for Bangladesh, Bhutan and Nepal are unavailable, the average of two consecutive fiscal years is used for regional aggregates.

unchanged relative to the April edition of this report and, by themselves, do not warrant changes in country-level forecasts. The exception is India, which had been expected to face lower tariffs than its competitors in April and now faces considerably higher tariffs.

Because South Asia is the EMDE region that is least open to trade, it is less exposed to tariff changes and trade policy uncertainty than other regions. A significant proportion of South Asia's trade is in services or categories of goods unaffected by tariffs, such as business services, tourism, or pharmaceuticals.

There is considerable uncertainty, however, about future tariff developments relating to both South Asia and countries that export similar goods. There is also considerable uncertainty about the extent to which U.S. importers are able to absorb higher prices—more likely for goods such as electronics, less so for textiles—and the extent to which South Asian exporters are able to divert their products elsewhere.

Outlook for South Asian countries

In **Bangladesh**, growth is expected to continue accelerating as it recovers from the disruptions around the collapse of the government last year. Nevertheless, the growth forecast remains below the country's pre-pandemic average—the result of financial system fragilities, fiscal consolidation, and a challenging external environment.

The forecast depends on continued growth in the ready-made garment industry, which accounts for about 10 percent of GDP, one-third of manufacturing employment, and more than four-fifths of exports (Islam and Halim 2022). The removal of Bangladesh's "least-developed country" status under the Multi-Fiber Arrangement in November 2026 is not expected to halt export momentum. Bangladesh will retain duty-free access to several major markets, including its largest market, the European Union, until 2029.

On the domestic side, the financial sector is being weakened by a large number of non-performing loans, weak deposit growth, and tight monetary policy. As a result, the financial sector is providing little support to private investment, which is also being burdened by political uncertainty and high input costs. The government is focusing on fiscal consolidation and structural reforms, which may take time to yield growth dividends. A more pronounced acceleration in growth is expected in the 2026/27 fiscal year, to 6.3 percent, as investment picks up amid easing political uncertainty.

In **Bhutan**, delays to hydropower construction projects have contributed to a 0.3-percentage-point downgrade to growth in 2025/26. This is reversed in 2026/27 as construction speed picks up.

India is expected to remain the world's fastest-growing major economy, underpinned by continued strength in consumption growth. Domestic conditions, particularly agricultural output and rural wage growth, have been better than expected. The government's reforms to the Goods and Services Tax (GST)—reducing the number of tax brackets and simplifying compliance—are expected to support activity.

The forecast for FY26/27 has been downgraded, however, as a result of the imposition of a 50 percent tariff on about three-quarters of India's goods exports to the United States. India had been expected to face lower U.S. tariffs than its competitors in April but as of the end of August it faces considerably higher tariffs. Almost one-fifth of India's goods exports went to the United States in 2024, equivalent to about 2 percent of GDP.

In **Maldives**, tourism is expected to be the main source of growth. The substantial current account and fiscal deficits give rise to downside risks to the baseline forecast. The government has substantial upcoming debt repayment obligations, which it may struggle to meet given low foreign exchange reserves. The forecast incorporates a contraction in activity for the non-tourism parts of the economy.

In **Nepal**, recent unrest and heightened political and economic uncertainty is expected to cause growth to decline to 2.1 percent in FY25/26, with a potential range of negative 1.5–2.6 percent. International tourist arrivals are expected to decline sharply and asset losses will affect the insurance industry. Weaker investor confidence is expected to impede private investment and non-hydro construction. Delayed rainfall in a major rice-producing province will hamper the agricultural sector. Reconstruction efforts are expected to support the recovery in FY26/27 and gain momentum in FY27/28.

In **Sri Lanka**, the growth of tourism and remittances has been stronger than expected, and the economy is expected to regain its 2018 level of real output in 2026. Tariffs on exports to the United States are expected to have a modest impact on the growth of overall exports—their impact will be mitigated by the depreciation of the Sri Lankan rupee, efforts at market diversification, and strong growth of service exports (which are unaffected by tariffs). Consumption is expected to remain strong. While industry is rebounding in the short term, medium- to long-term industrial growth will continue to be restrained by shortages of skilled workers and other scarring effects from the recent recession and sovereign default. Fiscal consolidation is also expected to weigh on growth.

Risks and vulnerabilities

South Asia's growth prospects face heightened downside risks from an uncertain global environment, labor market shocks from AI, geopolitical shocks, and social unrest. Each of these shocks could interact with elevated debt levels and weaknesses in the financial sector to create financing pressures. These forces present downside risks to growth in the short term but, in some cases, may promise productivity gains in the long term, beyond the forecast horizon of this report.

Persistent global economic slowdown

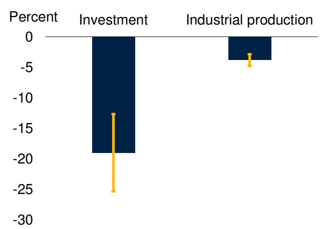
After decades of gradual deceleration, the pace of global growth appears to have stabilized. However, the global stabilization of growth may be undermined by a variety of factors, with negative spillovers to South Asia.

Investment is a critical pillar of long-term growth because it builds capital stock and enables the adoption of productivity-enhancing new technologies. Globally, investment growth has been slowing steadily since around 2007. Recent policy uncertainty may further deter investment if it leads businesses to postpone capital expenditures. In the United States, for example, a rise in policy uncertainty comparable to the increase observed between the 2022–23 average and the first six months of 2025 has been associated with a peak decline in gross investment of nearly 20 percent (figure 1.7; Baker, Bloom, and Davis 2016).

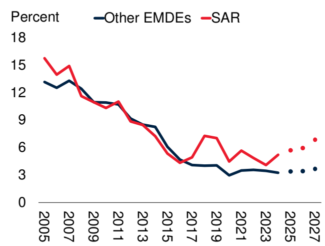
FIGURE 1.7 Persistent global economic slowdown

Global growth could slow if policy uncertainty further undermines investment. Rising trade barriers could slow the diffusion of innovation and hamper productivity growth. South Asia's tariffs are in the top quartile among EMDEs. Income gains could double if tariff cuts are accompanied by reforms to facilitate job switching. Minimally protected jobs have been the main source of employment growth in South Asia and have offered higher wages, particularly for more skilled and younger workers.

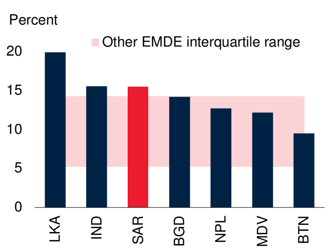
A. Predicted impact of uncertainty on U.S. investment and industrial production



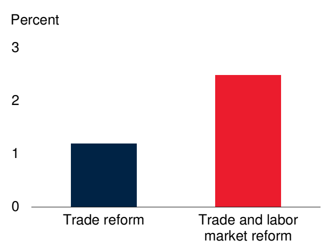
B. Real private investment growth and forecasts



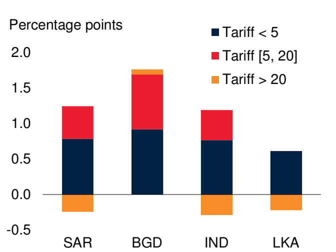
C. Tariffs on manufacturing products, 2024



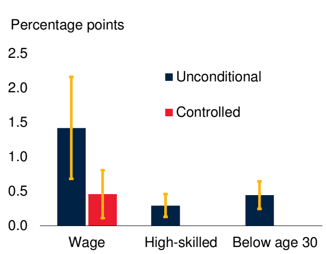
D. Real GDP per capita gain from tariff cuts and labor reform



E. South Asia: Contribution to average annual employment growth, 2010–2023



F. South Asia: Change in worker characteristics with 1 percentage point lower tariff



Sources: ADB Multiregional Input-Output Tables (database); Baker, Bloom, and Davis (2016); Global Labor Database; Government of Sri Lanka; IMF World Economic Outlook (database); Kilic Celik, Kose, and Ohnsorge (2023); Kose and Ohnsorge (2024); World Bank Macro Poverty Outlook; World Development Indicators (database); World Trade Organization Analytical Database; World Bank.

Note: BGD = Bangladesh; BTN = Bhutan; EMDEs = emerging market and developing economies; IND = India; LKA = Sri Lanka; MDV = Maldives; NPL = Nepal; SAR = South Asia; TFP = total factor productivity.

A. Chart shows the impact on U.S. investment and industrial production from an increase in economic policy uncertainty equivalent to the rise between the 2022–2023 average and the average of the first 6 months of 2025, based on VAR estimates.

B. Figure shows MPO projections of real private investment growth of India, Bangladesh, Bhutan and 70 other EMDEs. Regional growth is calculated using total private investment in real dollars. The line represents the 5-year moving average of growth, while points indicate projections.

C. Figure shows average of ad valorem most favored nation duties on manufacturing products. South Asia is the nominal GDP weighted average of 6 economies. Other EMDEs include 29 economies.

D. Chart shows the effects on real GDP per capita of a halving of the gap from the EMDE average for trade policy cost in each country and sector and labor market reform (5 percent reduction in the cost of switching jobs) in South Asian countries. General equilibrium effects are estimated using a dynamic quantitative multi-sector open-economy model following Caliendo, Dvorkin, and Parro (2019). Model calibrated in changes relative to data in 2023 for 73 economies.

E. South Asia sample includes only Bangladesh, India, and Sri Lanka due to availability of employment data on the 2-digit level between 2010 and 2014. See chapter 3 for more details.

F. See chapter 3 for more details. Whiskers indicate 90 percent confidence intervals. Regression results in annex tables 3.1.11 and 3.1.12.

Much of the current policy uncertainty centers on trade policy. The expansion of global trade has been an engine for technology diffusion, growth, and poverty reduction (Goldberg and Reed 2023). Many poorer countries have rapidly increased per capita income through export-led development strategies (World Bank 2020). Technology diffusion and other benefits were already waning when global trade plateaued around 2008, but may evaporate entirely if uncertainty leads to trade declines (Nana, Ouedraogo, and Tapsoba 2025). Increasing restrictions on international trade could result in the slower diffusion of productive technologies and less efficient resource allocation, resulting in weaker-than-expected growth.

South Asia would not be immune to a period of global trade weakness. The region's high growth is predicated on continued improvements in capital accumulation and productivity. Improvements in both could be undermined by weak growth in investment and trade. Investment growth in the region already shows signs of chronic weakness. Uncertainty has particularly damaging and persistent effects on investment in countries with weaker institutional quality and financial markets (Ahir, Bloom, and Furceri 2022; Carrière-Swallow and Céspedes 2013).

Conversely, South Asian governments may seize the opportunity of global tariff uncertainty to lower their own tariffs, ideally in the context of broader free trade agreements, as a tool to unlock higher long-term growth potential. South Asia's tariffs are in the top quartile among EMDEs: at 16 percent on average, they are double the EMDE average of 8 percent. High tariffs increase the cost of production, damage South Asia's competitiveness, and discourage foreign direct investment in traded sectors (chapter 3). For intermediate inputs used in the manufacturing sector, for example, tariffs on intermediate inputs amount to 11 percent compared with 4 percent in other EMDEs. If tariff cuts are undertaken in the context of broader free trade agreements that broaden access to export markets, employment and output gains could be considerable.

The experience with past episodes of major trade liberalizations suggests that ambitious tariff cuts could generate significant output and employment gains, particularly if combined with reforms to facilitate the relocation of workers across firms, sectors, and locations. South Asia's main source of employment has been the one-third of jobs with the lowest tariffs: they have accounted for three-quarters of employment growth. These jobs have also offered significantly higher wages and employed more skilled and younger workers. Broad-based tariff cuts could also trigger disruptive shifts in labor markets, which could be mitigated by improvements in social safety nets (see below).

Labor market disruptions from AI

The rapid development of AI—in which computers perform activities generally associated with human intelligence—has the potential to transform the global economy and could significantly boost productivity. In the short term, however, these benefits must be weighed against the risk of many people losing their jobs.

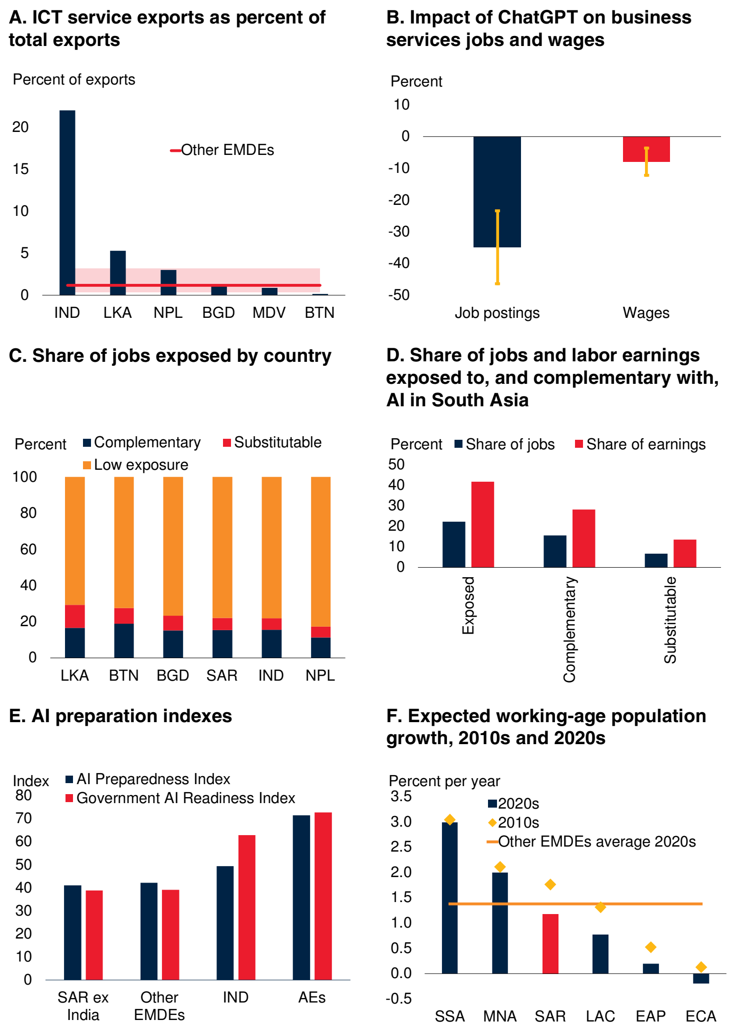
Maintaining and creating jobs is crucial for South Asia, given its rapidly-growing working-age populations. Although South Asian labor market exposures to AI are less than in other EMDEs, the effects differ across segments of the workforce, and the region's economies generally score poorly on AI readiness indicators, suggesting that they may struggle to reap the full benefits of the technology.

Previous technological revolutions have caused major labor market disruptions. For example, automation through industrial robots and information and communication technologies (ICT) has depressed employment and wages in advanced economies over recent decades and contributed to labor market polarization (Acemoglu and Restrepo 2020; Autor and Dorn 2013).

AI would be most disruptive to a broad range of non-routine, white-collar service sector jobs, such as call centers, data entry, payroll processing, business process management (BPM), and ICT (Webb 2020). These jobs tend to be held by

FIGURE 1.8 Labor market disruptions from AI

ICT services are an important element of South Asia's exports. The proportion of jobs benefiting from AI, in terms of productivity and earnings, exceeds those that are substitutable by AI. India's AI readiness outperforms EMDEs' median value, although a gap remains compared to AEs. The expected rapid growth of the working-age population in South Asia will support human capital development.



Sources: Felten, Raj, and Seamans (2023); Global Labor Database labor force surveys; Kilic Celik, Kose, and Ohnsorge (2023); Lightcast (database); Pizzinelli et al. (2023); World Development Indicators (database); World Bank.

Note: AEs = advanced economies; BGD = Bangladesh; BTN = Bhutan; EAP = East Asia and the Pacific; ECA = Europe and Central Asia; EMDEs = emerging market and developing economies; ex. = excluding; ICT = information and communication technology; IND = India; LAC = Latin America and the Caribbean; LKA = Sri Lanka; MDV = Maldives; MNA = Middle East and North Africa; NPL = Nepal; SAR = South Asia; SSA = Sub-Saharan Africa.

A. Data for 2024, except for Sri Lanka which is for 2023. Pink area indicates the interquartile range for "Other EMDEs".

B. Bars show coefficients from occupation-month regressions of log of job postings and log of wages on the interaction between post-ChatGPT and a business services occupation indicator, conditional on occupation and month fixed effects (annex table 10 from chapter 2).

C. Bars show the percentage of occupations exposed to AI across countries in SAR. Exposure defined as a composite AIOE score greater than the median score across occupations. Complementary (substitutable) jobs are defined as a complementarity score above (below) the median score across occupations and above-median exposure.

D. Bars show the share of jobs and total wage earnings that are either exposed to AI, complementary with AI, or substitutable with AI.

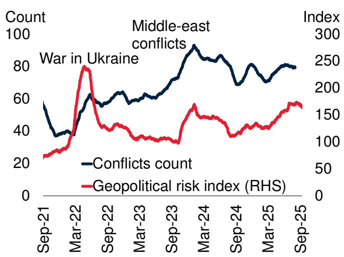
E. The AI Preparedness Index (AIPI) has 4 key dimensions: digital infrastructure, human capital, technological innovation, and legal frameworks. The numbers represent the median index value for each region. The Government AI Readiness index examines 40 indicators across government, the technology sector, and data and infrastructure. "Other EMDEs" includes 143 economies.

F. Working-age population is the number of people between the ages of 15 and 64. Regions use population-weighted averages.

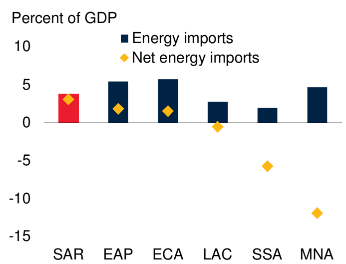
FIGURE 1.9 Geopolitical pressures and energy security

The number of conflicts in the world is rising which, alongside other geopolitical pressures, could raise energy prices in South Asia. Heavy reliance on imported fossil fuels makes the region vulnerable to global energy price shocks. The region can protect against this risk through greater energy efficiency and investments in renewable energy, the price of which has fallen rapidly as global capital expenditures have surged.

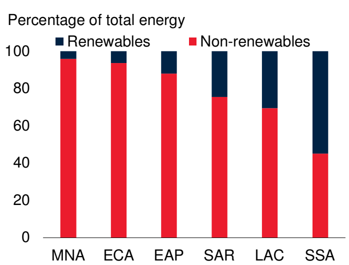
A. Geopolitical risk index and global conflicts



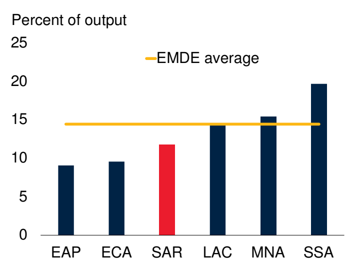
B. Energy imports, 2021



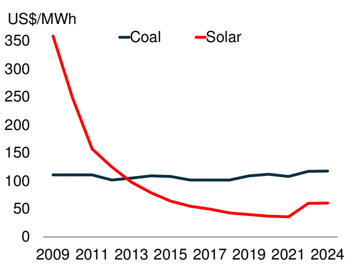
C. Mix of renewable and non-renewable energy supply sources, 2022



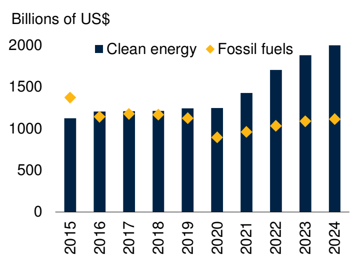
D. Electric power transmission losses, 2022



E. Price of solar power generation



F. Global capital expenditure in energy



Sources: Caldara and Iacoviello (2022); CEPII CHELEM trade database; International Energy Agency, Global Energy Investment (2024); Lazard 2024 LCOE+ Report; OECD Green Growth database; RHS = right-hand side; Sundberg and Melander (2013); United Nations Energy Balances (2022); Uppsala Conflict Data Program (UCDP); World Bank; World Development Indicators (database).

Note: EAP = East Asia and Pacific; ECA = Europe and Central Asia; EMDEs = emerging market and developing economies; LAC = Latin America and the Caribbean; MNA = Middle East and North Africa; SAR = South Asia; SSA = Sub-Saharan Africa; US$/MWh = U.S. dollars per megawatt hour.

A. Lines are 3-month moving averages. Conflicts are defined as "an incident where armed force was used by an organized actor against another organized actor, or against civilians, resulting in at least 1 direct death at a specific location and a specific date." Last observation is September 18th, 2025.

B. Chart shows energy as a share of total imports, net of re-exports, as the single bar for each region. Energy imports include imports of coal, crude oil, natural gas, coke, refined petroleum products, and electricity. Regional values are simple averages of country-level data. SAR includes Bangladesh, India, and Sri Lanka. LAC includes 10 countries, EAP 7, MNA 6, SSA 5, and ECA 13.

C. Renewable energy sources include biomass, geothermal, and solar thermal electricity production. Regional values are simple averages. SAR includes 6 countries, MNA 18, ECA 21, LAC 20, EAP 10, and SSA 30.

D. Electric power losses include those in transmission between sources of supply and points of distribution and in the distribution to consumers, including pilferage. Regional values are simple averages. SAR includes 6 countries, SSA 44, MNA 15, LAC 23, ECA 17, and EAP 21.

E. Price of energy sources is calculated as the levelized cost of energy (LCOE) which captures the cost of building the power plant itself as well as the ongoing costs for fuel and operating the power plant over its lifetime. Values reflect the average of the high and low LCOE for each technology in each respective year. No data for 2022.

F. 2024 data are estimates.

younger, mid-skilled workers. White-collar services work is critical for South Asia—it accounts for an unusually high share of GDP, exports, and formal sector job growth in India, Sri Lanka, and Nepal (figure 1.8; chapter 3; Liu 2024). A slowdown in labor demand for some of the occupations that are most exposed to AI can already be observed from trends in job postings before and after the public release of ChatGPT in November 2022 (chapter 2).

Across South Asia, around 22 percent of jobs are exposed to AI, as measured by the overlap between the skills required in an occupation and the capabilities of generative AI (chapter 2; Felten, Raj, and Seamans 2021). These jobs are disproportionately well-paying, and account for 42 percent of all wage earnings.

A large share of exposed jobs in South Asia are also complementary with AI, in that they are more likely to enjoy productivity gains from AI adoption and are less likely to be replaced. These jobs include doctors and managers, for example. They tend to require the highest levels of skills and experience, and involve tasks such as face-to-face communication, decision-making responsibility, and domain expertise.

Benefiting from AI requires that countries have the right preconditions in place, however, and this is often not the case, particularly outside India. South Asia scores below the EMDE average in indexes of five key dimensions of AI readiness: government readiness, digital infrastructure, human capital, technological innovation and economic integration, and legal frameworks and regulations. Investing in the technological and institutional framework for a supportive digital economy could help boost growth and avoid job losses from the spread of AI.

Geopolitical pressures and energy security

The number of conflicts around the world has been rising steadily for several years (figure 1.9). Conflict can have a ruinous impact on those directly affected, including loss of life and destruction of property. On a national level, conflicts can lead to recessions and a significant worsening of fiscal positions through a combination of greater expenditures, weaker growth, and higher borrowing costs (Federle et al. 2024).

International spillovers from conflict can come in the form of disruptions to trade, higher prices, reduced confidence, increased uncertainty, and financial market volatility. Even the threat of conflict can have similar consequences, and persistent tensions between countries can cause the fragmentation of trading blocs, which can lead to decreased competition, specialization, and economies of scale that ultimately result in worse economic and fiscal outcomes.

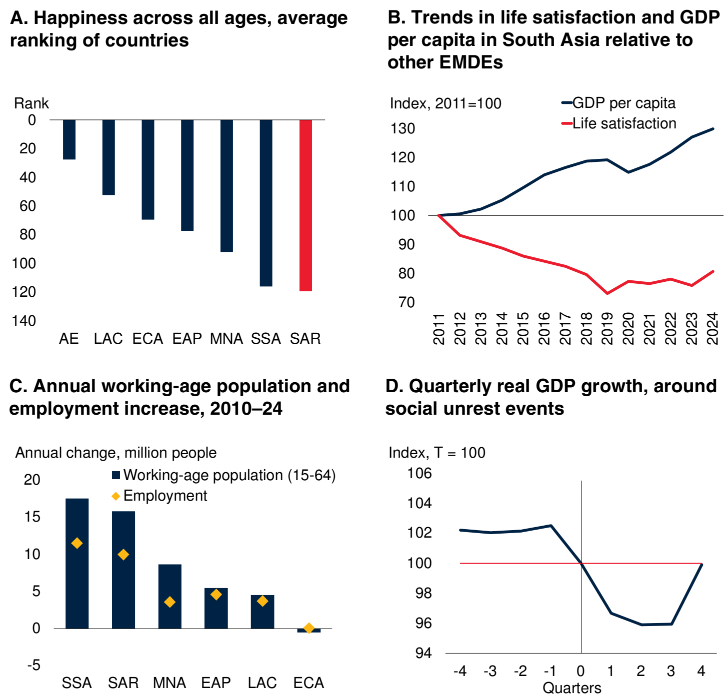
South Asia has particular vulnerability to rising energy cost spillovers from conflict. The region has large and growing energy needs, and relies heavily on imported nonrenewable energy. The energy intensity of its output is twice the global average (World Bank 2023a). India is expected to be the world's fastest-growing source of energy demand in the medium term and surpass China to become the single largest source of energy demand by 2050 (IEA 2024).

At present, South Asia depends on imported energy more than any other EMDE region. Outside of Nepal and Bhutan, domestic energy production is modest and consists mostly of fossil fuels. Net energy imports are equivalent to about one fifth of the region's imports and 4 percent of GDP. The region's domestic energy industry is small and heavily dependent on nonrenewables.

South Asia's vulnerability to global energy market disruptions is amplified by significant leakage in electricity transmission and frequent power outages. A shift toward more decentralized renewable energy production would improve South Asia's energy security, make access to electricity more reliable, and reduce air pollution. This shift would be hastened by low tariffs on intermediate imports such as solar panels, regulatory streamlining, modernization of the electric grid, reduction of fossil fuel subsidies, and pricing terms that de-risk private green energy investments.

FIGURE 1.10 Worsening social unrest

Life satisfaction in South Asia is low and has not improved as per capita incomes have increased. Some of this dissatisfaction may be because the economy is not generating enough jobs for the region's rapidly growing working-age population. Social unrest can have substantial negative impacts on activity.



Sources: CEIC; Haver Analytics; Helliwell et al. (2025); International Labour Organization; Penn World Table (database); United Nations World Population Prospects (database); Wellbeing Research Centre (2025); World Development Indicators (database); October 2024 South Asia Development Update; World Bank.

Note: AE = Advanced economies; EAP = East Asia and Pacific; ECA = Europe and Central Asia; EMDEs = emerging market and developing economies; LAC = Latin America and the Caribbean; MNA = Middle East and North Africa; SAR = South Asia; SSA = Sub-Saharan Africa.

A. Average life evaluation rank by region (whole population). Happiest country has a rank of 1, with increasing unhappiness as rank increases.

B. Lines show the development of GDP per capita and self-reported life satisfaction (from the Wellbeing Research Centre) in South Asia compared to other EMDEs. The South Asia group includes India, Bangladesh, Sri Lanka, and Nepal, while the comparison group covers 90 other EMDEs. For both groups, weighted averages are calculated using population size.

C. Working age population defined as individuals between the ages of 15 and 64.

D. GDP growth rate is the median of 7 countries around major episodes of social unrest (those with a peak crowd size above 10,000 people).

The economic rationale for shifting toward renewable energy sources is becoming more compelling. The cost of solar power generation has fallen precipitously in recent years, such that solar energy is now cheaper than coal-fueled energy by some metrics. Globally, investment in clean energy has exceeded that in fossil fuels since 2016—and by an increasing amount, such that it was twice as large in 2024. Unlike coal, renewables produce energy intermittently. This shortcoming can be partially overcome by energy storage technologies such as batteries, the price of which has declined by 97 percent in the past three decades (Ziegler and Trancik 2021).

Worsening social unrest

Many countries in South Asia have experienced bouts of social unrest in recent years. Public uprisings led to the collapse of the government in Nepal in September, in Bangladesh in August 2024, and in Sri Lanka in July 2022.

Despite South Asia's rapid economic progress, life satisfaction in the region is low. In the latest World Happiness Ranking of 143 countries, Bangladesh ranks 129th, Sri Lanka 128th, and India 126th (figure 1.10). The region's life satisfaction has trended down over time relative to other EMDEs.

Popular uprisings may provide an opportunity for countries to implement necessary economic and social reforms. In the short term, however, they often disrupt economic activity. In the 24 EMDEs where social unrest has toppled the government between 2000 and 2022, GDP has fallen by an average of 5 percent in subsequent quarters. Countries typically also see an acceleration in inflation and sharp declines in financial market valuations (Acemoglu, Hassan, and Tahoun 2018; Barrett et al. 2021; Ghosh 2016).

These impacts tended to be more pronounced following more prolonged periods of unrest, larger in more authoritarian regimes, and larger around violent uprisings than around collective protests (Ghate, Le, and Zak 2003). Impacts can also be mitigated by stronger institutions (Bernal-Verdugo, Furceri, and Guillaume 2013).

In South Asia, some governments' ability to respond to social unrest with expansive fiscal policy is limited by the region's elevated debt levels. Policymakers might instead focus on ensuring that sufficient jobs are being created to absorb the large number of new job entrants. Over 2010–24, the working age population in South Asia grew by about 16 million every year, but the economy created fewer than 10 million new jobs annually. Harnessing the ability of trade openness and AI to create new opportunities may help create more jobs and stem public dissatisfaction.

Policy challenges

South Asia faces the considerable challenge of creating enough jobs for its rapidly growing population. At the same time, it must also sustainably boost per capita incomes while adjusting to major shifts in the economic environment. Adapting to the spread of AI and a changing global trade environment will require workers to be able to move easily between shrinking and growing sectors, firms, and regions. A number of policies can facilitate such movement, including investment in connectivity, upskilling, streamlining size-dependent regulations that discourage firm growth, more efficient housing markets, and better job matching. Robust safety nets for those in between jobs can also encourage job switching.

Sustaining public investment

Most South Asian countries have stocks of public capital well below the average of other EMDEs (figure 1.11). Additional public investment can deliver substantial benefits, both directly and indirectly. Infrastructure projects, for example, can improve connectivity, expand market access, and reduce transaction costs, resulting in stronger long-term growth. A 10 percent increase in the public capital stock can increase long-run aggregate productivity by 0.7–1.0 percent (Calderón, Moral-Benito, and Servén 2015).

The region is catching up, however, thanks to growing public investment. In Nepal and India, for example, public investment growth averaged 12 and 10 percent, respectively, from 2022 to 2024, substantially higher than the EMDE average of 0.6 percent. In the right circumstances, these expenditures can crowd in private investment. In India, central government capital expenditures increased aggregate activity by 3–4 times as much as was spent (World Bank 2025a). Similarly, investments in climate resilience can generate benefits four times as large as expenditures (World Bank 2023b).

South Asia has a number of challenges with respect to public investment. Foremost among these is limited government revenues to finance such investments. During 2019–23, South Asian governments' revenues (excluding grants) averaged 18 percent of GDP, the lowest among all EMDE regions and well below the EMDE average of 24 percent of GDP (World Bank 2025b). More than one-quarter of this revenue goes to interest payments, constraining funding capability for basic government services or public investment.

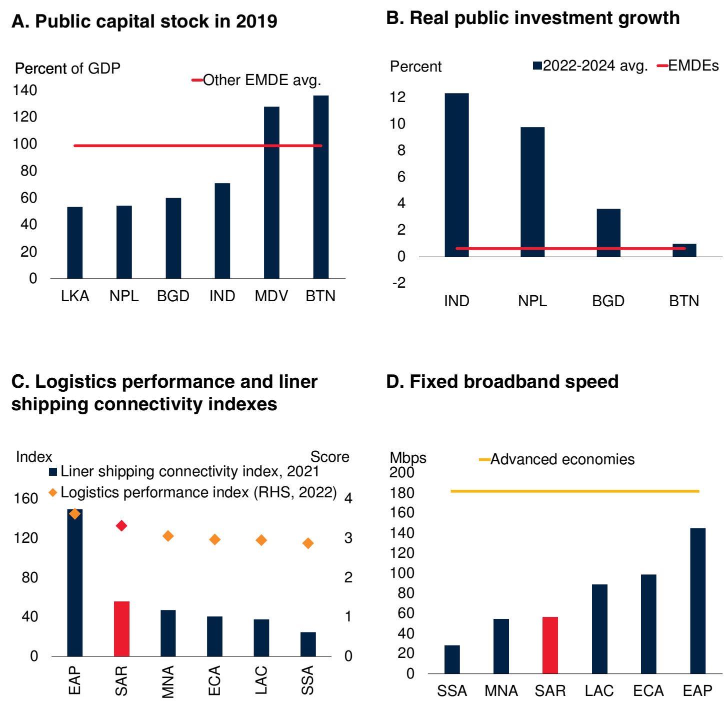
Even when resources are available for public investment, many countries have a low execution rate of capital expenditures, meaning that they are unable to effectively spend as much as is budgeted. In some cases, this is due to insufficient project management expertise in public bureaucracies. In other cases, such as with the expansion of the international airport in Maldives, it is due to financing challenges caused by high levels of debt. In Nepal, large infrastructure projects are delayed for years by cumbersome procedures that make it difficult to acquire land or even simply cut down trees.

To benefit from changes in global trade patterns, additional public investment is needed in transport infrastructure. The cost of trading goods between South Asia and the rest of the world has been measured at around 140 percent of the cost of trading them domestically, the second highest among EMDE regions (Ohnsorge and Quaglietti 2023). This is partly due to tariff and non-tariff trade barriers, but also to poor transport connectivity. South Asia has made rapid progress in recent years on increasing the quality of its transport infrastructure, but it remains less advanced than in the East Asia and Pacific region. Trade between countries is easily impeded by the delays caused by poor shipping connectivity and inadequate logistics infrastructure (Freund and Rocha 2011). A 10 percent increase in transport times can reduce trade by 5–25 percent (Ohnsorge and Quaglietti 2023).

High-quality, well-maintained transport infrastructure—at ports, airports, and on land—together with efficient shipping services can lower transport and logistics costs. Improvements to roads, railways, ports, and airports—whether

FIGURE 1.11 Public investment

South Asia has a lower stock of public capital than other EMDE regions but is catching up. The region's transport connectivity has improved but remains below that of the East Asia and Pacific region. Fixed broadband speeds are slow.



Sources: IMF Investment and Capital Stock database; Ookla (database); Macro Poverty Outlook; World Development Indicators (database); World Bank.

Note: avg. = average; BGD = Bangladesh; BTN = Bhutan; EAP = East Asia and Pacific; ECA = Europe and Central Asia; EMDEs = emerging market and developing economies; IND = India; LAC = Latin America and the Caribbean; LKA = Sri Lanka; MDV = Maldives; MNA = Middle East and North Africa; NPL = Nepal; SAR = South Asia; SSA = Sub-Saharan Africa.

A. "Other EMDE average" is calculated using real GDP in U.S. dollars as weights.

B. EMDE growth reflects total public investment growth across 87 EMDEs, measured in real U.S. dollars.

C. Linear Shipping Connectivity Index is set to 100 for the country with the highest value in 2004. Logistics Performance Index ranges from 0 to 5, with 5 indicating the highest performance. Regional aggregates are weighted using average real GDP from 2010–19. Sample includes 117 EMDEs.

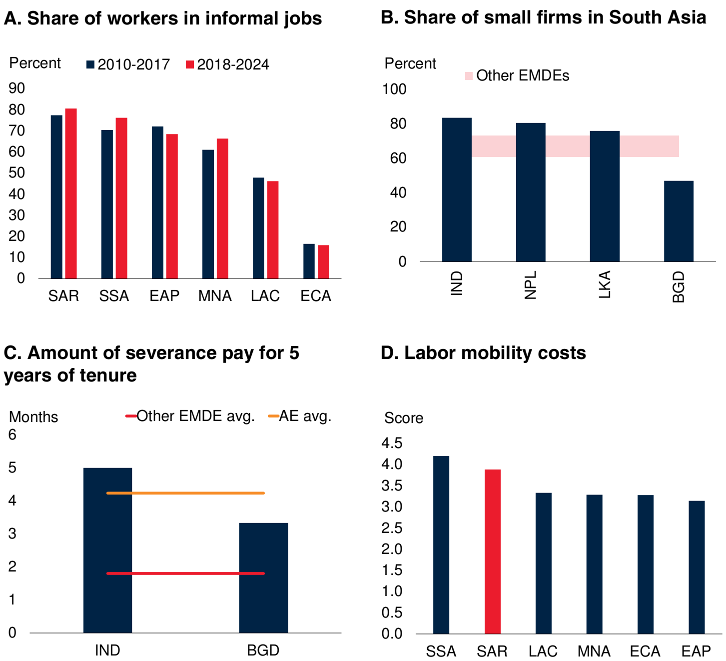
D. Median download speeds are shown for each region.

through direct public investment or private sector participation—can help countries integrate into global supply chains, increase productivity, and flexibly access global sources of demand.

AI applications access, process, and transmit large volumes of data. To maximize the benefits of AI, additional investment is needed in digital infrastructure, including reliable sources of electricity, high-speed internet, and data processing services. South Asia has made rapid progress by these metrics in recent years. Nearly 100 percent of the population has access to electricity and about 67 percent uses the internet.

FIGURE 1.12 Creating more jobs

South Asian labor markets are characterized by a high level of informality and the predominance of small firms. Some firms stay small and informal to avoid burdensome regulations, such as high levels of mandated severance pay. Labor mobility costs in the region are high, discouraging workers from seeking opportunities in rapidly growing hubs within their own countries.



Sources: Artuc, Lederman, and Porto (2015); International Labour Organization International Labour Statistics (database); IMF Government Financial Statistics (database); World Bank Enterprise Survey; World Development Indicators (database); World Bank.

Note: AE = Advanced economies; avg. = average; BGD = Bangladesh; BTN = Bhutan; EAP = East Asia and Pacific; ECA = Europe and Central Asia; EMDEs = emerging market and developing economies; IND = India; LAC = Latin America and the Caribbean; LKA = Sri Lanka; MDV = Maldives; MNA = Middle East and North Africa; NPL = Nepal; SAR = South Asia; SSA = Sub-Saharan Africa.

A. Chart shows weighted averages across 68 countries, using the working-age population as weights for each region and time period. South Asia average is based on Bangladesh, India, Maldives, and Sri Lanka.

B. Sampled among formal firms. Small firms have 20 employees or fewer. For World Bank Enterprise Surveys, South Asia sample includes Bangladesh and India for 2022, Nepal for 2023, and Sri Lanka for 2011. "Other EMDEs" shows interquartile range for 71 countries between 2017 and 2023.

C. Averages calculated using working-age population as weights: advanced economy sample includes 13 countries, other EMDE sample include 48 countries.

D. Higher scores indicate higher mobility costs. Bars show the median level across regional economies. SAR includes Bangladesh and India. Sample includes 33 EMDEs.

But the region's capacity for intensive data processing and transmission is limited: fixed broadband data transmission rates average about one-quarter of the speed of advanced economies, and the number of secure internet servers per capita is only 1.4 percent of the advanced-economy average. Even where digital capacity exists, uptake has not necessarily followed. Across South Asia, only 33 percent of people have made or received a digital payment (compared to 93 percent in high-income countries), and less than 10 percent have ever bought something online (World Bank 2024a).

To remedy this, governments could provide a combination of direct public investment in telecommunications alongside policies that encourage private investment and competition in broadband deployment. Private investment is often burdened by excessive costs of regulatory compliance, and inputs such as land and credit are often difficult to obtain—public support and guarantees can help ease these constraints and fund public investments without straining public finances. Updating power grids and investing in renewable energy sources are already critical priorities for the region to safeguard energy security, meet the needs of its growing economy, expand access, and eliminate shortages (Zhang 2019). Effective reforms in the energy sector would also help provide the reliable, cheap power needed by AI.

Many of these reforms require increased expenditures, to some extent, and would therefore benefit from reforms to improve government fiscal positions. This could be done by cutting unproductive expenditures, such as some subsidies, or by raising revenues through eliminating tax exemptions, and unifying, simplifying, and harmonizing tax rates.

Creating more jobs

Creating employment opportunities for rapidly-growing working-age populations is a major challenge. Across Africa, the Middle East, and South Asia, job creation is struggling to keep pace with the number of people joining the working-age population between 2025 and 2050.

South Asia is the fastest-growing EMDE region, but job creation is still slower than needed to absorb the growing working-age population. Since 2010, the economy has created an average of about 10 million jobs for about 16 million new labor market entrants every year.

Increasing labor demand is critical for realizing South Asia's demographic dividend. Countries where workers are able to leave jobs with the confidence of finding another job are less likely to experience public unrest (World Bank 2013). A three-part approach could support job creation: building strong foundations of human and physical capital, creating business-friendly environments, and mobilizing private capital (Development Committee 2025).

Growing firms are a critical engine of job creation. In South Asia, however, firms often stay small, with few workers, and often remain informal. Close to 90 percent of workers in South Asia work in the informal sector, compared with 50 percent in other EMDEs (figure 1.12). Young small- and medium-sized enterprises in South Asia grow more slowly than in other EMDEs, both in terms of sales and employment (World Bank 2025a).

The drivers of firms' small size and informality are varied and complex. Local markets can be small and fragmented in South Asia, giving firms little incentive to expand. Small firms often lack access to the credit needed to grow. Sometimes small firms lack the skills needed for growth, such as formal management training.

Burdensome regulations encourage people and firms to operate informally, and are associated with lower entry and exit of firms (Bottasso, Conti, and Sulis 2017; Bussolo and Sharma 2022). Many firms in South Asia stay small rather than hiring workers and becoming subject to complex regulatory burdens—even among formal firms, those with fewer than 20 employees make up a greater proportion of firms in most South Asian countries than in other EMDEs.

In India, the Industrial Disputes Act requires official permission for any layoffs in factories above certain thresholds, and 90 days' advance notice for closure. Many manufacturing firms have fewer than 10 employees in order to avoid registering and becoming subject to taxes or regulations (Fattal-Jaef 2022; World Bank 2025a). Once firms cross this threshold, complying with regulations increases firms' unit labor costs by an estimated 35 percent (Amirapu and Gechter 2020). This may be one reason why garment-exporting plants in India are one-fifth the size of similar plants in Bangladesh (Muralidharan 2024). Similarly in Bhutan, firms report that compliance with government regulations is a considerable expense, and most small firms do not do so (Alaref et al. 2024). In Sri Lanka, land is predominantly owned by the state and governed by complex institutional and legal arrangements, with inefficient or non-existent markets; in this environment, large firms face greater difficulties obtaining land to expand production than smaller ones (Kumari et al. 2023).

Some labor market regulations can make it difficult or costly for firms to hire or dismiss workers, resulting in inefficiently long time spent in both employment and unemployment (Betcherman 2012). Prior government approval is sometimes needed to dismiss workers and can be denied or granted only after long delays. Laid-off workers can be entitled to substantial severance payments. Exit barriers of this type can trap resources in unproductive firms (Chatterjee et al. 2025).

Removing policies that stunt firm size could boost productivity and employment growth. Such policy changes often require coordination between different levels of government and therefore require buy-in from stakeholders at the municipal, state, and federal levels, alongside effective management and resource sharing.

Creating jobs for women is particularly important. Female labor force participation in South Asia is exceptionally low: it stood at 32 percent in 2023, well below the EMDE average of 54 percent, and South Asia's male labor force participation rate of 77 percent (World Bank 2024b). Women are more able and willing to join the labor force in the presence of supportive social norms and if they are able to access affordable and safe options for commuting, childcare, and education. Firms' demand for female labor can be linked to economic transformations such as urbanization, the shift to services, and increasing trade openness. The rapid growth of Bangladesh's export-oriented ready-made garment sector, for example, attracted many women into the labor market.

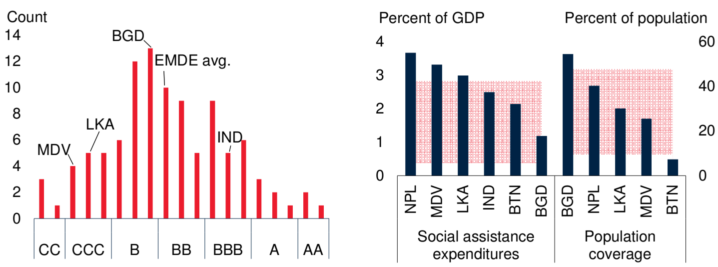
Facilitating internal worker migration can help people access higher-productivity jobs in booming regions. In India, five states account for more than half of India's value added in manufacturing and modern market services, more than half of total merchandise exports, and over three-quarters of total foreign direct investment. AI innovation is

FIGURE 1.13 Protecting displaced workers

Expanding social safety nets may be challenging given the high debt and low credit ratings of many South Asian countries. Almost all South Asian countries spend more of GDP on social assistance than the EMDE average, but social assistance coverage is often low.

A. Distribution of EMDE credit ratings

B. Expenditure and coverage of social assistance



Sources: Fitch; IMF Government Financial Statistics (database); Moody's; S&P; World Bank; World Development Indicators (database).

Note: avg. = average; BGD = Bangladesh; BTN = Bhutan; EMDEs = emerging market and developing economies; IND = India; LKA = Sri Lanka; MDV = Maldives; NPL = Nepal.

A. Credit ratings from S&P, Moody's, and Fitch mapped to a unified 1–22 scale (1 = lowest, 22 = highest), and averaged for each country. X-axis labels show rating categories (e.g., CC, CCC, B) corresponding to numeric brackets.

B. Red shading represents the range of 108 EMDEs for expenditures and 113 for population. Expenditure data represent the latest available year: Bangladesh, Maldives and Nepal for 2021; India and Sri Lanka for 2022; Bhutan for 2020. For coverage in population: 2010 for Nepal; 2019 for Maldives and Sri Lanka; 2022 for Bangladesh and Bhutan.

concentrated in a handful of cities characterized by high levels of innovation, ample capital, and an educated workforce (McElheran et al. 2023). These include several cities in southern India, such as Bangalore and Hyderabad.

Migration to these hubs would boost employment and output. Labor mobility costs in South Asia, however, are the second-highest among EMDE regions. In India, average migration between neighboring districts in the same state is at least 50 percent larger than between neighboring districts on different sides of a state border, even after accounting for linguistic differences (Kone et al. 2018). In Bangladesh, rural job seekers overwhelmingly migrate to higher-productivity work in Dhaka, but the city is struggling with increasing congestion.

Reallocating labor across states may be inhibited by poor infrastructure in some areas, as well as the poor portability of informal insurance and social welfare programs (World Bank 2025a). Investments in transportation, housing, and basic services could alleviate these problems, even if they are made in secondary cities to increase their attractiveness to migrants. Reducing migration costs can help workers relocate to where they can be most productive, alleviate skill constraints, and mitigate the costs of disruption from new technologies.

Both trade reform and the growing adoption of AI could spark major shifts in labor market opportunities. Seizing these opportunities requires efficient labor markets. Workers should be able to switch jobs easily, and productive firms should be able to grow and hire.

Protecting displaced workers

When safety nets are insufficient, the loss of a job can mean a devastating loss of income for a household. Some regulations have been put in place in an attempt to protect against this risk and to substitute for social protection programs. Programs that directly address redistribution, risk-sharing, and economic inclusion can cause fewer economic distortions and protect more people, but lower-income countries may lack the capacity to fund and manage them (World Bank 2025c).

Making investments in safety nets and skills programs can build this capacity and is a critical accompaniment to efforts to increase labor market flexibility (World Bank 2019). Adaptive social protections—an interlinked system of social safety nets, social insurance, and labor market programs that can adjust the size and coverage of its benefits rapidly in response to shocks—can help build the resilience of poor and vulnerable households against losses not only from unemployment, but also from natural disasters, sickness, or other disruptions (Bowen et al. 2020).

It can be expensive for governments to transition from a heavily regulated labor market and weak social protections to a flexible labor market and a strong system of adaptive social protections. This poses a challenge for countries in South Asia with high debt levels and weak credit ratings (figure 1.13). In the long term, however, this transition can pay continued dividends. These include stronger future growth and higher revenues as more of the economy operates formally, and as more workers feel safe enough for productive risk-taking and job-switching.

A switch of social benefits (including implicit benefits such as input subsidies) from support for specific activities to income support could be combined with a binding commitment to the gradual removal of obstacles to trade and domestic production (Muralidharan 2024). This would allow workers time to adjust and support those who cannot, while ensuring that productivity gains are eventually realized.

Safety nets can be designed to cover informal workers, who make up 79 percent of non-agricultural workers in South Asia. Digital payment systems can be leveraged to limit opportunities for waste and fraud, and can help programs scale up or down quickly in response to economic disruptions.

Except for Bangladesh, all South Asian countries spend more of their GDP on social assistance than the EMDE average. Nevertheless, only 43 percent of the population is covered by social protection systems, the second-lowest share among EMDE regions (World Bank 2025d).

Active labor market policies such as retraining programs can help ease the transition of workers from sectors threatened by AI or trade reform to those that benefit from new developments. Empirical evidence on the effectiveness of such programs is mixed, however (Crépon and van den Berg 2016; McKenzie 2017). Strengthening primary and secondary education systems to ensure that workers across the economy have key foundational skills that are not job specific can increase flexibility (Sharma and Winkler 2017). In Nepal, for example, businesses have identified a cross-cutting need for language, financial planning, and time management skills, as well as digital skills for an increasingly tech-driven economy (World Bank 2025e). The ability of AI to provide customized tutoring at scale could help improve educational outcomes in South Asia and ease difficult labor market transitions (Chiu et al. 2023; De Simone et al. 2025).

References

Acemoglu, D., T. A. Hassan, and A. Tahoun 2018. "The Power of the Street: Evidence from Egypt's Arab Spring." *Review of Financial Studies* 31 (1): 1–42.

Acemoglu, D., and P. Restrepo. 2020. "Robots and Jobs: Evidence from US Labor Markets." *Journal of Political Economy* 128 (6): 2188–2244.

Ahir, H., N. Bloom, and D. Furceri. 2022. "The World Uncertainty Index." *National Bureau of Economic Research*, February.

Alaref, J., L. Martinoty, M. Viollaz, E. Bartl, P. Leite, and A. E. Ndip. 2024. *Bhutan Labor Market Assessment Report.* 187640. Washington, DC: World Bank.

Amirapu, A., and M. Gechter. 2020. "Labor Regulations and the Cost of Corruption: Evidence from the Indian Firm Size Distribution." *The Review of Economics and Statistics* 102 (1): 34–48.

Artuc, E., D. Lederman, and G. Porto. 2015. "A Mapping of Labor Mobility Costs in the Developing World." *Journal of International Economics* 95 (1): 28–41.

Autor, D., and D. Dorn. 2013. "The Growth of Low-Skill Service Jobs and the Polarization of the US Labor Market." *American Economic Review* 103 (5): 1553–97.

Baker, S. R., N. Bloom, and S. J. Davis. 2016. "Measuring Economic Policy Uncertainty." *The Quarterly Journal of Economics* 131 (4): 1593–1636.

Barrett, P., M. Bondar, S. Chen, M. Chivakul, and D. O. Igan. 2021. "Pricing Protest: The Response of Financial Markets to Social Unrest." *Review of Finance* 28 (4): 1419–50.

Bernal-Verdugo, L. E., D. Furceri, and D. Guillaume. 2013. "The Dynamic Effect of Social and Political Instability on Output: The Role of Reforms." IMF Working Paper, WP/13/91. International Monetary Fund, Washington DC.

Betcherman, G. 2012. "Labor Market Institutions: A Review of the Literature." SSRN Scholarly Paper 2181285. Social Science Research Network, Rochester, NY.

Bottasso, A., M. Conti, and G. Sulis. 2017. "Firm Dynamics and Employment Protection: Evidence from Sectoral Data." *Labour Economics* 48 (October): 35–53.

Bowen, T., C. del Ninno, C. Andrews, S. Coll-Black, U. Gentilini, K. Johnson, Y. Kawasoe, A. Kryeziu, B. Maher, and A. Williams. 2020. *Adaptive Social Protection: Building Resilience to Shocks*. Washington, DC: World Bank.

Bussolo, M., and S. Sharma, eds. 2022. *Hidden Potential: Rethinking Informality in South Asia*. Washington, DC: World Bank.

Calderón, C., E. Moral-Benito, and L. Servén. 2015. "Is Infrastructure Capital Productive? A Dynamic Heterogeneous Approach." *Journal of Applied Econometrics* 30 (2): 177–98.

Caldara, D., and M. Iacoviello. 2022. "Measuring Geopolitical Risk." *American Economic Review* 112 (4): 1194–1225.

Caldara, D., M. Iacoviello, P. Molligo, A. Prestipino, and A. Raffo. 2020. "The Economic Effects of Trade Policy Uncertainty." *Journal of Monetary Economics* 109 (January): 38–59.

Carrière-Swallow, Y., and L. F. Céspedes. 2013. "The Impact of Uncertainty Shocks in Emerging Economies." *Journal of International Economics* 90 (2): 316–25.

CBO. 2025. "Congressional Budget Office, Budget and Economic Data (database)."

Chatterjee, S., K. Krishna, K. Padmakumar, and Y. Zhao. 2025. "No Country for Dying Firms: Evidence from India." NBER Working Paper 33830, National Bureau of Economic Research, Cambridge, MA.

Chiu, T. K. F., Q. Xia, X. Zhou, C. S. Chai, and M. Cheng. 2023. "Systematic Literature Review on Opportunities, Challenges, and Future Research Recommendations of Artificial

Intelligence in Education." *Computers and Education: Artificial Intelligence* 4 (January): 100118.

Crépon, B., and G. J. van den Berg. 2016. "Active Labor Market Policies." *Annual Review of Economics* 8 (Volume 8, 2016): 521–46.

De Simone, M., F. Tiberti, M. Barron Rodriguez, F. Manolio, W. Mosuro, and E. J. Dikoru. 2025. "From Chalkboards to Chatbots: Evaluating the Impact of Generative AI on Learning Outcomes in Nigeria." Policy Research Working Paper 11125 World Bank, Washington, DC.

Development Committee. 2025. *Jobs: The Path to Prosperity.* Washington, DC: World Bank and International Monetary Fund.

Fattal-Jaef, R. N. 2022. "Entry Barriers, Idiosyncratic Distortions, and the Firm Size Distribution." *American Economic Journal: Macroeconomics* 14 (2): 416–68.

Federle, J., A. Meier, G. Müller, W. Mutschler, and M. Schularick. 2024. "The Price of War." Kiel Working Papers 2262, Kiel Institute for the World, Kiel.

Felten, E., M. Raj, and R. Seamans. 2021. "Occupational, Industry, and Geographic Exposure to Artificial Intelligence: A Novel Dataset and Its Potential Uses." *Strategic Management Journal* 42 (12): 2195–2217.

Freund, C., and N. Rocha. 2011. "What Constrains Africa's Exports?" *The World Bank Economic Review* 25 (3): 361–86.

Ghate, C., Q. V. Le, and P. J. Zak. 2003. "Optimal Fiscal Policy in an Economy Facing Sociopolitical Instability." *Review of Development Economics* 7 (4): 583–98.

Ghosh, S. 2016. "Political Transition and Bank Performance: How Important Was the Arab Spring?" *Journal of Comparative Economics* 44 (2): 372–82.

Goldberg, P. K., and T. Reed. 2023. "Presidential Address: Demand Side Constraints in Development. The Role of Market Size, Trade, and (In)Equality." *Econometrica* 91 (6): 1915–50.

Helliwell, J., R. Layard, J. D. Sachs, J. D. Neve, L. B. Aknin, and S. Wang. 2025. "World Happiness Report." IEA. 2024. *World Energy Outlook 2024*. France: International Energy Agency.

Islam, T., and M. A. Halim. 2022. "Impact of Ready-Made Garments (RMG) Industries and Sustainability: Perspective of the Pandemic Period in Developing Country." *Cleaner Engineering and Technology* 11 (December): 100567.

Kilic Celik, S., M. A. Kose, and F. Ohnsorge. 2023. "Potential Growth Prospects: Risks, Rewards, and Policies." Policy Research Working Paper 10355, World Bank, Washington, DC.

Kone, Z. L., M. Y. Liu, A. Mattoo, and C. Ozden. 2018. "Internal Borders and Migration in India." *Journal of Economic Geography*, 729–59.

Kose, M. A., and F. Ohnsorge. 2024. *Falling Long -Term Growth Prospects: Trends, Expectations, and Policies.* Washington, DC: World Bank.

Kumari, R. D. S., S. X. Chen, B. Li, and S. H. K. Tang. 2023. "Can Land Misallocation Be a Greater Barrier to Development than Capital? Evidence from Manufacturing Firms in Sri Lanka." *Economic Modelling* 126 (September): 106368.

Liu, Y. 2024. "Generative AI: Catalyst for Growth or Harbinger of Premature De-Professionalization?" Policy Research Working Paper 10915, World Bank, Washington, DC.

McElheran, K., J. F. Li, E. Brynjolfsson, Z. Kroff, E. Dinlersoz, L. Foster, and N. Zolas. 2023. "AI Adoption in America: Who, What, and Where." NBER Working Paper 31178, National Bureau of Economic Research, Cambridge, MA.

McKenzie, D. 2017. "How Effective Are Active Labor Market Policies in Developing Countries? A Critical Review of Recent Evidence." *The World Bank Research Observer* 32 (2): 127–54.

Muralidharan, K. 2024. *Accelerating India's Development: A State-Led Roadmap for Effective Governance.* Gurugram, Haryana, India: Penguin Viking.

Nana, I., R. Ouedraogo, and S. J. Tapsoba. 2025. "The Heterogeneous Effects of Uncertainty on Trade." *The World Economy* 48(8): 1881–1896.

Ohnsorge, F., and L. Quaglietti. 2023. "Trade as an Engine of Growth: Sputtering but Fixable." Policy Research Working Paper 10356, World Bank, Washington DC.

Pizzinelli, C., A. Panton, M. Tavares, M Cazzaniga, and L. Li. 2023. "Labor Market Exposure to AI: Cross-Country Differences and Distributional Implications." IMF Working Paper WP/23/216, International Monetary Fund, Washington, DC.

Sharma, S., and H. Winkler. 2017. "The Labour Market Effects of Financial Crises: The Role of Temporary Contracts in Central and Western Europe." *Economics of Transition* 26 (1): 35–60.

Sundberg, R., and E. Melander. 2013. "Introducing the UCDP Georeferenced Event Dataset." *Journal of Peace Research* 50 (4): 523–32.

Webb, M. 2020. "The Impact of Artificial Intelligence on the Labor Market." Working Paper.

World Bank. 2013. *World Development Report 2013: Jobs*. Washington, DC: World Bank.

World Bank. 2019. *World Development Report 2019: The Changing Nature of Work.* Washington, DC: World Bank.

World Bank. 2020. *World Development Report 2020: Trading for Development in the Age of Global Value Chains.* Washington, DC: World Bank.

World Bank. 2023a. *South Asia Development Update: Toward Faster, Cleaner Growth.* October. Washington, DC: World Bank.

World Bank. 2023b. *Expanding Opportunities: Toward Inclusive Growth.* April. World Bank.

World Bank. 2024a. *Digital Progress and Trends Report 2023.* World Bank.

World Bank. 2024b. *South Asia Development Update: Women, Jobs, and Growth. October*. Washington, DC: World Bank.

World Bank. 2025a. *India Country Economic Memorandum – Becoming a High-Income Economy in a Generation.* Washington, DC: World Bank.

World Bank. 2025b. *South Asia Development Update: Taxing Times* April Washington, DC: World Bank.

World Bank. 2025c. "Regulating Markets So More People Find Better Jobs." Social Protection & Jobs Discussion Paper 2502 Washington, DC: World Bank.

World Bank. 2025d. State of Social Protection Report 2025: The 2-Billion-Person Challenge. Washington, DC: World Bank.

World Bank. 2025e. *Nepal Country Economic Memorandum, March 2025: Unlocking Nepal's Growth Potential.* Washington, DC: World Bank.

Zhang, F. 2019. *In the Dark: How Much Do Power Sector Distortions Cost South Asia?* Washington, DC: World Bank.

Ziegler, M. S., and J. E. Trancik. 2021. "Re-Examining Rates of Lithium-Ion Battery Technology Improvement and Cost Decline." *Energy & Environmental Science* 14 (4): 1635–51.

CHAPTER 2

Artificial Intelligence, Real Impact:

Labor Market Implications of AI Adoption in South Asia

Chapter 2: Artificial Intelligence, Real Impact: Labor Market Implications of AI Adoption in South Asia

South Asia's workforce is only moderately exposed to changes caused by the adoption of artificial intelligence (AI) owing to the predominance of low-skill, agricultural, and manual jobs, which tend to be those least likely to be replaced by AI. But demand for AI skills has grown rapidly, and jobs requiring these skills command a wage premium of nearly 30 percent relative to other white-collar jobs. Productivity gains could be substantial for the 15 percent of South Asian workers who are in jobs with strong complementarities with AI and who tend to be highly educated, experienced workers. Only 7 percent of South Asia's jobs are highly exposed to AI without being complementary to its use, and are thus at risk of automation—well below the 15-percent exposure in other emerging markets. Moderately educated, young workers are the most vulnerable to job displacement. The introduction of Generative AI has already reduced monthly job listings by around 20 percent for the most exposed and most substitutable white-collar occupations. The largest relative job losses have occurred in the business services and information technology sectors, and among upper-middle-skilled and entry-level workers. South Asia could strengthen the foundations for maximizing the benefits of AI by raising the share of skilled workers and ensuring reliable electricity, as well as consistent and fast internet access. Improving infrastructure and facilitating labor mobility can help maximize AI's benefits while minimizing labor market disruptions.

Introduction

Rapid global take-up of AI. The rapid development of artificial intelligence (AI), technology that allows computers to simulate human intelligence, could transform the global economy. The latest wave of AI has centered on Generative AI (GenAI), which can respond to human prompts and generate content in a variety of formats. Such models include OpenAI's ChatGPT, Anthropic's Claude, X's Grok, Google's Gemini, Microsoft's Copilot, and DeepSeek. Globally, AI-related research and patenting, startup activity, and corporate investment have grown exponentially over the past decade, and the take-up of AI tools has been unusually rapid (figure 2.1). AI is already solving complex problems across a variety of sectors, with applications in such fields as manufacturing, precision agriculture, medical diagnostics, personalized education, power grid management, media content generation, and pharmaceutical development. The economic shifts caused by AI will likely have profound consequences for labor markets in South Asia, bringing both opportunities and risks for sustained, rapid job creation.

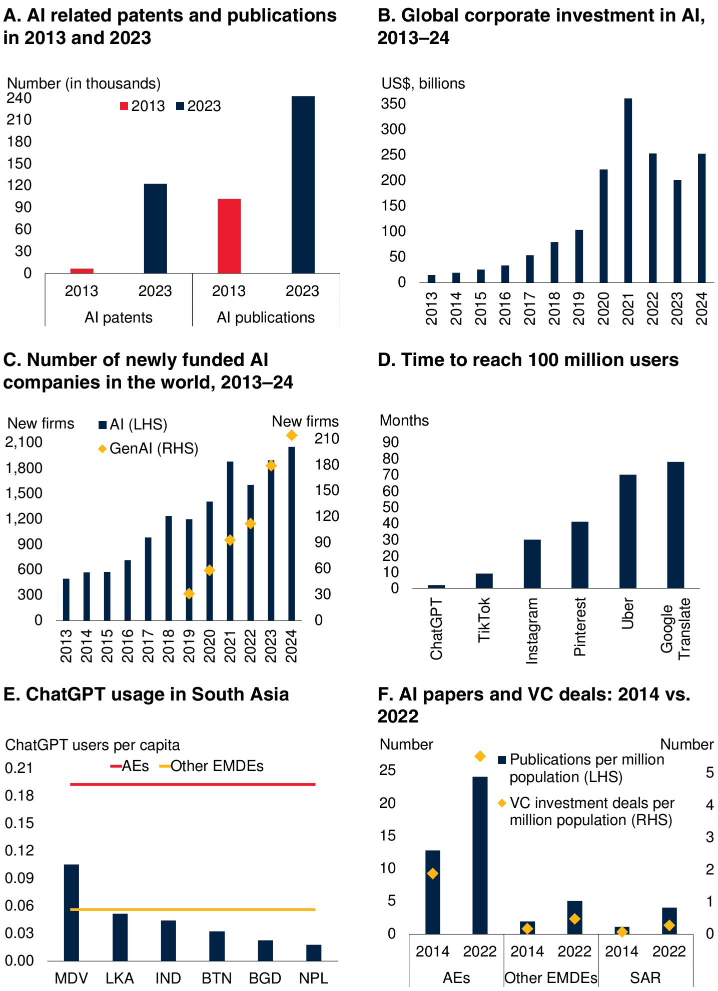
Note: This chapter was prepared by Patrick Kirby, Jonah Rexer, and Siddharth Sharma. Generative AI was used in this chapter to help classify occupations. See annex 2.2 for details.

Low but growing take-up of AI in EMDEs. The global rise in AI-related research and entrepreneurship has occurred mainly in advanced economies. Available measures of AI use, although limited, suggest that levels of AI penetration and engagement are relatively low in emerging market and developing economies (EMDEs). For example, the number of visitors per capita to GenAI websites is well below advanced-economy levels in EMDEs, including South Asian countries (figure 2.1). However, engagement with AI technologies is on the rise in South Asia and other EMDE regions. For example, the number of AI-related research publications per capita, as well as venture capital deals in South Asian countries and other EMDEs, remain lower than in advanced economies but have risen markedly in the past decade.

Productivity-boosting potential. AI could boost productivity significantly in South Asia if the preconditions are in place for its successful adoption by the region's firms. Early firm-level evidence points to the potential for substantial labor productivity gains from deploying generative AI technologies in the types of jobs that have strong human-AI complementarities (Brynjolfsson, Li, and Raymond 2023). Much of the existing research on AI's macroeconomic implications has concentrated on advanced

FIGURE 2.1 Artificial intelligence adoption, research, and development

Globally, research related to artificial intelligence (AI)—and the patenting, startup activity, and corporate investment surrounding it—has been accelerating exponentially, and AI tools have been adopted at an unprecedented pace. Emerging market and developing economies are behind advanced economies in AI-related research and startup activity, although the gap is narrowing.



Sources: Bryan (2025); Liu and Wang (2024); Maslej et al. (2025); Organisation for Economic Co-operation and Development (2025); World Development Indicators (database); World Bank.

Note: AEs = advanced economies; AI = artificial intelligence; EMDEs = emerging market and developing economies; BGD = Bangladesh; BTN = Bhutan; GenAI = generative artificial intelligence; IND = India; LHS = left-hand side; LKA = Sri Lanka; MDV = Maldives; NPL = Nepal; RHS = right-hand side; VC = venture capital; SAR = South Asia.

A. Blue bars show the number of AI-related patents in 2013 and 2023. Red bars show the number of AI-related publications in journals, conferences, books, repositories, and other outlets.

B. Bars represent total AI investments made by corporations globally from 2013 to 2024.

C. Bars represent the number of newly funded AI companies in the world from 2013 to 2024. Yellow diamonds show the number of newly funded generative AI companies in the world from 2019 to 2024.

D. Bars represent the number of months required for each software or website to reach 100 million users globally.

E. Bars show the number of ChatGPT users per capita in SAR countries. Yellow line shows the ratio in other EMDEs, and red line shows the ratio in advanced economies. "Other EMDEs" are EMDEs excluding SAR countries.

F. Bars show the annual average number of AI-related papers published per million people in SAR, other EMDEs, and advanced economies, in 2012–2016 and 2020–2024. Papers are assigned to countries based on the location of authors' institutions. Yellow diamonds represent the annual average number of VC investment deals per million people in these periods in SAR, other EMDEs and advanced economies. "Other EMDEs" are EMDEs excluding SAR countries. Weighted by population.

economies, where most GenAI development has occurred and initial adoption rates are higher. Still, EMDEs, including in South Asia, also stand to benefit from AI adoption and diffusion. For example, Indian firms, with their existing strengths in modern services sectors where scope for AI use is high, may be especially well suited to reap productivity gains. More broadly in South Asia, AI could lift the region's total factor productivity, which averaged two-thirds the level in other EMDEs and half the level in advanced economies in 2019 (figure 2.2). The region's economy is characterized by a preponderance of small, informal enterprises that tend to have low productivity levels (World Bank 2024a). AI could enable more dynamism among South Asia's firms, provided they have access to reliable electric power, as well as the skills and information and communication technology (ICT) infrastructure that underpin AI use.

Labor market disruption. The potential productivity gains from AI adoption must be weighed against potential employment displacement. Although new technologies typically create opportunities for more and better jobs over the long term, they can also generate significant labor market disruptions during their initial deployment phase. For example, automation through industrial robots and ICTs has depressed employment and wages in advanced economies over recent decades and contributed to labor market polarization (Acemoglu and Restrepo 2020; Autor and Dorn 2013). Emerging evidence already points to negative employment effects from AI adoption in advanced economies (Bonfiglioli et al. 2025; Huang 2024; Liu, Wang, and Yu forthcoming). The potential for adverse labor market consequences from AI adoption is particularly acute in South Asia. The region's job markets must accommodate a working-age population projected to expand at rates above the EMDE average throughout the 2020s, while simultaneously generating more non-agricultural employment opportunities for its current labor force (figure 2.2; World Bank 2024a). On the other hand, it may be easier for South Asia to adopt AI given the relatively young and growing labor force, provided there is access to opportunities for building AI-related skills.

Challenges to services-led growth. Unlike previous waves of automation, AI technologies have the potential to displace a range of non-routine, white-collar service sector jobs, such as in customer support, accounting, web development, and payroll processing (Webb 2020). This risk of so-called premature de-professionalization is particularly relevant for South Asia because its economies are disproportionately services-driven, with an above-average share of ICT services in exports, including an internationally competitive software development sector (Liu 2024). India's non-agricultural labor market depends heavily on white-collar services work; in 2023, the ICT-BPM market in India generated 5.4 million jobs and contributed 7.5 percent of GDP (figure 2.2).

Questions. This chapter examines the following questions:

- Which jobs in South Asia are most exposed to AI?
- What is the impact of AI adoption on labor demand in South Asia?
- Which policy options are available to maximize productivity benefits and minimize job disruption from AI?

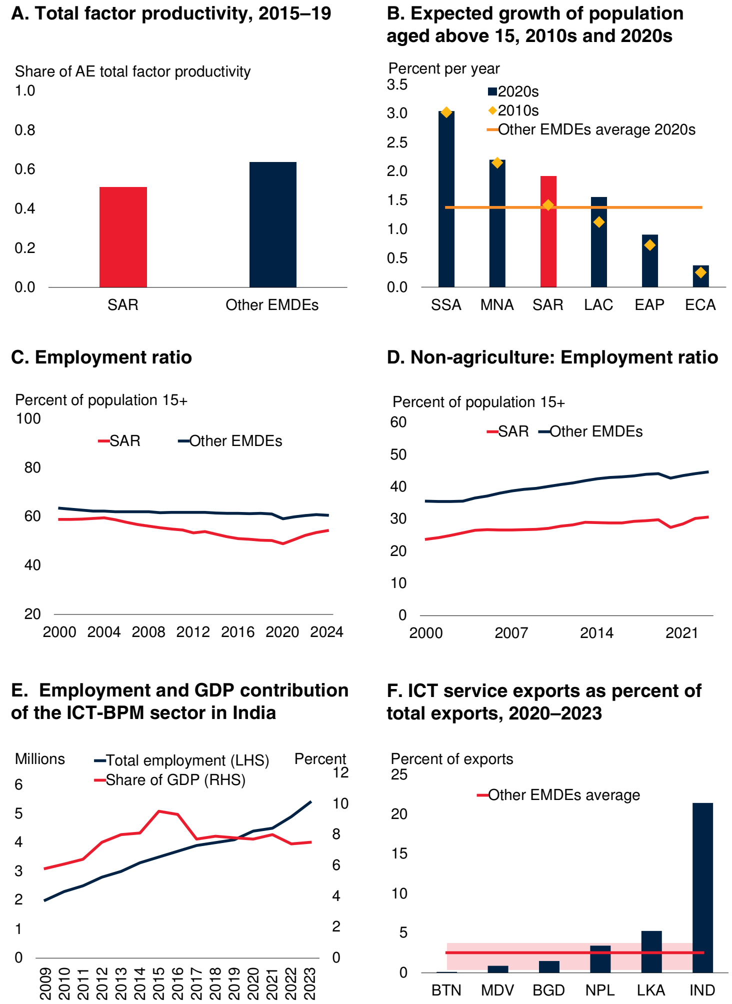
Main findings

Several findings emerge from this study.

First, South Asia faces lower AI automation risk than other EMDEs, with only 7 percent of jobs having high exposure to AI and low AI-human complementarity—well below the 15 percent average in other EMDEs. These jobs involve mostly routine cognitive tasks (such as call center agents, secretaries, or digital application programmers). This below-average exposure reflects the region's concentration in low-productivity manual work, particularly in agriculture and light manufacturing, where AI has limited impact. About 15 percent of South Asian workers are in jobs with both high AI exposure and high AI-human complementarity because they involve interpersonal interaction, responsibility, or expert judgment (e.g., CEOs,

FIGURE 2.2 South Asia's job market challenges

Productivity levels in South Asia are low, as is the share of its rapidly growing working-age population employed in non-agricultural jobs. South Asia's economies are disproportionately services-driven, with an above-average share of ICT services in exports.



Sources: Groningen Growth and Development Center/United Nations University World Institute for Development Economics Research, Economic Transformation Database; International Labour Organization; Kilic Celik, Kose, and Ohnsorge (2023); Nasscom; national statistical offices; Penn World Tables (database); World Development Indicators (database); World Bank.

Note: AEs = advanced economies; BGD = Bangladesh; BPM = business process management; BTN = Bhutan; EAP = East Asia and Pacific; ECA = Europe and Central Asia; EMDEs = emerging market and developing economies; ICT = information and communication technology; IND = India; LAC = Latin America and the Caribbean; LKA = Sri Lanka; MDV = Maldives; MNA = Middle East and North Africa; NPL = Nepal; SAR = South Asia; SSA = Sub-Saharan Africa.

A. Red bars show the average total factor productivity (TFP) in SAR; blue bars show the average total factor productivity in other EMDEs and advanced economies. TFP is calculated from 2015–19. "Other EMDEs" are EMDEs excluding SAR countries. Weighted by GDP.

B. Working-age population is the number of persons aged above 15 in a country. "Other EMDEs" are EMDEs excluding SAR countries. Weighted averages.

C. Employment ratios are defined as employment as a percent of the working-age population (persons aged 15+). Sample comprises 128 EMDEs. "Other EMDEs" are EMDEs excluding SAR countries. Working-age population-weighted averages of country groups.

D. Employment ratios are defined as employment as a percent of the working-age population (persons aged 15+). Latest available data for sectoral employment in a large sample of countries is for 2023; missing 2023 data is assumed to be at the 2022 level. Sample comprises 128 EMDEs. "Other EMDEs" are EMDEs excluding SAR countries.

E. Data is for India from 2009–23.

F. Bars show the ICT sector exports relative to total exports, averaged from 2020–23. Pink shaded region indicates the interquartile range for Other EMDEs. "Other EMDEs" are EMDEs excluding SAR countries. Weighted by population.

doctors, teachers, and lawyers). This segment of workers could experience productivity augmentation from AI adoption.

Second, higher-wage, higher-skill jobs are more exposed to AI than lower-skill positions, while entry-level workers are more exposed than more experienced ones. At the same time, jobs requiring the highest levels of skills and experience also show the strongest potential for AI-human complementarity. Taken together, these patterns suggest that young, moderately-educated workers are the most vulnerable to job displacement, while experienced, highly-educated workers have the greatest scope for productivity gains from AI.

Third, job listings data indicate rapidly growing demand for AI skills, driven primarily by an explosion of demand in India and Sri Lanka. Jobs that require AI skills command a wage premium of nearly 30 percent over other white-collar jobs.

Fourth, the introduction of GenAI has already reduced monthly job listings by about 20 percent for the most highly exposed, least complementary white-collar occupations, such as call center agents and software developers. However, this effect has been mitigated by complementarity: job listings for exposed jobs with high AI-human complementarity have not declined. The largest slowdowns in job listings have been concentrated among middle-skilled and entry-level workers and in the business services sector (notwithstanding a recent export surge).

Fifth, South Asia lacks several preconditions for maximizing the benefits from AI, in particular a large share of skilled workers, reliable electricity, and consistent and fast internet access. Improving infrastructure and education can help maximize AI's benefits while minimizing labor market disruptions. These investments could also help retain skilled AI innovators who might otherwise emigrate. Meanwhile, efforts to increase labor mobility—such as removing obstacles to firms' growth and improving physical connectivity, housing market efficiency, and job matching—could accelerate job creation, potentially outpacing any job displacement from AI.

Contribution to the literature

The emerging evidence base on the economic effects of AI adoption is largely from advanced economies and examines three interrelated aspects of AI: job exposure, employment impacts, and productivity impacts. Annex 2.1 provides a detailed literature review, which is briefly summarized here. Existing studies quantify the total number of current jobs that are highly exposed to AI, and analyze the relationship between AI exposure and occupational attributes. Unlike previous technological revolutions that automated routine tasks, AI replaces more complex tasks performed by higher-skilled workers. Observational studies find that AI adoption is already reducing employment in specific, highly exposed job categories, including internet freelance writers and designers, and equity analysts at trading firms. A collection of experimental or quasi-experimental studies finds that AI boosts productivity in specific occupations such as copywriters or customer service agents, and a select few find firm- or industry-level impacts. Estimates of AI's aggregate macroeconomic impact on GDP are sparse and often require unverifiable assumptions.

This chapter makes several contributions to this literature.

First, it presents the first in-depth analysis of labor market exposure to AI in South Asia, using the most recent labor force survey data and comparing South Asia with other EMDE regions. Unlike previous work, it explores differences in workers' exposure across the wage distribution, as well as by education, skill level, gender, and other key dimensions in detail.

Second, in contrast to most of the existing literature, it distinguishes between jobs (that is, occupations) at risk of AI displacement and jobs in which AI could augment workers because of AI-human complementarities. Standard indices of AI exposure measure the extent to which AI can be used in the performance of specific tasks that comprise an occupation (that is, "AI overlap"). They remain neutral about the scope for AI to either substitute or complement human labor in an occupation. Addressing this ambiguity, researchers have recently developed another type of index: one that identifies the extent to which AI and human inputs are complementary in the performance of the constituent tasks of an occupation. Used in combination with AI exposure indices, this type of index can help distinguish more clearly between AI substitution and augmentation potential (Gmyrek, Berg, and Bescond 2023; Pizzinelli et al. 2023). Specifically, jobs where AI exposure is high and AI-human complementarity is low are more at risk of AI replacing labor, while jobs where both AI exposure and complementarity are high are more likely to experience AI augmentation of labor productivity. The chapter applies this combination of exposure and complementarity measures in depth to labor force survey data from South Asia, as well as 25 other EMDEs.

Third, this chapter presents new evidence on the actual impact of AI adoption on labor demand in an EMDE region: South Asia. To assess how AI adoption is already changing the types of skills being demanded by firms, it employs an event study design that leverages a large, high-frequency database of online job postings and indices of job exposure and complementarity. This new combination of techniques and data enables this study to rigorously identify the net labor demand effect of AI for new hires. Unlike prior studies, the high-frequency data used in this study are sufficiently recent to estimate the impacts of the most recent wave of AI (GenAI). Furthermore, this study is the first to estimate the labor market effects of AI in the business services sector, along the skill distribution, and for entry-level jobs.

Methodology and data

Analyses of surveys and job postings data. The analysis draws on harmonized individual-level labor force survey data from the World Bank's *Global Labor Database* (GLD) for five South Asian countries and 25 other EMDEs, covering detailed worker and job characteristics (annex table A2.2). Aggregate measures, such as sector-level exposure, are constructed by aggregating the individual-level data using sampling weights to ensure their representativeness. Monthly data on job postings in South Asian countries come from Lightcast, a labor market research and consulting firm, covering 28 million listings between 2020 and 2025. These data are skewed toward white-collar roles in Indian cities. Fixed effects regressions assess wage premiums for AI and digital skills, while a difference-in-differences design evaluates labor demand effects from the introduction of GenAI around the launch of ChatGPT (annex 2.2).

AI exposure. This chapter uses two types of AI indices. First, it uses the AI exposure index from Felten, Raj, and Seamans (2021, 2023). This is an occupation-level index that estimates the overlap between the skills required in the constituent tasks of an occupation and generative AI capabilities. These index scores are averaged over text and image generation and are standardized across occupations relative to the average job. A higher index indicates greater overlap and, hence, exposure. Low-exposure jobs tend to be manual—farmers, firefighters, or factory workers (figure 2.3). High-exposure jobs, in contrast, tend to involve knowledge work.

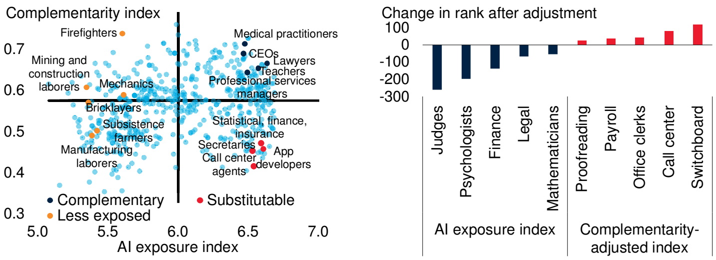
Complementarity. Second, this chapter uses the index of human-AI complementarity from Pizzinelli et al. (2023), which reflects the degree to which humans are likely to remain essential in certain occupations—for example, in jobs involving face-to-face communication, decision-making responsibility, domain expertise, and unstructured tasks. Among highly AI-exposed occupations, routine, remote jobs such as call center agents, secretaries, or digital application programmers tend to have lower complementarity (figure 2.3). High-complementarity, high-exposure jobs instead often involve interpersonal interaction, responsibility, and expert judgment, such as CEOs, doctors, teachers, and lawyers. Where appropriate, following Pizzinelli et al. (2023), the chapter uses a variant of the AI exposure index that has been adjusted for human-AI complementarity by marking down AI occupation exposure scores if their complementarity score is high. This adjustment makes a meaningful difference in which jobs are most exposed. In the unadjusted index, high-level

FIGURE 2.3 Occupational exposure to artificial intelligence

Occupational suitability for AI automation depends on both task overlap with AI abilities and the extent of complementarity. After adjusting for complementarity, the most exposed jobs tend to fall substantially in ranking, while more routine, lower-skilled jobs tend to rise.

A. AI exposure and complementarity by occupation

B. Change in rank for top five most exposed occupations after complementarity adjustment



Sources: Felten, Raj, and Seamans (2023); Pizzinelli et al. (2023).

Note: AI = artificial intelligence. Charts are based on exposure and complementarity levels for 583 4-digit ISIC occupations. Exposure to AI is defined as a composite AI exposure score above the median across occupations. Complementary (substitutable) jobs are defined as a complementarity score above (below) the median score across occupations and above-median exposure.

A. Black lines indicate median values for complementarity and exposure indices. Colored points highlight example occupations in each exposure group.

B. Bars show the change in exposure ranking before and after adjusting for complementarity. Blue bars are for occupations in the top five most exposed by the unadjusted exposure index, while red bars are for occupations in the top five most exposed by the complementarity-adjusted exposure index.

cognitive jobs such as judges, finance professionals, and mathematicians rank as most exposed. But in the complementarity-adjusted index, these fall substantially in exposure and are replaced by more routine, administrative jobs such as payroll clerks, call center agents, and proofreaders (figure 2.3).

Limitations of the data. The data have several key limitations: *i)* AI exposure indices measure the potential for using AI in each task in an idealized environment, but the extent to which firms may ultimately choose to use AI inputs in real-life tasks could depend on contextual factors; *ii)* estimates of labor demand effects are unable to capture the entirely new job categories that may emerge from AI; *iii)* due to rapid AI advancement, current occupational indices likely understate both exposure and potential productivity gains; and *iv)* the AI exposure measures are based on task and occupational mappings originally developed in advanced economy contexts, which may not apply exactly to EMDEs. Finally, *v)* the job postings analysis reveals early impacts, as it is too soon to assess long-term jobs impacts.

Exposure to, and complementarity with, AI

South Asia's labor market is less exposed than other EMDEs to AI as a result of its large agricultural sector and lower average skill levels. Only 7 percent of jobs are highly exposed with low complementarity, and therefore at increased risk of displacement. About 15 percent of jobs are highly exposed with high complementarity; therefore, there is potential for workers in these jobs to become more productive through AI adoption. Higher-wage, higher-skill jobs in the region are more exposed, but those at the top of the employment ladder are also most complementary with AI. Entry-level jobs appear most at risk of being displaced by AI, which may threaten the prospects of younger workers.

Aggregate exposure

Low average exposure. South Asia's average occupational AI exposure is somewhat below the EMDE benchmark: the typical job in SAR scores about 0.6 standard deviations below the occupational average, compared with 0.4 below for the average EMDE. Indeed, together with Sub-Saharan Africa, SAR has the lowest average exposure to AI among all EMDE regions, consistent with a broad pattern in which AI exposure rises with overall development (figure 2.4). Within South Asia, exposure varies by country: Nepal has the lowest average exposure, while Bhutan and Sri Lanka exhibit the highest exposure rates, reflecting their relatively more skilled and educated workforces.

Moderate share of exposed jobs. An occupation is classified as "exposed" if it ranks in the top 50 percent when occupations are ordered by their AI exposure index scores. Because average exposure in South Asia is low, only a small share of jobs meets this threshold. Across South Asia, only around 22 percent of jobs are classified as exposed—again, highest in Sri Lanka and lowest in Nepal (figure 2.4). These rates are similar to those observed in Sub-Saharan Africa and East Asia and the Pacific. However, because these jobs are disproportionately well-paying, AI-exposed jobs account for 42 percent of all wage earnings.

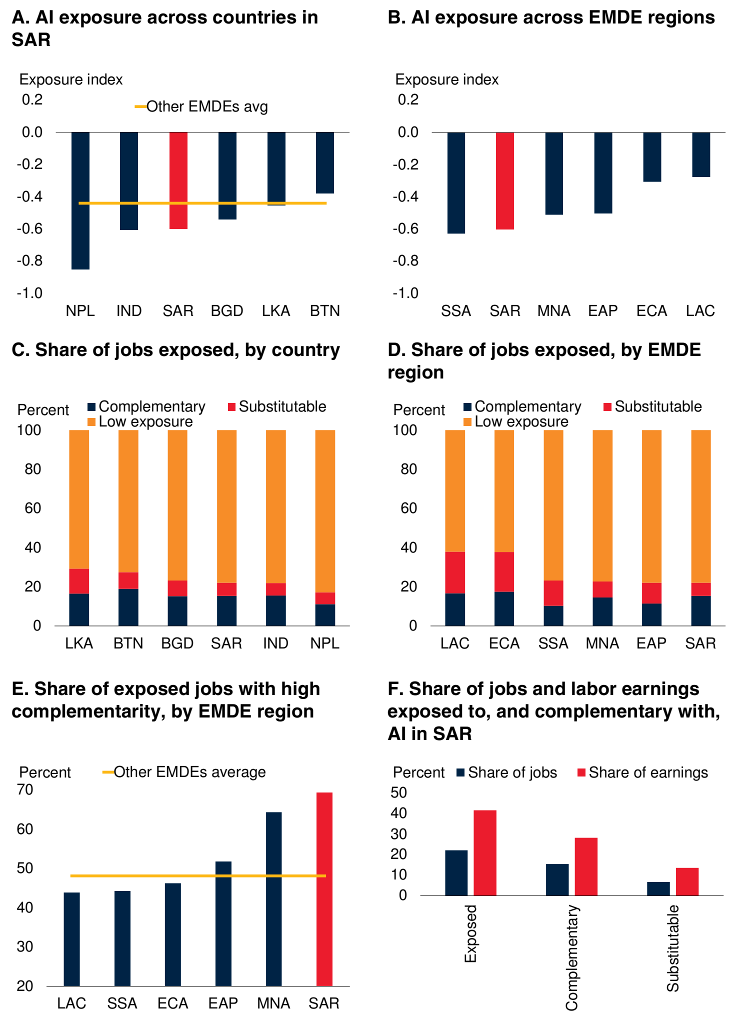
Drivers of low AI exposure. Two key factors underlie AI exposure at the country level: the prevalence of skilled occupations and the share of agricultural employment. AI exposure tends to be very low in agriculture and increases with occupational skill content. As a result, across countries, AI exposure rises as the proportion of skilled workers rises and as the agricultural employment share falls (figure 2.5). In South Asia, nations with less agricultural employment and more highly skilled workforces—Sri Lanka and Bhutan—exhibit the highest average AI exposure. Conversely, India and Nepal, which combine large agricultural workforces with lower average skill levels, record the region's lowest exposure.

High complementarity among exposed jobs. Many of South Asia's AI-exposed occupations feature high complementarity between humans and AI. Mirroring the exposure definition, an occupation is classified as "complementary" with AI if it is both exposed to AI *and* ranks in the top 50 percent when occupations are ordered by their human-AI complementarity index scores. By this metric, South Asia is better placed than other EMDE regions: about 70-percent of AI-exposed jobs (amounting to 15 percent of all jobs) are also complementary, and therefore less likely to be displaced by AI and more likely to enjoy productivity gains from AI adoption. This 70 percent share is by far the highest among EMDE regions, where the overall share of complementary jobs is 48 percent (figure 2.4). Within South Asia, India ranks highest in the share of exposed jobs that are complementary, while Sri Lanka ranks lowest. These estimates suggest that about 15 percent of jobs in South Asia, and 28 percent of total labor earnings, are exposed in a highly complementary manner and may therefore reap substantial productivity gains from AI adoption. Only 7 percent of jobs are highly exposed with low complementarity, and therefore at increased risk of displacement.

High exposure in white-collar services. Even within a generally low-exposure labor market, the distribution of exposure across sectors follows job quality. White-collar professionals in business services, commerce, and public administration face the highest AI exposure, whereas manual labor

FIGURE 2.4 Artificial intelligence exposure and complementarity

While exposure to AI in South Asia is somewhat lower than in other EMDEs, exposed jobs account for a disproportionately large share of total earnings. Most exposed jobs exhibit complementarities with AI, suggesting potential productivity gains; only 7 percent of jobs are at high risk of being displaced by AI.



Sources: Felten, Raj, and Seamans (2023); Global Labor Database; Pizzinelli et al. (2023); World Bank.

Note: AI = artificial intelligence; BGD = Bangladesh; BTN = Bhutan; EAP = East Asia and Pacific; ECA = Europe and Central Asia; EMDEs = emerging market and developing economies; IND = India; LAC = Latin America and the Caribbean; LKA = Sri Lanka; MDV = Maldives; MNA = Middle East and North Africa; NPL = Nepal; SAR = South Asia; SSA = Sub-Saharan Africa. "Other EMDEs" are 25 non-SAR economies for which labor force surveys are available (annex table A2.2). All EMDE and regional averages are weighted by working population (aged 15+). Exposure to AI is defined as a composite AI exposure score above the median across occupations. Complementary (substitutable) jobs are defined as having a complementarity score above (below) the median across occupations and above-median exposure. Generative AI (GenAI) occupational exposure scores are averaged across text and image and defined as standard deviations relative to the average occupational exposure.

A. Bars show the average GenAI exposure index in SAR countries. Yellow line shows the average GenAI exposure index in 25 EMDEs for which labor force surveys are available, excluding SAR.

B. Bars show the average GenAI exposure index across different EMDE regions.

C. Bars show the percentage of occupations exposed to AI across countries in SAR.

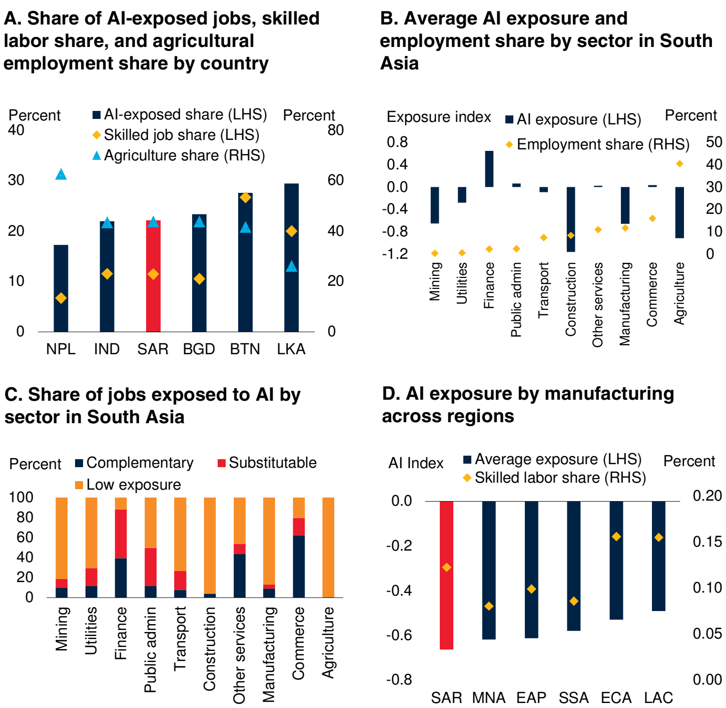
D. Bars show the percentage of occupations exposed to AI across EMDE regions.

E. Bars show the share of jobs exposed to AI that also have complementarity with AI. The yellow line shows the average share of other EMDEs excluding SAR.

F. Bars show the share of jobs and total wage earnings exposed to AI, complementary to AI, or substitutable with AI.

FIGURE 2.5 Artificial intelligence exposure in sectors

Exposure to AI is lowest in countries with low shares of skilled labor and high shares of agricultural employment. AI exposure is high in white-collar sectors and occupations and low in manual ones. The skill content of manufacturing is only weakly correlated with manufacturing exposure.



Sources: Felten, Raj, and Seamans (2023); Global Labor Database; Pizzinelli et al. (2023); World Bank.

Note: AI = artificial intelligence; BGD = Bangladesh; BTN = Bhutan; EAP = East Asia and the Pacific; ECA = Europe and Central Asia; EMDEs = emerging market and developing economies; IND = India; LAC = Latin America and the Caribbean; LHS = left-hand side; LKA = Sri Lanka; MDV = Maldives; MNA = Middle East and North Africa; NPL = Nepal; SAR = South Asia; SSA = Sub-Saharan Africa. “Other EMDEs” include 25 EMDEs excluding SAR countries for which labor force surveys are available (annex table A2.2). All EMDE and regional averages are weighted by working population (aged 15+). Exposure to AI is defined as a composite AI exposure score above the median across occupations. Complementary (substitutable) jobs are defined as a complementarity score above (below) the median across occupations and above-median exposure. Generative AI (GenAI) occupational exposure scores are averaged across text and image and defined as standard deviations relative to the average occupational exposure.

A. Bars show the share of jobs with above-median AI exposure across SAR countries; gold diamonds indicate the skilled labor employment share; blue triangles indicate the agricultural employment share.

B. Blue bars indicate industrial sector exposure to GenAI; gold diamonds indicate sector share in total employment.

C. Bars show industrial sector exposure to AI by complementarity. Bars sorted by sector share in total employment.

D. Blue bars indicate regional exposure in manufacturing jobs to GenAI. Gold diamonds show skilled labor share of manufacturing.

roles in agriculture, manufacturing, and basic services remain the least exposed (figure 2.5). Less-exposed sectors generally account for larger shares of total employment, which explains the region’s low overall exposure. This pattern poses a challenge for South Asian countries that aim to foster high-skill services sectors as engines of growth: productivity gains from AI may not translate into employment if white-collar roles become subject to automation. However, in South Asia’s services-driven growth model, human-AI complementarity serves as a mitigating factor, because many higher-skill occupations demonstrate complementarity with AI. Within the white-collar segment, most professional and managerial roles remain AI-complementary—providing room for productivity gains rather than displacement—while some types of clerical, technical, and sales positions show lower complementarity. Sectors dominated by manual jobs, in contrast, uniformly exhibit both low exposure and low complementarity.

Most exposed groups

Greatest exposure in urban, male workers in mid-sized firms. Exposure in South Asia varies systematically by worker and firm characteristics. Urban workers face greater AI exposure than rural workers, reflecting the geographic concentration of knowledge and professional sectors. Male workers face higher exposure than female workers, in contrast to findings in other advanced economies, where women’s concentration in cognitive work leads to higher AI exposure (Felten, Raj, and Seamans 2023; figure 2.6). In South Asia, however, female labor force participation is low overall and tends to be skewed toward agricultural and low-productivity jobs, which limits overall exposure (World Bank 2024b). Finally, AI exposure tends to be highest among workers in mid-sized firms, and very low among microenterprises and small firms. This is consistent with low exposure in the informal sector: among the 90 percent of South Asian workers who are informally employed, just 17 percent are exposed to AI. This rises to 60 percent among workers who have formal employment arrangements.

Greatest complementary exposure in skilled, high-wage jobs. There is a clear relationship between years of education, wages, and occupational AI exposure among South Asian workers.

- ***Education.*** The most-educated professions score substantially higher in exposure than the least-educated (figure 2.6). However, at the highest education levels, once exposure is adjusted for complementarity, this relationship reverses. On a complementarity-adjusted basis, postgraduate occupations are no more exposed than high school-level roles, whereas exposure peaks for moderately well-educated workers. Once adjusted for complementarity, the correlation between education and AI exposure effect falls to 40 percent of its original value (annex tables A2.4 and A2.5).[1]

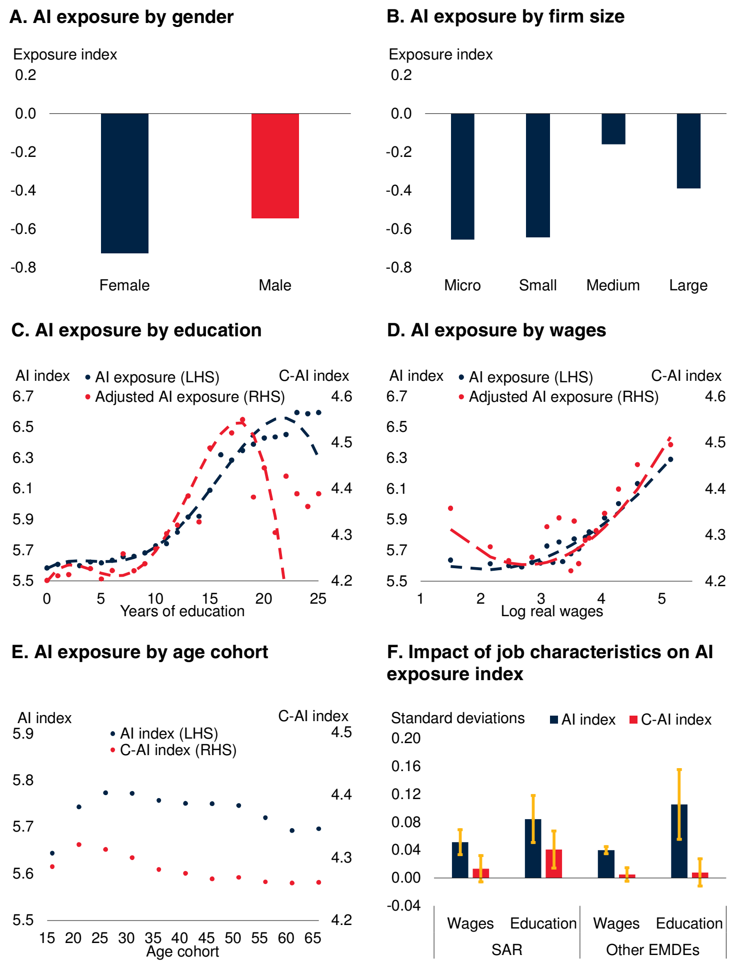
- *Wages.* A similar dynamic appears across the wage distribution: better-paying jobs have higher baseline exposure, but again the exposure of the highest-paid professions is highly human-AI complementary (figure 2.6D). As a result, after adjusting for complementarity, the relationship flattens and becomes U-shaped: certain low-wage, low-complementarity roles become relatively more exposed, while the relative exposure of the highest-wage professions declines. Accordingly, the strong positive relationship between baseline AI exposure and wages disappears once complementarity is accounted for. For both education and wages, similar patterns are observed for other EMDEs.

Entry-level jobs. A common concern is that AI may disproportionately affect entry-level and younger workers, who perform repetitive tasks that might be easier to automate (Rahman 2025). Young workers appear initially less exposed on average, though this likely reflects their concentration in low-wage, low-education roles. After adjusting for complementarity, younger cohorts in South Asia do, in fact, face higher exposure than older cohorts—complementarity-adjusted AI exposure peaks for South Asian workers aged 21–25 years (figure 2.6). This pattern holds for other EMDEs and within each major economic sector in South Asia (agriculture, industry, and services), reflecting the fact that, across countries and sectors, younger workers tend to occupy less complementary positions. The issue is particularly significant in South Asia, where a large share of the population is currently, or will soon be, entering the labor force, mostly without advanced levels of education and with aspirations for white-collar employment. One important

[1] Specifically, the regression coefficient on years of education in a regression where the complementarity-adjusted AI occupational exposure index is the outcome variable is 40 percent lower than that in a regression with the (non-adjusted) occupational exposure index as the outcome variable (annex table A2.5).

FIGURE 2.6 Artificial intelligence exposure, education, and wages

High-wage, high-skill occupations are more exposed to AI. However, these relationships diminish once exposure is adjusted for complementarities. In contrast, younger workers become more exposed than older workers after accounting for complementarities.



Sources: Felten, Raj, and Seamans (2023); Global Labor Database; Pizzinelli et al. (2023); World Bank.

Note: AI = artificial intelligence; EMDEs = emerging market and developing economies; LHS = left-hand side; RHS = right-hand side; SAR = South Asia. AI index is defined as average *unstandardized* exposure across all domains in Felten, Raj, and Seamans (2023). Complementarity-adjusted AI exposure (C-AI index) comes from Pizzinelli et al. (2023) and is calculated by multiplying the original AI exposure index by θ, where θ is the complementarity parameter. The sample contains five SAR countries and 25 other EMDEs for which labor force surveys are available (annex table A2.2). All regional and EMDE averages and regressions are weighted by the working population (aged 15+). Generative AI occupational exposure scores are averaged across text and image and defined as standard deviations relative to the average occupational exposure.

A. Blue bars represent female exposure; red bars represent male exposure to GenAI systems in SAR.

B. Bars indicate exposure to GenAI systems by firm-size category based on the number of employees. Micro = 1–5; Small = 6–9; Medium = 10–49; Large = 50+.

C. The scatter plot shows the relationship between years of education and the composite AI exposure index, for both unadjusted and complementarity-adjusted exposure. Dashed curves indicate quartic polynomial fit on the underlying data.

D. Scatter plot shows the binned relationship between log real wages and composite AI exposure index, binned at 20 quantiles of the wage distribution, for both unadjusted and complementarity-adjusted exposure. Dashed curves indicate quadratic fits on the underlying data.

E. Scatter plot shows the relationship between age cohorts and composite AI exposure indices. Blue dots represent the average AI exposure index; red dots represent the average complementarity-adjusted AI (C-AI) exposure index.

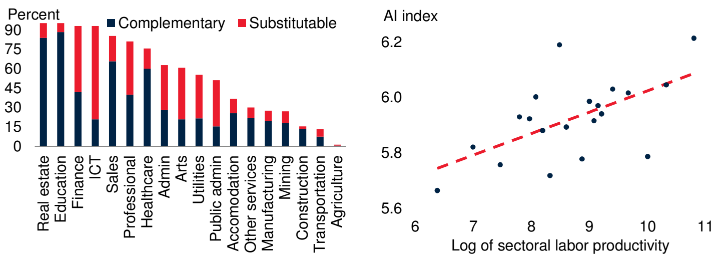
F. Chart shows estimated coefficients from regressions of AI exposure and complementarity-adjusted AI exposure on wages and education, controlling for country and year fixed effects. Bars represent standardized coefficients of a 1 log-point increase in wages or a 1-year increase in education for SAR and other EMDEs, with blue for the AI index and red for the complementarity-adjusted AI index. “Other EMDEs” are EMDEs excluding SAR countries. Yellow whiskers indicate 95 percent confidence intervals, with standard errors clustered at the occupation level (annex tables A2.4-5).

FIGURE 2.7 Productivity gains from artificial intelligence by sector

Finance and ICT are among the sectors expected to have the largest productivity gains from AI. Expected gains are largest in sectors that are already more productive.

A. Share of total earnings exposed to AI by sector

B. Sectoral AI exposure by labor productivity



Sources: Felten, Raj, and Seamans (2023); Global Labor Database; Pizzinelli et al. (2023); World Bank.
Note: AI = artificial intelligence; ICT = Information and Communication Technology. Sectors are defined as 1-digit ISIC sectors (sections).
A. Bars show share of total labor earnings with differing levels of AI exposure by sector of activity. Exposure to AI is defined as a composite AI exposure score above the median across occupations. Complementary (substitutable) jobs are defined as a complementarity score above (below) the median across occupations *and* above-median exposure.
B. Scatter plot shows the binned relationship between log sector-level average labor productivity and the unadjusted AI exposure index, binned at 20 quantiles of the distribution of sectoral labor productivity. Red dashed line represents a linear fit on the underlying data.

FIGURE 2.8 Job postings for artificial intelligence skills

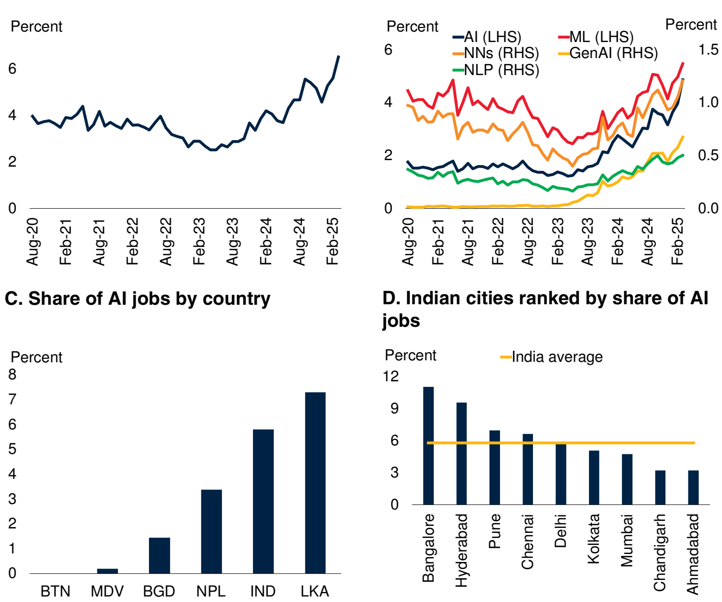
The share of Lightcast job postings requiring AI-related skills doubled following the public release of ChatGPT in late 2022. These postings are concentrated in India and Sri Lanka, specifically in the major tech centers of southern India.

A. AI-related jobs over time

B. AI jobs and their required skills

C. Share of AI jobs by country

D. Indian cities ranked by share of AI jobs



Source: Lightcast (database); World Bank.
Note: AI = artificial intelligence; BGD = Bangladesh; BTN = Bhutan; GenAI = generative artificial intelligence; IND = India; LHS = left-hand side; LKA = Sri Lanka; MDV = Maldives; ML = machine learning; NLP = natural language processing; NNs = neural networks; NPL = Nepal; RHS = right-hand side; SAR = South Asia.
A. Line shows the share of AI-related job postings in all Lightcast South Asia postings from August 2020 to February 2025.
B. Lines show the share of AI-related job postings in all Lightcast South Asia postings by AI skill required from August 2020 to February 2025.
C. Bars show the share of AI-related job postings across SAR countries for postings in 2025.
D. Bars show cities in India with the highest share of AI-related jobs postings in 2025. Yellow line shows the overall share of AI jobs in Indian postings.

caveat, however, is that complementarity does not capture the likelihood of AI adoption, which might ultimately give younger workers an advantage if they are faster than older workers at adopting AI.

Sectors with scope for productivity gains from AI. In South Asia, finance, ICT, and other professional services sectors—which include the business services sector—dominate the list of sectors with the largest shares of labor earnings exposed to AI (figure 2.7). Because AI technologies can effectively perform tasks that comprise a large share of labor value addition in these sectors, they may have particularly high potential for productivity gains from AI adoption. The share of labor earnings that is AI-complementary versus AI-substitutable varies across these sectors. This suggests that the sectors with the largest scope for productivity gains from AI are not always those with the largest risk of job displacement by AI. The sectors with the highest potential gains from AI also tend to be more productive already, suggesting that widespread adoption could increase productivity dispersion across the economy.

AI-related labor demand

Job postings data show rapid growth in demand for AI skills since the public release of ChatGPT in late 2022. Postings for jobs that are highly exposed to AI grew more slowly than postings for less-exposed jobs, particularly in occupations with limited human-AI complementarity.

The rise of AI-related jobs

Rapidly growing demand for AI skills. Lightcast job-posting data indicate that between January 2023 and March 2025, the share of AI-related postings more than doubled—from 2.9 to 6.5 percent of all listings—and demand for AI skills grew 75 percent faster than overall non-AI listings (figure 2.8). These data are disproportionately composed of high-wage, urban, white-collar positions, so these numbers can be interpreted as reflecting the penetration of AI roles within the high-skill, white-collar labor market rather than the overall economy (annex table A2.3). This expansion encompasses a broad array of AI competencies, including machine learning, neural networks, natural language processing, and generative AI. All series exhibit a pronounced inflection point around late 2022 to early 2023, closely coinciding with the public release of ChatGPT and the rapid emergence of generative AI applications.

Wage premium for AI skills. Both digital skills and AI skills command a wage premium. But the premium for AI skills is almost triple that for digital skills. Positions requiring general digital skills offer a 12-percent wage premium, whereas AI-focused roles yield a 28-percent premium, underscoring the substantial market value of AI competencies (figure 2.9; annex table A2.6).

Southern India as an AI hub. Geographically, AI-skill jobs are overwhelmingly concentrated in Sri Lanka, where 7.3 percent of white-collar listings in 2025 required AI expertise, and in India, where 5.8 percent of white-collar listings did (figure 2.8). Within India—which comprises the vast majority of all listings in Lightcast—the southern technology corridor drives this pattern: Bangalore and Hyderabad lead in AI job share, followed by Pune in Maharashtra, with Chennai also featuring prominently.

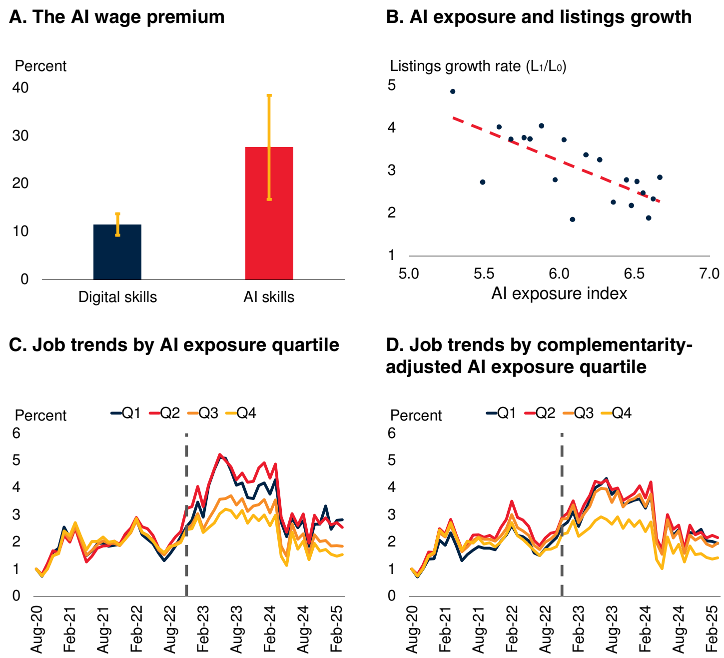
AI-related changes in labor demand

More exposed occupations have grown less rapidly. Within each occupational category, postings for jobs with greater AI exposure have grown more slowly between 2020 and 2025 than those for other jobs. The least-exposed occupation categories roughly quadrupled their listings over this period, while those with the highest exposure grew at only about half that rate (figure 2.9). The gap in listings growth between the most- and least-exposed occupations widened after the introduction of ChatGPT. Listings growth averaged 41 percent for the most-exposed occupations without human-AI complementarity, compared with 96 percent for the least-exposed jobs.

Falling labor demand among most exposed, least complementary. A slowdown in labor demand is already underway for the most exposed jobs that are least complementary to AI. Postings for more-exposed jobs declined immediately and substantially relative to the trend in postings for less-exposed jobs after public release of ChatGPT in November 2022 (annex 2.2; figure 2.10). This drop is driven by cutbacks in job postings for the most-exposed jobs with the lowest human-AI complementarity, such as software developers, call center agents, accountants, and proofreaders. Among these less-complementary jobs, labor demand for call center agents (top quartile exposure) fell 24 percent relative to machine operators (bottom quartile exposure). In contrast, in the most exposed but also most complementary jobs—such as lawyers, R&D managers, teachers, and architects—postings followed trends similar to less-exposed jobs.

FIGURE 2.9 Artificial intelligence wage premium and exposure

There is a substantial wage premium for AI-related skills. Occupations more exposed to AI have grown less rapidly, particularly after the public release of ChatGPT in November 2022.

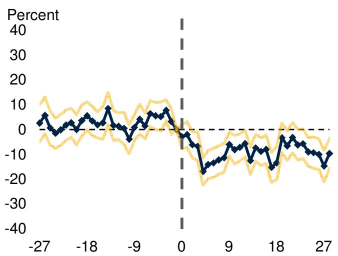


Sources: Felten, Raj, and Seamans (2023); Lightcast (database); Pizzinelli et al. (2023); World Bank.
Note: AI = artificial intelligence. Vertical dashed gray line indicates the release of ChatGPT.
A. Bars show the estimated wage premiums associated with digital and AI skills. Wage premiums are estimated from a job listing-level regression of log posted salaries on indicators for digital or AI skills, controlling for country-year, location, and occupation fixed effects. Yellow whiskers represent 95 percent confidence intervals, with standard errors clustered at the occupation level (annex table A2.6).
B. Scatter plot shows the binned relationship between AI exposure and job listings growth (L1/L0) at the 4-digit ISCO occupation level. Red line represents a linear fit on the underlying data.
C. Lines show indexed job postings by AI occupational exposure quartile (Q1–Q4) from August 2020 to February 2025 for 4-digit ISCO occupations. August 2020 = 1.
D. Lines show indexed job postings by complementarity-adjusted AI occupational exposure quartile (Q1–Q4) from August 2020 to February 2025 for 4-digit ISCO occupations. August 2020 = 1.

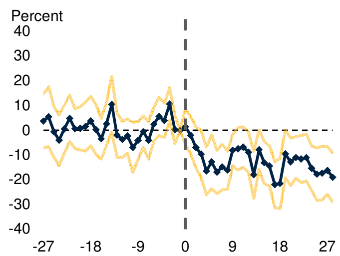
FIGURE 2.10 Event study of labor demand following the release of ChatGPT

After the public release of ChatGPT in November 2022, more AI-exposed occupations experienced an immediate and substantial reduction in job postings relative to less-exposed occupations. These effects were largest for the least complementary occupations.

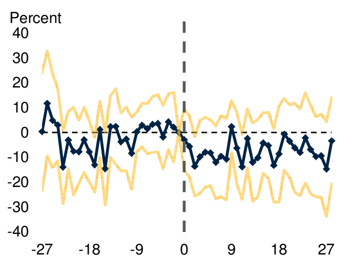
A. Event study estimates of the impact of ChatGPT on job listings



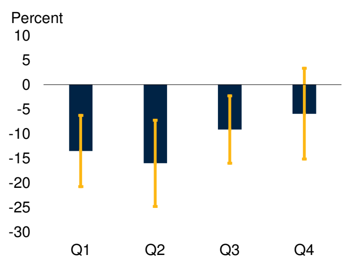
B. Event study: bottom quartile complementarity



C. Event study: top quartile complementarity



D. Average impact of ChatGPT on job postings by complementarity quartile



Sources: Felten, Raj, and Seamans (2023); Lightcast (database); Pizzinelli et al. (2023); World Bank.
Note: AI = artificial intelligence. Q1–Q4 refer to quartiles of occupation-level AI complementarity. Charts show coefficients and 95 percent confidence intervals from event-study and difference-in-differences regressions at the 4-digit occupation sector by month level, where the log of total occupation-level job listings is regressed on an indicator for post-ChatGPT release interacted with AI exposure, with occupation and month fixed effects. Coefficients show impact of a 1-standatd-deviation increase in exposure. Gold whiskers are 95 percent confidence intervals from standard errors clustered at the occupation level. Methodological details are in annex 2.2 and regression estimates are in annex tables A2.7 and A2.8.

A-C. The dashed vertical gray line marks the public release of ChatGPT. Charts show event-study coefficients and 95 percent confidence intervals for the full sample of occupations (A), occupations in the bottom quartile of complementarity (B), and occupations in the top quartile of complementarity (C).

D. Bars show average effects of a 1-standard deviation increase in occupation-level AI exposure on job listings after the release of ChatGPT. This effect is estimated at each quartile of occupation-level complementarity: Q1 represents occupations with the lowest complementarity and Q4 the highest.

Wage discount for the most-exposed, least-complementary jobs. The weakening in labor demand for the most-exposed, least-complementary jobs is also reflected in relative wage declines. In the least-complementary jobs, wages grew 10 percent slower in the bottom quartile relative to the trend in the top quartile of exposure, whereas wages in the most-complementary quartile did not change in response to AI exposure (annex table A2.8).

Automation with export growth in the business services sector. The business services sector is rapidly being transformed by AI. Firms in South Asia that outsource business support functions for international firms are composed predominantly of the back office, IT, and software jobs that have high exposure to AI and low complementarity (figure 2.11). As a result of the automation opportunities that this creates, AI adoption in the sector is higher than average. By March 2025, 12 percent of business services jobs required AI skills, compared with just 4 percent for other jobs, representing a doubling of pre-ChatGPT levels. As adoption has risen, so has job displacement. Business services jobs grew 35 percent slower and wages fell by 8 percent relative to other jobs following the release of ChatGPT (figure 2.11; annex table A2.10). ICT services are a key export sector for South Asia, particularly India and Sri Lanka (figure 2.2). Although not captured in the data used in this chapter, online freelancing is another significant source of employment among mid-skilled South Asian youth that might be exposed to AI-led substitution similar to that occurring in the broader business services sector. If the drop in job listings is driven by automation on the part of domestic firms, this could yield substantial local productivity gains; but if it is driven by foreign firms, it could displace South Asian countries in the global value chain of knowledge work. Early evidence suggests that technology services firms are experiencing productivity gains, as exports continue to grow rapidly, even as hiring slows (figure 2.11). This may be particularly relevant in India, which is moving up the professional services value chain from business to knowledge process outsourcing, potentially yielding greater AI complementarity (Chua et al. 2025).

Entry-level, mid-skilled jobs most affected. The analysis of exposure indices suggest that entry-level and mid-skilled jobs are most exposed to AI automation after accounting for complementarity (figure 2.6). This vulnerability is also reflected in job postings. After the introduction of ChatGPT, postings of jobs requiring only secondary education fell by 24 percent across the interquartile range of exposure, while demand for jobs requiring college and graduate degrees did not change (figure 2.11). Similarly, entry-level jobs with the exposure level of a software developer grew 21 percent more slowly than those with the exposure-level of an electrician. In contrast, more senior roles saw no change.

Positioning South Asia to benefit from AI

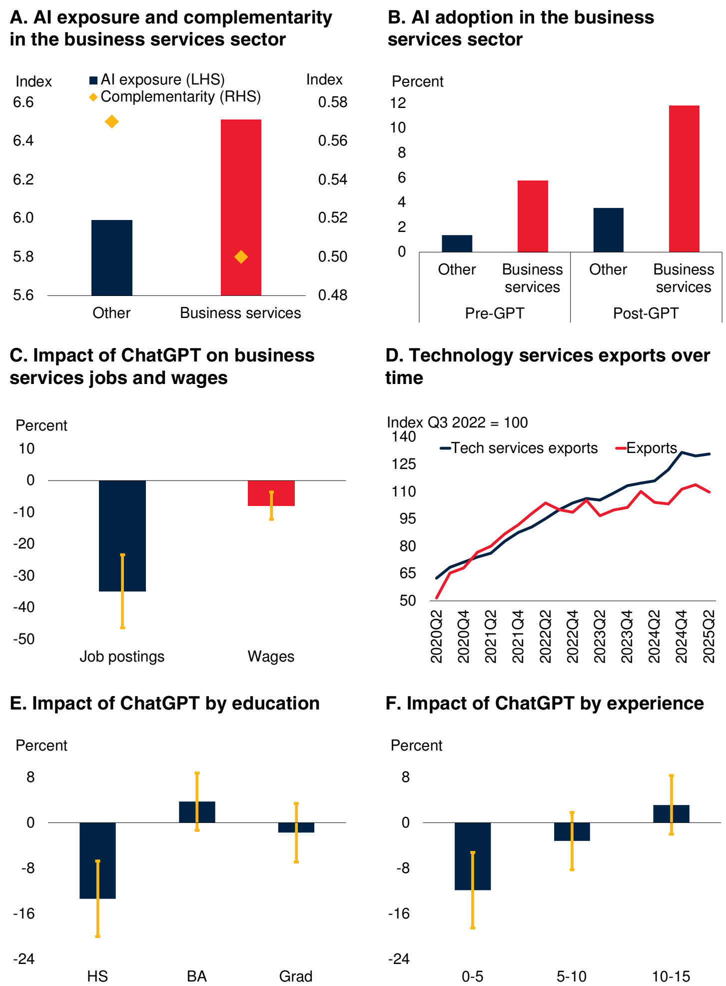
Previous technologies led to sectoral labor disruptions that were compensated by increased demand from other sectors, and by aggregate productivity gains. Benefiting from AI will require appropriate digital and energy infrastructure, relevant skills, and a robust policy framework.

Previous structural transformations. This chapter shows that AI will disproportionately displace jobs for mid-skilled, entry-level workers. During previous technological transformations, job losses in one area have been accompanied by job gains in the overall economy (Autor 2015). Between 1860 and 2023, for example, amid soaring agricultural productivity, the share of U.S. jobs in agriculture fell from 55 to 1 percent; this coincided with a 15-percentage-point increase in aggregate labor force participation in the country (figure 2.12). About 60 percent of current jobs in the United States are in categories that did not exist in 1940 (Autor et al. 2022). AI differs from previous technological revolutions primarily in that it affects non-routine cognitive work in the upper end of the skill distribution, while previous automation technologies—for example, industrial robots or software—affected manual or routine cognitive work.

Maximizing the benefits of AI. The rollout of AI is likely to follow some of the dynamics of previous technological revolutions. The right preconditions can help countries benefit from the associated productivity gains and minimize the disruption from job losses. These include reliable and widely accessible digital infrastructure, a skilled workforce equipped with both digital skills and resilience to disruption, and an enabling business environment. The AI Preparedness Index, developed by the International Monetary Fund, summarizes four key dimensions of preparedness: digital infrastructure, human capital, technological innovation and economic integration, and legal frameworks and regulations. With the exception of India, South Asia scores below the EMDE average in all four areas (figure 2.13).

FIGURE 2.11 ChatGPT effects on business services workers and entry-level jobs

AI exposure is high and complementarity is low in jobs associated with the business services sector, leading to faster AI adoption and declining labor demand following the release of ChatGPT in November 2022. AI-driven automation has disproportionately affected middle-skilled and entry-level jobs.



Sources: Felten, Raj, and Seamans (2023); Lightcast (database); Pizzinelli et al. (2023); Reserve Bank of India; World Bank.

Note: AI = artificial intelligence; BA = bachelors degree; Grad = graduate degree; HS = high-school degree; LHS = left-hand side; RHS = right-hand side. Gold whiskers represent 95 percent confidence intervals, with standard errors clustered at the occupation level.

A. Bars show average unadjusted AI exposure index score. Yellow diamonds show average complementarity parameter θ. Averages are unweighted and taken across all 4-digit ISCO occupations within business services and other sectors observed in Lightcast data. List of business services occupations is available in annex table A2.9.

B. Bars show the share of jobs that require AI-related skills by sector, before and after the introduction of ChatGPT. Pre-GPT shares are measured in November 2022, the month of ChatGPT's release, while post-GPT shares are measured in March 2025, the final month of data.

C. Bars show coefficients from occupation-month regressions of log of job postings and log of wages on the interaction between post-ChatGPT and a business services occupation indicator, conditional on occupation and month fixed effects (annex table A2.10).

D. Lines show indexed values of technology services exports and total exports (Q3 2022 = 100) in India from Q2 2020 to Q2 2025, with Q3 2022 marking the quarter before the release of ChatGPT.

E. Bars show coefficients from a difference-in-differences regression at the 4-digit occupation-by-month level. The log of total occupation-level job listings for each education category is regressed on an indicator for post-ChatGPT release, with occupation and month fixed effects. Coefficients show impacts from a 1-standard-deviation-increase in occupational exposure (annex tables A2.11, A2.12).

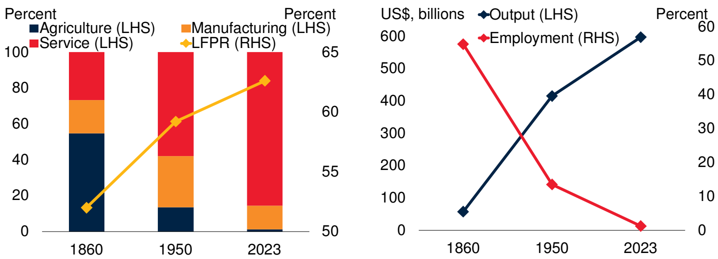
F. Bars show coefficients from a difference-in-differences regression at the 4-digit occupation-by-month level. The log of total occupation-level job listings for experience category is regressed on an indicator for post-ChatGPT release, with occupation and month fixed effects. Coefficients show impacts from a 1-standard-deviation increase in occupational exposure. Experience is measured in years (annex tables A2.11, A2.12).

FIGURE 2.12 Lessons from previous technological revolutions

Previous waves of technological innovation have disrupted labor in existing sectors, but also created new types of jobs, resulting in higher productivity and no permanent reduction in labor force participation.

A. Share of total U.S. employment by sector and labor force participation rate

B. Real agricultural output and employment share of agriculture



Sources: Sahr (2014); U.S. Bureau of Labor Statistics; U.S. Census Bureau; U.S. Department of Agriculture, Economic Research Service.

Note: LFPR = labor force participation rate; LHS = left-hand side; RHS = right-hand side; US = United States.

A. Figure shows the sectoral composition of employment in the United States—agriculture, manufacturing, and services—at three key points in time: 1860 (when agricultural employment was highest), 1950 (when manufacturing employment peaked), and the most recent data. The 1860 and 1950 figures are based on historical estimates. The agriculture sector comprises forestry, fishing, hunting, and mining. The manufacturing sector includes construction. All remaining activities are categorized as services.

B. Nominal agricultural output data for 1950 and 2023 come from the U.S. Department of Agriculture; data for 1860 come from historical U.S. Census records. All nominal values are adjusted to constant dollars using historical consumer price index estimates from Sahr (2014).

Digital infrastructure. AI applications require the ability to access, process, and transmit large volumes of data. This demands reliable access to electricity, high-speed internet, and data processing services. South Asia has made rapid progress by these metrics in recent years. The share of the population with access to electricity has risen to nearly 100 percent. The share of the population using the internet was just over 60 percent in 2023, although that is lower than in most EMDE regions (figure 2.13). South Asia's capacity for intensive data processing and transmission is limited: fixed broadband data transmission rates average about one-quarter that of advanced economies and, on a per capita basis, secure internet servers are few. Government policies can promote AI adoption with reliable and affordable access to energy and to the internet. This is particularly important for equity and inclusion in rural areas, where only 36 percent of people have internet access. The 32-percentage-point gap between rural and urban internet access is the largest of any EMDE region, and could be narrowed by competition and private investment in broadband deployment, facilitated by removing monopolies and lifting restrictions on foreign investment in telecom services (World Bank 2024c). Updated power grids and greater use of renewable energy sources are already critical priorities for the region to meet the needs of its growing economy, expand access, and eliminate shortages (Zhang 2019).

Human capital. A talent pool with the skills needed to apply or develop AI tools can diffuse productivity gains from AI more quickly. More broadly, more-skilled workers are typically better equipped to switch to different firms, sectors, and locations as labor demand shifts. The region produces a large number of highly educated workers, including AI researchers with publications in the most prestigious outlets. However, the vast majority of these researchers emigrate abroad (figure 2.13). Broader education outcomes in much of South Asia are below the EMDE average—only 75 percent of people in the region are literate, for example, compared with the EMDE average of 85 percent. Traditional education systems could be transformed by AI, especially if governments embrace AI to respond to local needs and provide workers with skills that are complementary with AI. For example, AI can provide customized tutoring at scale (Chiu et al. 2023; De Simone et al. 2025). Retraining and upskilling programs could help ease the transition of workers to new jobs, but evidence on the effectiveness of such programs is mixed (Crépon and Van Den Berg 2016; McKenzie 2017).

Enabling environment. At the moment, AI innovation is concentrated in a handful of "AI hub" cities characterized by high levels of innovation, capital availability, and workforce education (McElheran et al. 2023). AI adoption tends to be concentrated within larger firms (Acemoglu et al. 2023); South Asian firms tend to be small and grow slowly. Competition policies, greater openness to trade, and regulatory reforms might provide a boost to the type of firm more likely to make use of AI (Chapter 1). Other factors may be constraining AI adoption among South Asian firms, such as limited access to credit and skills. Unlocking private capital for investment, in both AI and more broadly, could support growth and job creation. Robust data security frameworks may spur AI adoption by reducing risks of data breaches. These reforms to the enabling environment might also entice South Asia's large and highly skilled diasporas either to return or collaborate with local entrepreneurs. Governments themselves could use AI to streamline official processes, predict demand for services, and automate routine tasks, thereby reducing wait times and reducing opportunities for corruption. AI chatbots can facilitate communication between citizens and government agencies, providing information, addressing grievances, and gathering feedback more efficiently. This would be particularly useful in South Asia, because many young, small- and medium-sized enterprises in the region report that they encounter corruption and spend more time on regulatory compliance than do similar firms in other EMDEs (World Bank 2024a).

Annex 2.1: Literature review

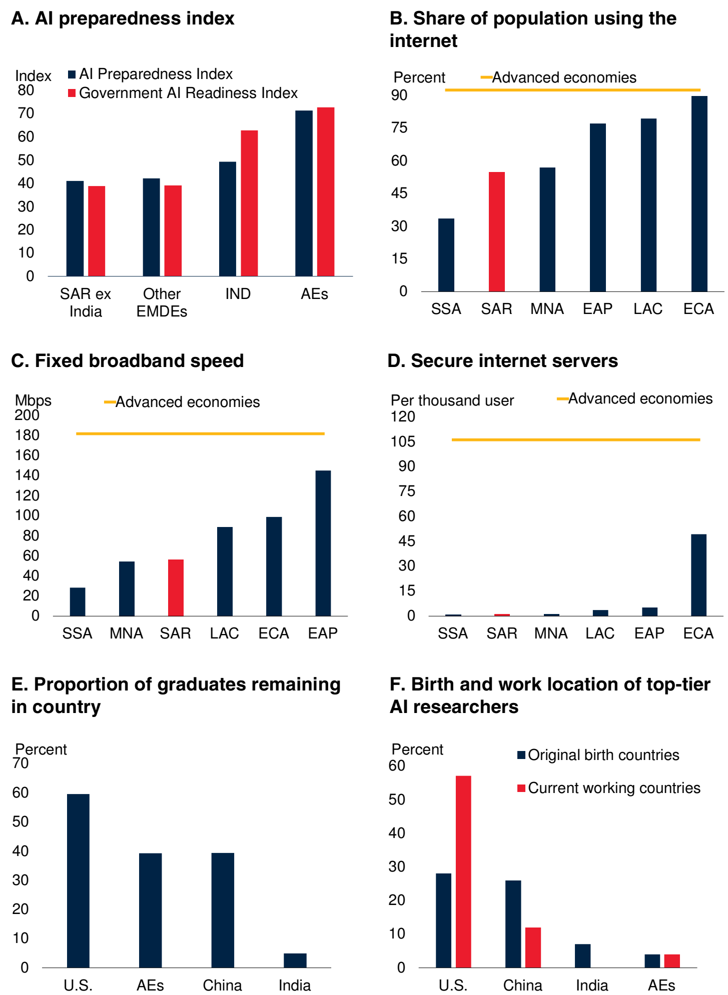
This annex provides an overview of the main messages from the literature on AI, with the main papers summarized in Annex table 1.

Measuring AI exposure and impact. In recent years, researchers have generated indices of job-level AI exposure by decomposing a job (that is, occupation) into its constituent tasks and measuring the share of those tasks that could be performed by AI (Brynjolfsson, Mitchell, and Rock 2018; Eloundou et al. 2024; Felten, Raj, and Seamans 2023; Webb 2020).[2] These indices can be used to measure the number and types of current jobs that could be augmented, altered or potentially displaced by AI. In addition to such forward-looking analysis of *exposure*, indices of AI exposure have also been used to measure the impact of AI in observational studies. Such studies essentially compare changes in employment and other outcomes after the introduction of AI across firms or local labor markets that differed in the fraction of jobs exposed to AI prior to the introduction of AI.

[2] These indices are all based on the insights of Acemoglu and Restrepo (2018) and Autor, Levy, and Murnane (2003) – that a job is fundamentally a collection of tasks with different degrees of exposure to technological automation. Similarly constructed indices have been used to measure the impact of automations through industrial robots and software in previous waves of research (Acemoglu and Restrepo 2020; Autor and Dorn 2013).

FIGURE 2.13 Preconditions for artificial intelligence use: Infrastructure and education

South Asia ranks below other EMDEs in many preconditions for AI adoption. Several infrastructure indicators—including the share of population using the internet, broadband speed, and availability of secure internet servers—are below other EMDE regions. South Asia also produces many highly educated workers, including a significant share of top-tier AI researchers, but many of these emigrate abroad.



Sources: Global AI Talent Tracker 2.0; International Monetary Fund, Artificial Intelligence Preparedness Index (AIPI); Oxford University, Government AI Readiness Index; Stanford University; Tortoise Media; World Bank.

Note: AEs = advanced economies; AI = artificial intelligence; EAP = East Asia and Pacific; ECA = Europe and Central Asia; EMDEs = emerging market and developing economies; IND = India; LAC = Latin America and the Caribbean; MNA = Middle East and North Africa; SAR = South Asia; SSA = Sub-Saharan Africa; U.S. = United States.

A. The AI Preparedness Index (AIPI) has 4 key dimensions: digital infrastructure, human capital, technological innovation, and legal frameworks. The numbers represent the median index value for each region. The Government AI Readiness index examines 40 indicators across government, the technology sector, and data and infrastructure. "Other EMDEs" includes 143 economies.

B. Bars show the average of the proportion of individuals who used the Internet from any location in 2023 in each region, weighted by population. Access can be via a fixed or mobile network.

C. Median download speeds are shown for each region.

D. Bars show the average number of distinct, publicly-trusted TLS/SSL certificates found in the Netcraft Secure Server Survey (by hosting country), per thousand people in 2024. Weighted by population.

E. Proportion of "Top-tier AI researchers" with an undergraduate degree in a country and stayed for work, regardless of whether they pursued their graduate degree in the same country or elsewhere. "AEs" includes Canada, France, Germany, and United Kingdom. Data from 2022.

F. "Top-tier AI researchers" are identified as authors of papers chosen for oral presentations at NeurIPS, a leading AI conference, which represent the most prestigious class of submissions. 'AEs' includes Canada, France, Germany, and United Kingdom. Data from 2022. "Current working countries" value for India is not available.

Patterns of exposure to AI. Existing studies quantify the total number of current jobs that are highly exposed to AI, and analyze the relationship between AI exposure and occupational attributes—such as sector, location, and worker earnings, skill, educational attainment, age and gender. There are two key patterns in AI job exposure within and across countries. First, within countries, although a broad variety of jobs have overlaps with AI, the most exposed jobs tend to be white-collar, high-skill jobs that are just below the highest levels of income and education (Eloundou et al. 2024; Felten, Raj, and Seamans 2023). For example, clinical laboratory technicians, chemical engineers, optometrists, and power plant operators are exposed to AI pattern detection and prediction (Webb 2020). University professors, legal professionals, and engineers are among those most exposed to AI language or image generation (Felten, Raj, and Seamans 2023). In contrast, previous waves of automation through robots and software mainly affected mid-skill occupations involving manual and cognitive routine tasks, such as assembly line workers and accountants (Acemoglu and Restrepo 2020; Autor and Dorn 2013). Second, a small but growing set of studies focus on EMDE, often comparing them with advanced economies in terms of AI exposure, but these are largely aggregate analyses with very limited coverage of South Asian countries. Across countries, AI exposure is substantially higher in advanced economies than EMDEs because of the greater concentration of high-skills jobs in advanced economies (Cazzaniga 2024; Demombynes, Langbein, and Weber 2025; Pizzinelli et al. 2023; World Bank 2024d).

Exposure gaps after adjusting for complementarity. Standard measures of AI exposure are neutral about the scope for AI to either substitute or complement human labor, and do not necessarily predict the potential for AI to fully replace humans. Researchers have developed indices that distinguish more clearly between AI substitutability and complementarity (Gmyrek, Berg, and Bescond 2023; Pizzinelli et al. 2023). They find that high-paying occupations, such as professionals and managers, tend to be highly exposed to AI but also display elevated levels of human complementarity; that is, their constituent tasks include difficult-to-replace human roles. Accounting for such complementarities narrows the gap in exposure to AI replacement across advanced economies and EMDEs (Pizzinelli et al. 2023).

Employment impacts of AI. AI adoption is having negative impacts on employment in specific, highly exposed job categories, but evidence on aggregate employment effects is mixed. Jobs displaying evidence of shrinkage due to AI include internet freelancers who specialize in writing services and art/design, and equity analysts at trading firms (Grennan and Michaely 2020; Hui, Reshef, and Zhou 2024). Firms whose pre-existing employment structure is concentrated in occupations more exposed to AI reduce hiring as AI technologies become available, in both the United States (Acemoglu et al. 2022) and India (Copestake et al. 2023). In comparison, AI adoption has not had a significant effect on employment at more aggregate levels, such as in exposed U.S. industries and occupations (Acemoglu et al. 2022). This could be because negative substitution effects are being offset by complementarities and countervailing positive impacts on firm productivity (Hampole et al. 2025). However, some recent analysis identifies negative aggregate employment effects from AI technology diffusion on local U.S. labor markets (Bonfiglioli et al. 2025; Huang 2024).

Productivity impacts. AI use can improve worker productivity and earnings in specific occupations, as suggested by recent experimental or quasi-experimental studies. AI use caused a 14-percent increase in productivity among customer service agents at a large Fortune 500 company (Brynjolfsson, Li, and Raymond 2023). Taxi drivers and professional writers have become more productive by using AI applications (Kanazawa et al. 2022; Noy and Zhang 2023). However, evidence on AI's impacts on firm and industry level productivity is limited. Several studies found AI use is associated with higher output per worker in firms (Acemoglu et al. 2023; Calvino et al. 2022; Calvino and Fontanelli 2023). But this could be because better firms are more likely to explore AI use. Indeed, a recent qualitative study based on interviews with business leaders (not included in the quantitative research literature review listed in annex table A2.1) suggests that only a small fraction of AI-adopter firms have experienced significant productivity gains from it (Challapally et al. 2025). AI adoption, enabled by access to graduates with AI skills, was found to improve sales, employment, market valuation and product innovation levels in one study (Babina et al. 2024).

Impact on inequality. The effects of AI on wage inequality are mixed so far. In select occupations where AI has been found to complement workers, less-skilled workers experience larger gains (Brynjolfsson, Li, and Raymond 2023; Kanazawa et al. 2022; Noy and Zhang 2023). Similarly, the impact of AI assistance on student performance is larger among initially lower-performing students (Choi and Schwarcz 2024). In firms, the negative impacts of AI on employment are larger among more skilled occupations (Copestake et al. 2023; Hampole et al. 2025). These findings suggest that AI reduces inequality. However, other estimates suggest that workers at the top of the distribution who retain specialized knowledge are less at risk of displacement, suggesting that AI adoption could increase income inequality (Bonfiglioli et al. 2025; Huang 2024).

Annex 2.2: Data and methods

Data

Labor force surveys. The core of the analysis relies on harmonized labor force surveys (LFS) drawn from the World Bank's *Global Labor Database* (GLD). These surveys contain 1.15 million observations of working-age (15 to 64) South Asians across five countries—Bangladesh, Bhutan, India, Nepal, and Sri Lanka—for the most recent year in which labor force surveys are available. The GLD provides detailed information on labor force status, sector of work (4-digit ISIC level), occupational code (4-digit ISCO level, 3-digit for India), wages for wage workers, skill and education levels, age, gender, urban/rural residence, and a full set of demographic characteristics. For comparison, harmonized LFS data for 25 non-SAR EMDE countries, covering 3.4 million working-age individuals, are also included. The complete list of GLD countries and survey rounds is reported in annex table A2.2.

AI exposure measures. To measure the exposure of the labor market to AI automation, we leverage the AI occupational exposure (AIOE) indices developed by Felten, Raj, and Seamans (2021; 2023), which quantify exposure at the occupation (SOC-10) level by estimating the overlap between a given job's required abilities and existing AI capabilities using the Occupational Information Network (O*NET), a comprehensive database on occupations and tasks published by the U.S. Department of Labor. SOC-10 scores are collapsed to the 4-digit ISCO level via a standard crosswalk, taking a simple average across all SOC occupations mapped to each ISCO occupation. These scores are calculated for both text and image generation (Generative AI), then standardized across occupations and expressed in standard deviations of exposure relative to the median job. A higher index indicates greater overlap and, hence, exposure.

Complementarity. The degree of complementarity between humans and AI in a given occupation is measured using data from Pizzinelli et al. (2023), which captures the degree to which humans are likely to remain essential even if specific tasks can be performed by AI—for example, in occupations involving face-to-face communication, decision-making responsibility, domain expertise, and unstructured tasks. For example, doctors score high on both exposure and complementarity because, while many diagnostic tasks can be AI-assisted, patient interaction and judgement remain human-centric. The complementarity parameter, θ, is calculated using data on "work contexts" from O*NET. Work contexts are cross-cutting job characteristics: for example, the extent to which a job requires interpersonal communication, responsibility, or physical labor. O*NET assigns each occupation a score for each work context. Work contexts most relevant to automation are selected and aggregated into six categories (communication, responsibility, physical conditions, criticality, routine, skill requirements). The authors then take the average of the work context score within and across groups, normalizing the index to vary between 0 and 1, with larger scores indicating that an occupation tends to have work contexts that require a human. Next, the complementarity-adjusted exposure index (C-AIOE) is calculated by taking the unstandardized (Felten, Raj, and Seamans 2023) exposure score and scaling it down by $1-\theta$. Hence, a higher complementarity adjusted exposure index indicates a job that is more easily substituted by AI. Throughout the analysis, the standardized Felten exposure indices for text and image AI systems are used when presenting broad exposure patterns, while the raw AIOE and C-AIOE indices are used when explicitly discussing complementarity.

Job postings data. Job listings come from Lightcast, an aggregator of online job platform data, which covers 28 million postings in South Asia from August 2020 to February 2025. Each listing reports required skills—including digital and AI skills (for example, machine learning, neural networks, natural language processing)—as well as sector, 4-digit ISCO occupation, location, and, for 16 percent of postings, a posted salary. While this dataset is rich, it is subject to strong selection bias: almost all listings originate from urban areas, the vast majority are in India, and listings are heavily skewed toward high-skill, white-collar professions. Annex table A2.3 compares the share of each one-digit occupation in total employment for the Lightcast data and the GLD, highlighting the strong white-collar bias. Consequently, our job-posting results are externally valid primarily for this subpopulation—a small slice of South Asia's labor force. The extent of these sampling biases may also change over time, driven by Lightcast's evolving data coverage.

Methods

Exposure aggregates. To calculate an exposure score for each surveyed worker, individual LFS records are merged with occupation-level exposure and complementarity indices at the four-digit ISCO level. To characterize exposure patterns, worker-weighted exposure levels are aggregated across sectors, occupations, countries, demographic groups, and skill levels. The correlates of AI exposure are estimated using worker-level OLS regressions relating AI exposure and complementarity to individual characteristics such as education, wages, age, gender, and urban/rural status.

Wage premiums. To assess wage premiums for AI and digital skills, fixed-effects regressions are estimated at the job-level, relating log posted salary to indicators for skills required in job postings, controlling for country-month, location, and occupation fixed effects. Thus, these wage premium estimates capture the percent gain in wages for jobs requiring digital or AI skills in narrowly defined occupational and regional groups, controlling for country-specific seasonality in wages.

Labor demand effects. For displacement effects, a difference-in-differences (DD) event-study model is estimated around the public release of ChatGPT in November 2022. At the occupation-month level, the baseline DD specification is:

$$\log(y_{it}) = \alpha + \beta_1 postChatGPT_t \times AIOE_i + \delta_i + \delta_t + \varepsilon_{it}$$

where $log(y_{it})$ is the log of total listings for occupation i in month t, $postChatGPT_t$ is an indicator variable equal to one after November 2022, $AIOE_i$ is the combined exposure index, and δ_i and δ_t are occupation and month fixed effects, respectively. β_1 represents the causal effect of ChatGPT introduction on labor demand for an occupation with an additional unit of exposure to AI automation. To explore the role of complementarity in moderating the impact of GenAI introduction, the following triple-difference specification:

$$\log(y_{it}) = \alpha + \beta postChatGPT_t \times AIOE_i + \sum_{k=2}^{4} \tau_k postChatGPT_t \times AIOE_i \times Q_{ik} + \delta_i + \delta_t + \varepsilon_{it,}$$

where Q_{ik} is an indicator variable for whether occupation i is in quartile k of the occupation-level complementarity distribution of θ_i. The fixed effects are also interacted with the complementarity quartiles. The τ_k coefficients represent the differential effect of ChatGPT on labor demand for each quartile of θ_i.

Differential effects are also estimated separately by education and experience. In this case, the outcome becomes the log of jobs of type *k*, $log\,(y_{it}^{k})$, where k indexes jobs requiring: *i)* only secondary education, *ii)* a bachelor's degree, *iii)* postgraduate education, *iv)* 0-5 years of experience, *v)* 5-10 years of experience, and *vi)* 10-15 years of experience. The impact of ChatGPT on the business services sector is estimated by replacing $postChatGPT_t \times AIOE_i$ with $postChatGPT_t \times BS_i$ in the main difference-in-differences regression. ISCO occupation codes associated with the business services sector were identified through a combination of large language model (LLM)-based predictions using ChatGPT and manual review of the output, and are listed in annex table A2.9.

By including occupation and month fixed effects, this approach controls for both baseline occupation characteristics and common time trends. The existing literature on the labor market impacts of AI adoption has produced mixed results (annex 2.1). Several study design issues reduce the likelihood of detecting effects. First, these studies typically use labor force survey data aggregated to the market level, which obscures effects that are likely to be highly concentrated in skilled, white-collar labor markets. Second, given the relative infrequency of standard labor force surveys, these studies typically cover periods before the introduction of GenAI. Finally, these studies also struggle to measure an exogenous shock to AI exposure, either through firm-level adoption or occupational exposure. Instead, the use of online job postings as a measure of labor demand allows the study to focus on the high-skill labor market most likely to be affected by AI. This data provides occupation-specific measures of labor demand at a high frequency, allowing estimation of the effects of the most recent GenAI technology. In addition, this study uses a clearly exogenous shock—the introduction of ChatGPT—and measures both occupational exposure and complementarity as determinants of displacement in response to GenAI.

Caveats and Limitations. First, "AI exposure" denotes overlap between an occupation's tasks and AI capabilities; it does not mean that exposed jobs are definitively "at risk" of automation. The prospective exposure analysis cannot predict the future with certainty—even with complementarity adjustments, the assessments remain inherently speculative. Second, the ChatGPT event study provides a firm short-term estimate of net labor demand effects—capturing both productivity-driven job creation and job displacement—but cannot disentangle these two forces; further, it does not account for entirely new occupations that may be created by AI. That means that any inference about *aggregate* employment effects is biased downwards. Third, ongoing improvements in AI capabilities mean that the Felten et al., (2023) and Pizzinelli et al. (2023) indices likely understate the true degree of exposure, and the estimates should be interpreted as lower bounds. Improvements in AI systems also lead to underestimating the complementarities and productivity gains that may be derived from AI adoption in the future. Fourth, the Lightcast data's urban and high-skill bias limits external validity for the broader South Asian workforce.

ANNEX TABLE A2.1 **Literature review of AI impacts**

Citation	Sample	Methodology	Comment
Labor market impacts			
Acemoglu et al. (2022)	United States, 2010–2018, Burning Glass job postings	Shift-share IV and event study	AI exposure leads to modest declines in job postings—10 pp increase reduces postings by 0.85 percent—suggesting limited short-run labor demand effects.
Acemoglu et al. (2023)	United States, 2016–18, Annual Business Survey & LBD	Descriptive analysis and event-style regressions	Advanced technology adoption is concentrated in already large and fast-growing firms, with little evidence of post-adoption employment gains.
Acemoglu (2024)	United States (task-level model-ing, not empirical)	Task-based macro model (theoretical + calibration using exposure estimates)	Using a task-based model and recent exposure data, the paper estimates AI will raise total factor productivity by only 0.55 percent over 10 years, with limited wage gains and potential increases in inequality.
Albanesi et al. (2025)	16 European countries, 2011–18, OECD STAN data	Shift-share analysis with AI exposure scores	AI exposure is associated with small positive net effects on employment across countries, driven by task restructuring rather than displacement.
Alderucci, Hovy, and Zolas (2024)	United States, firms with AI pa-tents, 1997–2016	Event study and panel re-gressions using matched census microdata and AI patent data	Firms with AI-related patents experienced 25 percent high-er employment and 40 percent higher revenue growth five years post-innovation, along with rising within-firm wage inequality
Babina et al. (2024)	United States, public firms, 2010–18	Long-differences regression, IV using AI-graduate supply	A one-SD increase in AI investment leads to a 19.5 percent rise in sales, 18.1 percent in employment, and 22.3 percent in valuation—driven by product innovation, not labor substi-tution.
Bonfiglioli et al. (2025)	United States, 2000–20	Two-stage least squares stacked first-differences models	AI exposure led to employment losses in affected local labor markets, especially among low-skill and production workers, while benefiting high-wage and STEM workers—suggesting AI contributed to job automation and rising inequality
Copestake et al. (2023)	India, 2010–19	Shift-share	Rapid growth in AI skill demand in India's services sector since 2016 has reduced non-AI job postings and wage offers, especially in high-skilled, non-routine occupations involving analytical and communication tasks.
Eloundou et al. (2024)	United States, 2020–22	Devise new framework for estimating exposure of jobs Exposure of a given task defined as capacity of large learning models to reduce human time by 50 percent while maintaining quality	The study estimates that while only 1.8 percent of jobs are currently highly exposed to large language models (LLMs), future software developments could raise this to over 46 percent, highlighting LLMs as general-purpose technologies with potentially widespread labor market impacts.
Gmyrek et al. (2025)	Global	Global Index of Occupation-al Exposure to Generative AI (GenAI); survey	
Grennan and Michaely (2020)	Comprehensive, 62 percent from United States, 2010Q–2016Q4	Two-stage least squares	Among security analysts, greater exposure to AI leads to task reallocation toward soft skills, shifts in coverage, and exits from the profession—especially by high performers—ultimately reducing research novelty and compensation despite some gains in forecast accuracy.

ANNEX TABLE A2.1 Literature review of AI impacts (*continued*)

Citation	Sample	Methodology	Comment
Labor market impacts			
Hampole et al. (2025)	United States, 2010–13	IV panel regression	AI exposure lowers labor demand for highly affected tasks but raises it for less-exposed ones, leading to muted net effects on employment, as productivity gains offset reduced demand in high-exposure occupations.
Huang (2024)	United States, 2010–21	Two-stage least squares	From 2010–2021, greater AI adoption led to sharper local declines in employment and wages—especially for middle-skill, non-STEM, and older or younger workers—with a 0.1 point rise in AI adoption reducing employment by up to 0.2 points and wages by up to 1 percent.
Hui, Reshef, and Zhou (2024)	Online freelancers, Jan. 2022–April 23	Difference-in-differences	Following the release of ChatGPT and other generative AI tools, freelancers in highly exposed occupations experienced declines in employment and earnings—with even top-performing freelancers disproportionately affected—suggesting generative AI reduces short-term demand for knowledge workers across the board.
Kanazawa et al. (2022)	December 2019 (main trial) and pre-trial data from October–November 2019	Hazard model	AI that guides taxi drivers to high-demand areas boosts productivity by reducing cruising time, with gains accruing only to low-skilled drivers—narrowing the productivity gap with high-skilled drivers by 13.4 percent and showing AI can substitute for skill.
Liu and Wang (2024)	Global, April 2023–March 2024	Panel regression	In an experiment with college-educated professionals, ChatGPT use significantly boosted productivity and task enjoyment—especially for lower-skilled participants—suggesting generative AI can reduce productivity inequality by complementing weaker workers.
Noy and Zhang (2023)	Jan. 27 to Feb. 21, 2023.	Randomized control trials	In an experiment with college-educated professionals, ChatGPT use significantly boosted productivity and task enjoyment—especially for lower-skilled participants—suggesting generative AI can reduce productivity inequality by complementing weaker workers.
Webb (2020)	United States, 1980–2010	Index measures are based on the overlap between the tasks in a given occupation and tasks described in the patents on a given technology	By March 2024, generative AI tools reached nearly 3 billion monthly visits globally—driven by young, educated users—with uptake strongest in middle-income countries, whose share of global traffic now exceeds 50 percent, highlighting rapid diffusion and productivity-focused use.
World Bank (2024d)	East Asian and Pacific countries	AI exposure mapping	While East Asia and Pacific countries are less exposed to AI displacement than advanced economies because of a higher share of manual jobs, AI-exposed occupations are already associated with lower earnings, limited employment growth, and growing inequality risks—especially for low-skilled and older workers.
Productivity			
Acemoglu et al. (2023)	United States, 2016–2018, Annual Business Survey & LBD	Descriptive analysis and event-study regressions	Advanced technology adoption is concentrated in already large and fast-growing firms, with little evidence of post-adoption employment gains.
Acemoglu (2024)	United States (task-level modeling, not empirical)	Task-based macro model (theoretical + calibration using exposure estimates)	Using a task-based model and recent exposure data, the paper estimates AI will raise total factor productivity by only 0.66 percent over 10 years, with limited wage gains and potential increase in inequality.

ANNEX TABLE A2.1 Literature review of AI impacts (*continued*)

Citation	Sample	Methodology	Comment
Productivity			
Alderucci, Hovy, and Zolas (2024)	United States; firms with AI patents, 1997–2016	Event study and panel regressions using matched census microdata and AI patent data	Firms with AI-related patents experienced 25 percent higher employment and 40 percent higher revenue growth five years post-innovation, along with rising within-firm wage inequality.
Brynjolfsson, Li, and Raymond (2023)	Global (Philippines, United States, and other countries), 2020–21	Randomized control trial	Access to a Generative AI tool increased productivity by 14 percent among customer support agents. The effects were concentrated among novice and low-skilled workers, with minimal impact on experienced and highly skilled workers.
Calvino, and L. Fontanelli (2023)	10 European countries + Israel, 2016-21	Firm-level regressions	Across 11 countries, AI adoption is most common in ICT and professional services and among large, productive firms—driven by such complementary factors as digital infrastructure, ICT skills, and use of other digital technologies that amplify productivity gains.
Calvino et al. (2022)	United Kingdom, 2019	Panel regression	In the UK, AI adopters are mainly large, productive firms in ICT and professional services near London, with young firms hiring more AI talent and human capital key to adoption and productivity gains.
Dell'Acqua et al. (2024)	Global, 2023	Randomized control trial	GPT-4 substantially improves consultants' productivity and work quality, with AI users completing 12.2 percent more tasks, working 25.1 percent faster, and producing results over 40 percent higher in quality. Gains were larger for lower-performing individuals. However, performance dropped significantly in tasks beyond AI's capability frontier.
Haslberger, Gingrich, and Bhatia (2023)	United Kingdon, 2023	Randomized control trial	Exposure to ChatGPT improved productivity across all tasks, with the largest gains in more complex and clearly defined work. While it generally narrowed performance gaps within the same occupation, it did not reduce inequalities between different occupations or education levels. The gap between younger and older workers widened.
Hampole et al. (2025)	United States, 2010–13	IV panel regression	AI exposure lowers labor demand for highly affected tasks but raises it for less-exposed ones, leading to muted net effects on employment, as productivity gains offset reduced demand in high-exposure occupations.
Kanazawa et al. (2022)	December 2019 (main trial) and pre-trial data from October–November 19	Hazard model	AI that helps taxi drivers find high-demand areas boosts productivity for low-skilled drivers only, narrowing their gap with high-skilled peers by 14 percent and showing AI's impact goes beyond simple job displacement.
Nie et al. (2024)	Global (146 countries), 2023	Randomized control trial	Providing access to GPT-4 in class resulted in a significant decrease in overall exam participation and course engagement. However, students who adopted GPT-4 showed improved exam scores, indicating potential benefits for adopters but also unexpected harms to engagement.
Noy and Zhang (2023)	United States, 2023	Randomized control trials	In an experiment with college-educated professionals, ChatGPT use significantly boosted productivity and task enjoyment—especially for lower-skilled participants—suggesting generative AI can reduce productivity inequality by complementing weaker workers.
World Bank (2024d)	East Asian and Pacific countries	AI exposure mapping	While East Asia and Pacific countries are less exposed to AI displacement than advanced economies because of a higher share of manual jobs, AI-exposed occupations are already associated with lower earnings, limited employment growth, and growing inequality risks—especially for low-skilled and older workers.

ANNEX TABLE A2.1 Literature review of AI impacts (*continued*)

Citation	Sample	Methodology	Comment
Exposure			
Babina et al. (2024)	United States public firms, 2010–18	Long-differences regression, IV using AI-graduate supply	A one-standard deviation increase in AI investment leads to a 19.5 percent rise in sales, 18.1 percent in employment, and 22.3 percent in valuation—driven by product innovation, not labor substitution.
Brynjolfsson, Mitchell and Rock (2018)	United States	Estimates the "suitability for machine learning" (SML) of tasks using O*NET task data.	Most occupations have some tasks suitable for machine learning (ML) but few have all tasks suitable for ML, suggesting the future ML impact will involve redesigning and reorganizing jobs rather than complete automation.
Eloundou et al. (2024)	United States, 2020–22	Devised a new framework for estimating exposure of jobs Exposure of a given task defined as capacity of large learning models to reduce human time by 50 percent while maintaining quality	The study estimates that while only 1.8% of jobs are currently highly exposed to large language models (LLMs), future software developments could raise this to over 46%, highlighting LLMs as general-purpose technologies with potentially widespread labor market impacts.
Felten, Raj, and Seamans (2021)	United States occupations and employment data (ONET, 2019)	AI exposure index based on AI–ability links from mTurk surveys and O*NET scores	The paper develops and validates new measures of AI exposure at occupational, industry, and geographic levels—showing how they can help assess AI's impact on jobs, firms, and regions for research and policy use.
Felten, Raj, and Seamans (2023)	United States occupational and demographic data from 2021	Exposure scores are computed using O*NET task data and AI-ability links from Felten, Raj, and Seamans (2021)	Generative AI most affects high-paid, highly educated white-collar jobs, with broad occupational and demographic variation—underscoring the need for policies to support workforce adaptation.
Gmyrek et al. (2025)	Global	Global Index of Occupational Exposure to Generative AI (GenAI); Survey	Updated global estimates show that 25 percent of workers are in occupations with some GenAI exposure, with 3.3 percent in the highest risk group—especially women and high-income country workers—suggesting GenAI will more likely transform jobs than replace them outright.
Hampole et al. (2025)	United States, 2010–13	IV panel regression	AI exposure lowers labor demand for highly affected tasks but raises it for less-exposed ones, leading to muted net effects on employment, as productivity gains offset reduced demand in high-exposure occupations.
Pizzinelli et al. (2023)	Microdata from labor force surveys in six countries spanning recent pre-COVID years	Complementarity-adjusted AI Occupational Exposure (C-AIOE) index	Across six countries, AI exposure is higher in advanced economies but differences shrink when accounting for complementarity; within countries, women and high earners face greater, often more complementary, exposure.
Webb (2020)	United States labor market, 1980–2010, occupation-industry cells.	Patent-task text overlap with regression analysis.	Using patent-task overlap, the study finds AI targets high-skilled tasks—unlike past technologies—and may reduce 90:10 wage inequality while leaving top 1% earnings unaffected, assuming historical substitution patterns persist.
World Bank (2024d)	East Asian and Pacific countries	AI exposure mapping	While East Asia and Pacific countries are less exposed to AI displacement than advanced economies because of a higher share of manual jobs, AI-exposed occupations are already associated with lower earnings, limited employment growth, and growing inequality risks—especially for low-skilled and older workers.

ANNEX TABLE A2.2 Labor force survey rounds

Country	Number of observations	Year
Albania	39,472	2013
Armenia	21,608	2023
Bangladesh	**343,121**	**2022**
Bolivia	147,979	2021
Brazil	298,362	2022
Bhutan	**31,331**	**2024**
Chile	172,150	2017
Cameroon	18,485	2010
Colombia	546,108	2021
Ethiopia	102,975	2021
Georgia	57,492	2023
Ghana	84,419	2023
Gambia	33,498	2023
Indonesia	76,801	2019
India	**311,661**	**2023**
Sri Lanka	**59,449**	**2023**
Morocco	243,111	2018
Mexico	1,328,664	2023
Mongolia	34,012	2022
Nepal	**50,927**	**2017**
Pakistan	321,393	2020
Philippines	1,168,689	2022
Rwanda	43,053	2021
Sierra Leone	14,712	2014
Tunisia	334,426	2017
Türkiye	358,668	2019
Tanzania	41,330	2020
South Africa	142,190	2020
Zambia	25,020	2022
Zimbabwe	97,820	2022

Sources: Global Labor Database (GLD), harmonized from individual countries' Labor Force Surveys (database); World Bank.
Note: South Asian countries are in bold. Sample sizes are total working age population (aged 15-64 years) in each survey round.

ANNEX TABLE A2.3 First-level occupation shares by data source

Occupation category	Lightcast share (%)	GLD share (%)
Armed forces	0.01	0.11
Managerial	22.02	2.64
Professionals	51.47	5.67
Technicians and Associate Professionals	15.64	3.86
Clerical Support Workers	4.97	1.95
Service and Sales Workers	3.37	14.54
Agricultural, Forestry, and Fishery Workers	0.05	36.25
Craft and Related Trades Workers	1.33	12.57
Plant and Machine Operators, and Assemblers	0.68	7.39
Elementary Occupations	0.45	15.01

Sources: Global Labor Database; Lightcast (database); World Bank.
Note: Table shows the share of total jobs in Lightcast and the GLD in each 1-digit ISCO occupation code.

ANNEX TABLE A2.4 Wages, education, and AI exposure in EMDEs

Outcome	AIOE	C-AIOE	AIOE	C-AIOE
	(1)	(2)	(3)	(4)
Log real wages	0.398***	0.026		
	(0.049)	(0.049)		
Years of education			0.105***	0.026**
			(0.008)	(0.010)
Country FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	1,838,707	1,838,707	1,815,432	1,815,432
R^2	0.147	0.014	0.277	0.042

Sources: Felten, Raj, and Seamans (2023); Global Labor Database; Pizzinelli et al. (2023); World Bank.
Note: FE = fixed effects. AIOE = AI Occupational Exposure Index. C-AIOE = Complementarity-adjusted AI Occupational Exposure Index. Standard errors in parentheses clustered at the occupation level. * p<0.1, **p<0.05, ***p<0.01.

ANNEX TABLE A2.5 Wages, education, and AI exposure in South Asia

Outcome	AIOE	C-AIOE	AIOE	C-AIOE
	(1)	(2)	(3)	(4)
Log real wages	0.512***	0.134		
	(0.091)	(0.096)		
Years of education			0.084***	0.041***
			(0.017)	(0.014)
Country FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	269,372	269,372	236,168	236,168
R^2	0.180	0.018	0.234	0.053

Sources: Felten, Raj, and Seamans (2023); Global Labor Database; Pizzinelli et al. (2023); World Bank.
Note: FE = fixed effects. AIOE = AI Occupational Exposure Index. C-AIOE = Complementarity-adjusted AI Occupational Exposure Index. Standard errors in parentheses clustered at the occupation level. * p<0.1, **p<0.05, ***p<0.01.

ANNEX TABLE A2.6 Digital and AI skills wage premiums

Outcome	Log salary			
	(1)	(2)	(3)	(4)
Digital skills	0.164***	0.139***	0.139***	0.115***
	(0.033)	(0.012)	(0.031)	(0.011)
Observations	3728229	3728228	3180123	3180122
R^2	0.031	0.141	0.066	0.175
AI skills	0.510***	0.315***	0.457***	0.276***
	(0.078)	(0.058)	(0.068)	(0.055)
Observations	3,728,229	3,728,228	3,180,123	3,180,122
R^2	0.024	0.135	0.062	0.171
Country-Month FE	Yes	Yes	Yes	Yes
Occupation FE	No	Yes	No	Yes
City FE	No	No	Yes	Yes

Sources: Felten, Raj, and Seamans (2023); Global Labor Database; Lightcast (database); Pizzinelli et al. (2023); World Bank.
Note: FE = fixed effects. Standard errors in parentheses clustered at the occupation level. * p<0.1, **p<0.05, ***p<0.01

ANNEX TABLE A2.7 Differences-in-differences regression results: job listings

Outcome	Log job listings					
Sample	All	Q1	Q2	Q3	Q4	All
	(1)	(2)	(3)	(4)	(5)	(6)
Post-ChatGPT × AIOE	-0.280***	-0.329***	-0.390***	-0.222**	-0.144	-0.994***
	(0.049)	(0.090)	(0.109)	(0.085)	(0.115)	(0.368)
Post-ChatGPT × Complementarity						-7.644*
						(3.962)
Post-ChatGPT × AIOE × Complementarity						1.269*
						(0.653)
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Occupation FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	17,795	4,421	4,455	4,462	4,457	17,795
R^2	0.972	0.975	0.970	0.972	0.970	0.972

Sources: Felten, Raj, and Seamans (2023); Global Labor Database; Lightcast (database); Pizzinelli et al. (2023); World Bank.
Note: FE = fixed effects. AIOE = AI Occupational Exposure Index. Complementarity parameter is θ, ranging from 0 to 1, with higher values indicating greater AI-human complementarity. Post-ChatGPT is an indicator equaling one in months after November 2022. Standard errors in parentheses clustered at the occupation level. * p<0.1, **p<0.05, ***p<0.01.

ANNEX TABLE A2.8 Differences-in-differences regression results: wages

Outcome	Log salary					
Sample	All	Q1	Q2	Q3	Q4	All
	(1)	(2)	(3)	(4)	(5)	(6)
Post-ChatGPT × AIOE	-0.093***	-0.142***	-0.131**	-0.008	-0.059	-0.278
	(0.022)	(0.035)	(0.050)	(0.047)	(0.049)	(0.174)
Post-ChatGPT × Complementarity						-2.163
						(1.903)
Post-ChatGPT × AIOE × Complementarity						0.334
						(0.309)
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Occupation FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	16,207	4,114	4,074	4,030	3,989	16,207
R^2	0.414	0.473	0.422	0.311	0.440	0.414

Sources: Felten, Raj, and Seamans (2023); Global Labor Database; Lightcast (database); Pizzinelli et al. (2023); World Bank.
Note: FE = fixed effects; AIOE = AI Occupational Exposure Index. Complementarity parameter is θ, ranging from 0 to 1, with higher values indicating greater AI-human complementarity. Post-ChatGPT is an indicator equaling one in months after November 2022. Standard errors in parentheses clustered at the occupation level. * p<0.1, **p<0.05, ***p<0.01.

ANNEX TABLE A2.9 Business Services Occupations

Occupation 4-digit ISCO code	Title
1219	Back-office operations manager
2411	Accountants
2412	Financial advisers
2413	Financial analysts
2511	Systems analysts
2512	Software developers
2513	Web and multimedia developers
2514	Applications programmers
2519	Software and app developers, not elsewhere classified
2521	Database designers and administrators
2522	Systems administrators
2523	Computer network professionals
2529	Database and network professionals not elsewhere classified
3312	Credit and loans officers
3313	Accounting associate professionals
3314	Statistical, mathematical and related associate professionals
3315	Valuers and loss assessors
3333	Employment agents and labor contractors
3341	Office supervisors
3342	Legal secretaries
3343	Administrative and executive secretaries
3344	Medical secretaries
3511	ICT operations technicians
3512	ICT user support technicians
3513	Computer network and systems technicians
3514	Web Technicians
4110	General office clerks
4120	Secretaries (general)
4131	Typists and word processing operators
4132	Data entry clerks
4222	Contact center information clerks
4311	Accounting and bookkeeping clerks
4312	Statistical, finance and insurance clerks
4313	Payroll clerks
4225	Inquiry clerks
4413	Coding, proofreading and related clerks
4416	Personnel clerks

ANNEX TABLE A2.10 Business services sector outcomes following the release of ChatGPT

Outcome	AI job share		Log job postings		Log salary	
	(1)	(2)	(3)	(4)	(5)	(6)
Post-ChatGPT × BS sector	0.006***	0.005***	-0.349***	-0.261***	-0.080***	-0.047**
	(0.002)	(0.002)	(0.059)	(0.063)	(0.022)	(0.024)
Post-ChatGPT × AIOE		0.002*		-0.217***		-0.079***
		(0.001)		(0.055)		(0.024)
Occupation FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	16,196	16,196	16,196	16,196	16,196	16,196
R^2	0.713	0.713	0.972	0.972	0.414	0.415

Sources: Felten, Raj, and Seamans (2023); Global Labor Database; Lightcast (database); Pizzinelli et al. (2023); World Bank.
Note: FE = fixed effects. AIOE = AI Occupational Exposure Index. BS = business services, an indicator equaling one if the job is associated with the business services sector. Post-ChatGPT is an indicator equaling one in months after November 2022. Standard errors in parentheses clustered at the occupation level. * p<0.1, **p<0.05, ***p<0.01.

ANNEX TABLE A2.11 Difference-in-differences regression results by education

Outcome	Log of job postings			Share of job postings		
Education requirement	**Secondary**	**College**	**Graduate**	**Secondary**	**College**	**Graduate**
	(1)	(2)	(3)	(4)	(5)	(6)
Post-ChatGPT × AIOE	-0.327***	0.090	-0.043	-0.119***	0.079***	0.041***
	(0.083)	(0.063)	(0.064)	(0.017)	(0.014)	(0.015)
Occupation FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	12,599	14,668	15,333	16,575	16,575	16,575
R^2	0.843	0.933	0.943	0.538	0.272	0.445

Sources: Felten, Raj, and Seamans (2023); Global Labor Database; Lightcast (database); Pizzinelli et al. (2023); World Bank.
Note: FE = fixed effects. AIOE = AI Occupational Exposure Index. Post-ChatGPT is an indicator equaling one in months after November 2022. Standard errors in parentheses clustered at the occupation level. * p<0.1, **p<0.05, ***p<0.01.

ANNEX TABLE A2.12 Difference-in-differences regression results by experience

Outcome	Log of job postings			Share of job postings		
Experience requirement	0-5 years	5-10 years	10-15 years	0-5 years	5-10 years	10-15 years
	(2)	(3)	(4)	(6)	(7)	(8)
Post-ChatGPT × AIOE	-0.290***	-0.078	0.076	-0.025**	0.011	0.014***
	(0.058)	(0.048)	(0.052)	(0.011)	(0.009)	(0.005)
Occupation FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	16,853	15,123	12,424	17,177	17,177	17,177
R^2	0.961	0.945	0.915	0.450	0.339	0.252

Sources: Felten, Raj, and Seamans (2023); Global Labor Database; Lightcast (database); Pizzinelli et al. (2023); World Bank.
Note: FE = fixed effects. AIOE = AI Occupational Exposure Index. Post-ChatGPT is an indicator equaling one in months after November 2022. Standard errors in parentheses clustered at the occupation level. * p<0.1, **p<0.05, ***p<0.01

References

Acemoglu, D. 2024. "The Simple Macroeconomics of AI." NBER Working Paper 32487, National Bureau of Economic Research, Cambridge, MA.

Acemoglu, D., G. Anderson, D. Beede, C. Buffington, E. Childress, E. Dinlersoz, L. Foster, et al. 2023. "Advanced Technology Adoption: Selection or Causal Effects?" *AEA Papers and Proceedings* 113 (May): 210–14.

Acemoglu, D., D. Autor, J. Hazell, and P. Restrepo. 2022. "Artificial Intelligence and Jobs: Evidence from Online Vacancies." *Journal of Labor Economics* 40 (S1): S293–340.

Acemoglu, D., and P. Restrepo. 2018. "The Race between Man and Machine: Implications of Technology for Growth, Factor Shares, and Employment." *American Economic Review* 108 (6): 1488–1542.

Acemoglu, D., and P. Restrepo. 2020. "Robots and Jobs: Evidence from US Labor Markets." *Journal of Political Economy* 128 (6): 2188–2244.

Albanesi, S., A. D. Da Silva, J. Jimeno, A. Lamo, and A. Wabitsch. 2025. "AI and Women's Employment in Europe." NBER Working Paper 33451, National Bureau of Economic Research, Cambridge, MA.

Alderucci, D., E. Hovy, and N. Zolas. 2024. "Quantifying the Impact of AI on Productivity and Labor Demand: Evidence from U.S. Census Microdata." Working Paper.

Autor, D., and D. Dorn. 2013. "The Growth of Low-Skill Service Jobs and the Polarization of the US Labor Market." *American Economic Review* 103 (5): 1553–97.

Autor, D. H. 2015. "Why Are There Still So Many Jobs? The History and Future of Workplace Automation." *Journal of Economic Perspectives* 29 (3): 3–30.

Autor, D. H., C. Chin, A. Salomons, and B. Seegmiller. 2022. "New Frontiers: The Origins and Content of New Work, 1940–2018." NBER Working Paper 30389, National Bureau of Economic Research, Cambridge, MA.

Autor, D. H., F. Levy, and R.J. Murnane. 2003. "The Skill Content of Recent Technological Change: An Empirical Exploration." *The Quarterly Journal of Economics* 118 (4): 1279–1333.

Babina, T., A. Fedyk, A. He, and J. Hodson. 2024. "Artificial Intelligence, Firm Growth, and Product Innovation." *Journal of Financial Economics* 151 (January): 103745.

Bonfiglioli, A., R. Crinò, G. Gancia, and I. Papadakis. 2025. "Artificial Intelligence and Jobs: Evidence from US Commuting Zones." *Economic Policy* 40 (121): 145–94.

Bryan, D. 2025. "ChatGPT: A 2023 Tipping Point To Rival the Internet in 1983, but Is OpenAI's 'O1' Model the Largest AI Inflection Point Yet?" *OPACE* (blog). June 8, 2025.

Brynjolfsson, E., D. Li, and L. Raymond. 2023. "Generative AI at Work." NBER Working Paper 31161, National Bureau of Economic Research, Cambridge, MA.

Brynjolfsson, E., T. Mitchell, and D. Rock. 2018. "What Can Machines Learn and What Does It Mean for Occupations and the Economy?" *AEA Papers and Proceedings* 108 (May): 43–47.

Calvino, F., and L. Fontanelli. 2023. "A Portrait of AI Adopters across Countries: Firm Characteristics, Assets' Complementarities and Productivity." OECD Science, Technology and Industry Working Papers 2023/02, Organisation for Economic Co-operation and Development, Paris.

Calvino, F., L. Samek, M. Squicciarini, and C. Morris. 2022. "Identifying and Characterising AI Adopters: A Novel Approach Based on Big Data." OECD Science, Technology and Industry Working Papers 2022/06, Organisation for Economic Co-operation and Development, Paris.

Cazzaniga, M. 2024. "Gen-AI." *Staff Discussion Notes* 2024 (001): 1.

Challapally, A., C. Pease, R. Raskar, and P. Chari. 2025. *The GenAI Divide: State of AI in Business 2025.* MIT NANDA.

Chiu, T. K. F., Q. Xia, X. Zhou, C.S. Chai, and M. Cheng. 2023. "Systematic Literature Review on Opportunities, Challenges, and Future Research Recommendations of Artificial Intelligence in Education." *Computers and Education: Artificial Intelligence* 4: 100118.

Choi, J.H., and D. Schwarcz. 2024. "AI Assistance in Legal Analysis: An Empirical Study." *Journal of Legal Education* 73(2): 384–420.

Chua, J., B. Zaidi, S. Chakravorty, and W. Kit. 2025. "Is GenAI Impacting Services Offshoring in India and the Philippines?" Citi Research, New York.

Copestake, A., M. Marczinek, A. Pople, and K. Stapleton. 2023. "AI and Services-Led Growth: Evidence from Indian Job Adverts." Structural Transformation and Economic Growth Working Paper, International Monetary Fund, Washington, DC.

Crépon, B., and G.J. Van Den Berg. 2016. "Active Labor Market Policies." *Annual Review of Economics* 8 (1): 521–46.

De Simone, M., F. Tiberti, M. Barron Rodriguez, F. Manolio, W. Mosuro, and E.J. Dikoru. 2025. "From Chalkboards to Chatbots: Evaluating the Impact of Generative AI on Learning Outcomes in Nigeria." Policy Research Working Paper 11125, World Bank, Washington, DC.

Demombynes, G., J. Langbein, and M. Weber. 2025. "The Exposure of Workers to Artificial Intelligence in Low- and Middle-Income Countries." Policy Research Working Paper 11057, World Bank, Washington, DC.

Eloundou, T., S. Manning, P. Mishkin, and D. Rock. 2024. "GPTs Are GPTs: Labor Market Impact Potential of LLMs." *Science* 384 (6702): 1306–8.

Felten, E., M. Raj, and R. Seamans. 2021. "Occupational, Industry, and Geographic Exposure to Artificial Intelligence: A Novel Dataset and Its Potential Uses." *Strategic Management Journal* 42 (12): 2195–2217.

Felten, E., M. Raj, and R. Seamans. 2023. "Occupational Heterogeneity in Exposure to Generative AI." Electronic Working Paper Series 4414065, SSRN, Rochester, NY.

Gmyrek, P., J. Berg, and D. Bescond. 2023. "Generative AI and Jobs: A Global Analysis of Potential Effects on Job Quantity and Quality." Working Paper 96, International Labour Organization, Geneva.

Gmyrek, P., J. Berg, K. Kamiński, F. Konopczyński, A. Ładna, B. Nafradi, K. Rosłaniec, and M. Troszyński. 2025. "Generative AI and Jobs: A Refined Global Index of Occupational Exposure." Working Paper 140, International Labour Organization, Geneva.

Grennan, J., and R. Michaely. 2020. "Artificial Intelligence and High-Skilled Work: Evidence from Analysts." Working Paper.

Hampole, M., D. Papanikolaou, L.D.W. Schmidt, and B. Seegmiller. 2025. "Artificial Intelligence and the Labor Market." NBER Working Paper 33509, National Bureau of Economic Research, Cambridge, MA.

Haslberger, M., J. Gingrich, and J. Bhatia. 2023. "No Great Equalizer: Experimental Evidence on AI in the UK Labor Market." Electronic Working Paper Series 4594466, SSRN, Rochester, NY.

Huang, Y. 2024. "The Labor Market Impact of Artificial Intelligence: Evidence from US Regions." IMF Working Paper 2024/199, International Monetary Fund, Washington, DC.

Hui, X., O. Reshef, and L. Zhou. 2024. "The Short-Term Effects of Generative Artificial Intelligence on Employment: Evidence from an Online Labor Market." Electronic Working Paper Series 4527336, SSRN, Rochester, NY.

Kanazawa, K., D. Kawaguchi, H. Shigeoka, and Y. Watanabe. 2022. "AI, Skill, and Productivity: The Case of Taxi Drivers." NBER Working Paper 30612, National Bureau of Economic Research, Cambridge, MA.

Kilic Celik, S., M. A. Kose, and F. Ohnsorge. 2023. "Potential Growth Prospects: Risks, Rewards, and Policies." Policy Research Working Paper 10355, World Bank, Washington, DC.

Liu, Y. 2024. *Generative AI: Catalyst for Growth or Harbinger of Premature De-Professionalization?* Washington, DC: World Bank.

Liu, Y., and H. Wang. 2024. "Who on Earth Is Using Generative AI?" Policy Research Working Paper 10870, World Bank, Washington, DC.

Liu, Y., H. Wang, and S. Yu (forthcoming). "Labor Demand in the Shadow of Generative AI: Evidence from the U.S. Job Market." Working Paper.

Maslej, N., L. Fattorini, R. Perrault, Y. Gil, V. Parli, N. Kariuki, E. Capstick, et al. 2025. "The AI Index 2025 Annual Report." AI Index Steering Committee, Institute for Human-Centered AI, Stanford, CA.

McElheran, K., J. F. Li, E. Brynjolfsson, Z. Kroff, E. Dinlersoz, L. Foster, and N. Zolas. 2023. "AI Adoption in America: Who, What, and Where." NBER Working Paper 31788, National Bureau of Economic Research, Cambridge, MA.

McKenzie, D. 2017. "How Effective Are Active Labor Market Policies in Developing Countries? A Critical Review of Recent Evidence." *The World Bank Research Observer* 32 (2): 127–54.

Nie, A., Y. Chandak, M. Suzara, A. Malik, J. Woodrow, M. Peng, M. Sahami, E. Brunskill, and C. Piech. 2024. "The GPT Surprise: Offering Large Language Model Chat in a Massive Coding Class Reduced Engagement but Increased Adopters Exam Performances." arXiv.

Noy, S., and W. Zhang. 2023. "Experimental Evidence on the Productivity Effects of Generative Artificial Intelligence." *Science* 381 (6654): 187–92.

Pizzinelli, C., A. J. Panton, M. M. Tavares, M. Cazzaniga, and L. Li. 2023. "Labor Market Exposure to AI: Cross-Country Differences and Distributional Implications." IMF Working Paper 2023/216, International Monetary Fund, Washington, DC.

Rahman, A. 2025. "I'm a LinkedIn Executive. I See the Bottom Rung of the Career Ladder Breaking." *The New York Times*, May 19, 2025, sec. Op-Ed.

Sahr, R. 2014. *Inflation and Conversion Factors for the United States: 1774 to Present*. Corvallis, Oregon: Oregon State University.

Webb, M. 2020. "The Impact of Artificial Intelligence on the Labor Market." Working Paper.

World Bank. 2024a. *South Asia Development Update: Jobs for Resilience*. April. Washington, DC: World Bank.

World Bank. 2024b. *South Asia Development Update: Women, Jobs, and Growth*. October. Washington, DC: World Bank.

World Bank. 2024c. *Digital Progress and Trends Report 2023*. Washington, DC: World Bank.

World Bank. 2024d. *World Bank East Asia and the Pacific Economic Update: Jobs and Technology*. October. Washington, DC: World Bank.

Zhang, F. 2019. *In the Dark: How Much Do Power Sector Distortions Cost South Asia?* South Asia Development Forum. Washington, DC: World Bank.

CHAPTER 3

Trading Protection for Jobs

Chapter 3. Trading Protection for Jobs

Carefully sequenced trade reforms could encourage private investment and create jobs for South Asia's growing working-age population. Historically, both in South Asia and around the world, major trade reforms have typically coincided with periods of significantly faster aggregate employment and output growth. However, higher-skilled and younger workers, and those in manufacturing, have benefited more than others. These patterns would likely be amplified in South Asia if governments decided to lower tariffs now. The one-third of South Asian workers in sectors with the lowest tariffs (mostly services) have accounted for more than three-quarters of aggregate employment growth. Ambitious tariff cuts in South Asia, especially in conjunction with broader free trade agreements, would particularly benefit younger and higher-skilled workers and those in manufacturing, who tend to work in trade-oriented sectors that are currently held back by elevated tariffs on inputs. Removing obstacles to a reallocation of workers across firms, sectors, and locations would help unlock gains for more workers. Governments can support this process through efforts such as improving connectivity, worker skilling, better job matching, the removal of obstacles to firms' growth, and an appropriate social safety net. Past experience suggests that the revenue implications of tariff cuts are manageable.

Introduction

The world is facing a jobs challenge as job creation struggles to keep up with the large number of people joining the working-age population between 2025 and 2050. And job creation in the coming years may be harder than in the past. It had slowed in many emerging market and developing economies (EMDEs) even before the overlapping crises of the past five years. Structural changes, including shifting trading patterns, climate change and the energy transition, and the development of new technologies, including artificial intelligence (AI), add further uncertainty.

South Asia is one of the three EMDE regions grappling with this jobs challenge (figure 3.1). While population growth rates have peaked in the region, it is still projected to add an additional 326 million working-age people (aged 15 years or older) between 2025 and 2050. South Asia has struggled to create enough jobs for its rapidly growing population. Employment ratios—employment in percent of the working-age population—in South Asia are among the lowest worldwide. On average, South Asia's employment ratio, particularly in the non-agricultural sector and among women, remains about 10 percentage points below the average in other EMDEs (figure 3.1). While a two-decade-long decline in South Asia's employment ratio started to reverse in 2020, the reversal was mainly due to rising agricultural employment. Employment ratios in non-agricultural sectors continued to rise only slowly (World Bank 2024a).

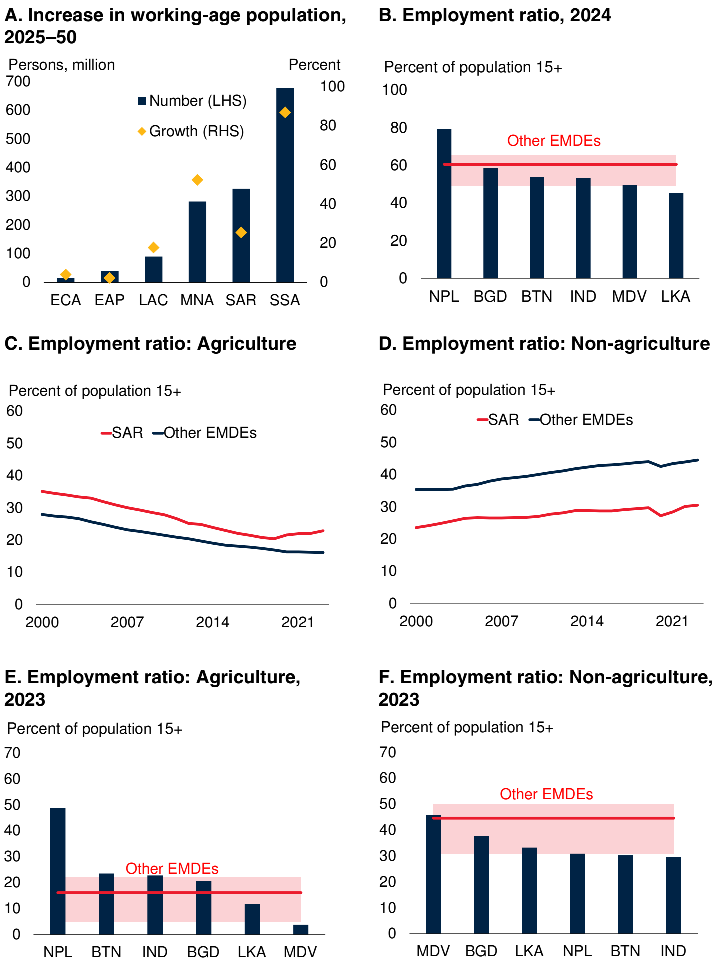
Unless job creation accelerates considerably, employment increases will continue to fall short of increases in the working-age population in all South Asian countries over the next two decades (figure 3.2). This could perpetuate migration pressures. About 2 percent of South Asia's working-age population emigrated from their home countries each year during 2023–24. In Bangladesh and Sri Lanka, emigration was 2–5 percent a year of the working-age population. In India, about 1 million people emigrated each year.

International experience suggests that trade can be an engine of job creation. Trade openness has been associated with significantly higher long-run employment ratios in the non-agricultural sector (World Bank 2024a) and with greater female employment shares (figure 3.3; World Bank 2024b). In addition to creating *more* jobs, trade openness may create *better* jobs since it is associated with higher labor productivity (Artuç et al. 2019; Irwin 2025a; Kambourov 2009). South Asia's labor productivity remains one-twentieth that of the advanced-economy average; for non-agricultural labor productivity, it remains in the bottom quartile of EMDEs.

Note: This chapter was prepared by Hagen Kruse, Margaret Triyana, and Zoe Xie, with inputs from Issac Yurui Hu and Xiao'ou Zhu. AI tools were used in the meta-analysis part of this chapter. See annex 3.1 for details.

FIGURE 3.1 Employment in South Asia

Employment ratios in South Asia lag those in most other EMDEs, mainly because of sluggish job creation in the non-agricultural sector.



Sources: International Labour Organization; Penn World Table (database); UN Population Prospects (database); World Development Indicators (database); World Bank.

Note: BGD = Bangladesh; BTN = Bhutan; EAP = East Asia and Pacific; ECA = Europe and Central Asia; EMDEs = emerging market and developing economies; IND = India; LAC = Latin America and the Caribbean; LHS = left-hand side; LKA = Sri Lanka; MDV = Maldives; MNA = Middle East, North Africa, Afghanistan and Pakistan; NPL = Nepal; RHS = right-hand side; SAR = South Asia; SSA = Sub-Saharan Africa. South Asia comprises Bangladesh, Bhutan, India, Maldives, Nepal, and Sri Lanka. Employment ratios are defined as employment share of the population aged 15 or older. Aggregate employment series is derived from Penn World Table, extended beyond 2019 using the employment growth rate of the ILO employment series. Sectoral employment is constructed using the aggregate employment series and sectoral employment shares from ILO.

A. Bars show the difference in levels in the total working-age population (people aged 15 and older) by country group. Diamonds show the percentage change in the working-age population.

C.D. Working-age population-weighted averages of country groups.

B.E.F. Shaded area is the interquartile range for EMDEs outside South Asia. The red line denotes the weighted average for other EMDEs. The sample comprises 126 EMDEs for aggregate employment in 2024 and 127 EMDEs for agriculture and non-agriculture employment in 2023.

Despite significant liberalization in the 1990s, South Asian countries remain among the most closed to international trade and finance (figure 3.4; Kathuria 2018). In part, this reflects restrictive policies such as tariffs and para-tariffs (border fees that resemble tariffs; World Bank 2024b). High tariffs have especially handicapped manufacturing. South Asia's manufacturing sector faces average tariffs on its inputs that are more than double those in other EMDEs. Lowering South Asia's above-average import tariffs would boost exports (Bernard et al. 2018; Dhyne et al. 2021; Feng, Li, and Swenson 2016) and private investment (World Bank 2024a). It would also help attract foreign direct investment (FDI), because a large share of FDI is targeted at trade-related activities (Hoekman and Sanfilippo 2023; McCaig, Pavcnik, and Wong 2025).

Several South Asian countries are currently considering lowering their trade barriers in the context of new free trade agreements (FTAs). India, for example, is currently in trade negotiations with Australia, Canada, the European Free Trade Association, the European Union, the Gulf Cooperation Council, the United Kingdom, and the United States. These economies were the destination for about half of South Asia's exports and the origin of more than one-quarter of the region's imports in 2023 (World Bank 2024b). Bangladesh is in negotiations with Korea and Japan, and negotiations with China, Malaysia, and the United Arab Emirates, are expected to start soon. Sri Lanka is in negotiations with China and aims to join the Regional Comprehensive Trade Agreement (RCEP). Lower import tariffs, especially in conjunction with broader FTAs that increase market size for competitive firms, could provide a major boost to growth and productivity.

The labor market impact of such an opening may favor some workers, firms, and locations over others and will depend on the speed and sequencing of trade and other reforms. This chapter examines the potential labor market effects of import tariff cuts in South Asia by addressing the following questions:

1. Does trade opening improve labor market outcomes?

2. Which segments of the labor market are most protected by current trade restrictions?

3. Which sequencing of tariff cuts and other reforms is likely to yield the best outcomes?

Main findings

This chapter offers several findings on the potential labor market impact of lowering import tariffs in South Asia.

Lessons from international experience

First, an event study of past episodes of major tariff cuts in EMDEs suggests that employment and output growth accelerated significantly during these episodes, although employment growth picked up with a lag. Trade flows expanded without significantly worsening current account balances. The small number of available studies shows that trade liberalization in South Asia in the 1970s–1990s was associated with higher aggregate employment in Bangladesh and Sri Lanka, but limited and uncertain aggregate impacts in India.

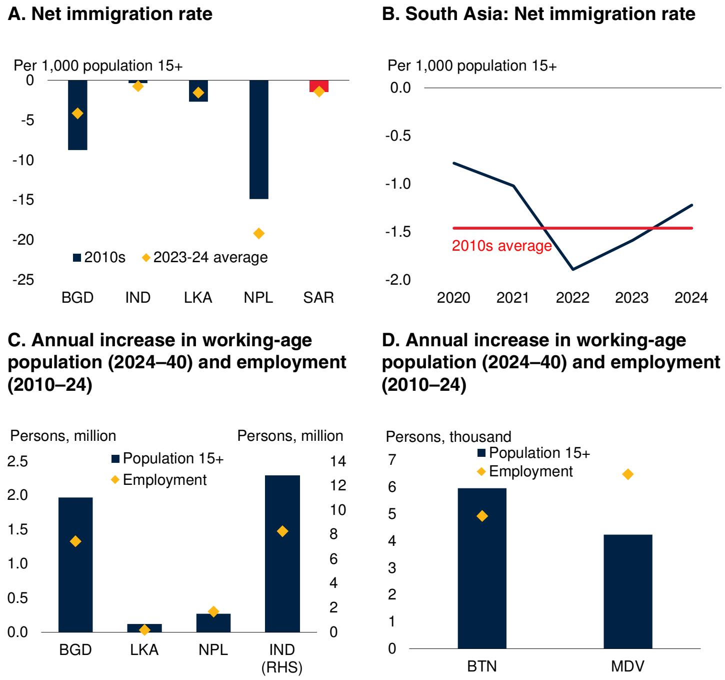
Second, the clear finding that emerges from the literature review is that past trade liberalizations benefited some groups more than others. Employment rose more often for skilled and younger workers than for others. Wages rose more often for skilled workers than unskilled workers, and among manufacturing firms than among non-manufacturing firms, likely because tariff cuts over the past decades have prioritized manufacturing. Impacts also differed by the type of tariff reform. In particular, cuts in tariffs on inputs into production were typically associated with employment and wage gains.

Job exposure to tariffs in South Asia

Third, microeconomic data on tariffs and worker characteristics reveals that 39 percent of South Asia's workers are in sectors that are sheltered by tariffs above 30 percent, almost all of them in agriculture. A different 32 percent of South Asia's workers are in sectors (mostly services) that are protected by tariffs of no more than 5 percent, but face tariffs on intermediate inputs of more than twice the EMDE average outside South Asia. Hence, tariff reduction on intermediate inputs, especially in conjunction with broader FTAs that expand market size, could generate substantial competitiveness gains.

FIGURE 3.2 Migration and population projections

Poor job prospects contribute to migration pressures. Unless the pace of job creation picks up, employment increases will continue to fall short of increases in the working-age population in South Asia.



Sources: International Labour Organization; Penn World Table (database); United Nations World Population Prospects (database); World Development Indicators (database); World Bank.

Note: BGD = Bangladesh; BTN = Bhutan; EMDEs = emerging market and developing economies; IND = India; LKA = Sri Lanka; MDV = Maldives; NPL = Nepal; RHS = right-hand side; SAR = South Asia. South Asia comprises Bangladesh, Bhutan, India, Maldives, Nepal, and Sri Lanka.

A.B. Weighted averages for aggregates. 2010s = annual average of net immigration rate for 2010–19. Latest available data for 2024.

C.D. Bar shows the average annual expected increase in the population of those aged 15 or older between 2024 and 2040. Diamond shows the average annual increase in employment between 2010 and 2024.

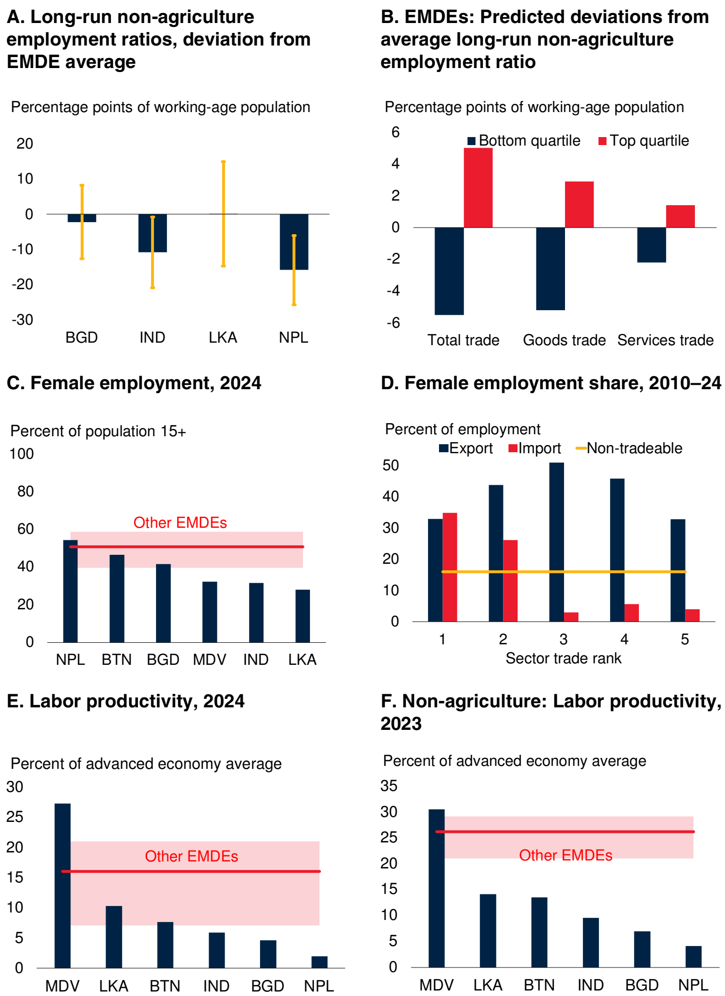
Fourth, the most dynamic parts of South Asia's labor markets are those that are least sheltered behind tariffs. Over the past decade, the least protected sectors—those with tariffs below 5 percent—have generated more than three-quarters of South Asia's employment growth, although they employ only one-third of its workers. This contrasts with other EMDEs where more than three-quarters of workers are minimally protected by tariffs. Workers in the least tariff-protected jobs (mostly in services) are paid 16 percent higher wages, on average, and tend to be significantly more skilled and younger.

Policy implications

Fifth, major tariff reductions could catalyze a reallocation of workers across firms, sectors, and

FIGURE 3.3 Labor market outcomes and trade

Trade openness is associated with higher long-run employment ratios, greater female employment share, and higher productivity. South Asia's labor productivity remains one-twentieth that of the advanced-economy average; for non-agricultural labor productivity, it remains in the bottom quartile of EMDEs.



Sources: International Labour Organization; Global Labor Database; Penn World Table (database); World Development Indicators (database); World Bank.

Note: BGD = Bangladesh; BTN = Bhutan; EMDEs = emerging market and developing economies; IND = India; LKA = Sri Lanka; MDV = Maldives; NPL = Nepal; SAR = South Asia. South Asia comprises Bangladesh, Bhutan, India, Maldives, Nepal, and Sri Lanka.

A.B. Results based on World Bank (2024a), which defines employment ratios as employment as a share of the population aged between 15 and 64. Regression sample includes 103 EMDEs that are not small states.

A. Bars show country fixed effects for 4 South Asian countries, recovered from regressions and scaled by the coefficient on the lagged employment ratio. These represent the deviations of country-specific long-run employment ratios from the EMDE average. Whiskers show 90 percent confidence interval.

B. Bars show predicted deviations from EMDE-average long-run employment ratios in non-agriculture, at the bottom and top EMDE quartiles of the export-to-GDP ratio.

C. Numbers include subsistence employment. For Nepal, female employment excluding subsistence employment is 27 percent of the population that was 15 or older in 2024. For all other South Asian countries, the two numbers are very close.

D. Figure based on analysis in World Bank (2024b) and shows the female share of total sector employment by sector trade rank across all South Asian countries. Sectors are ranked at the country-year level by export or import share in total trade. For net export and import sectors, the top-ranked export sector is the net exporting sector *s* in country *c* at year *t* for which $x_{sct} /(x_{sct} + m_{sct})$ is the highest. Sample years are 2010–21. Non-tradable sectors are those for which $x_{sct} = m_{sct} = 0$.

E.F. Sample includes 120 EMDEs and 35 advanced economies. Numbers are expressed as a percent of the employment-weighted average for advanced economies. Shaded area is the interquartile range for EMDEs outside South Asia. Red line denotes the employment-weighted average for other EMDEs.

locations. Such reallocation could be eased by removing impediments to labor market "churn" (that is, the speed of job entry and exit). The more churn the labor market can accommodate, the more easily workers will transition from jobs in declining industries to jobs in newly competitive industries (box 3.1). A dynamic general equilibrium modeling exercise shows that the per capita income gains from a trade reform can be significantly larger if combined with (or preceded by) even a modest reduction in job switching cost.

Sixth, the labor market adjustment to lower tariffs could be smoothed by carefully sequencing them, ideally in the context of an FTA and combined with trade facilitation and other reforms. Tariff cuts could start with tariffs on the most widely used intermediate inputs while the highest tariffs, which affect a large share of the workforce, could be lowered in a more gradual manner. Complementary policies could reduce the job switching cost for workers, such as better transport and digital connectivity, upskilling, more transparent job or housing search options, and the streamlining of size-dependent policies that discourage firms' growth.

Seventh, an event study suggests that the fiscal implications of even major tariff cuts would likely be manageable (box 3.2). Past episodes of large tariff cuts resulted in minor trade revenue losses—of less than 0.1 percentage points of GDP on average—because growing trade volumes offset tariff cuts. Total tax revenue-to-GDP ratios remained broadly flat, as rising non-trade tax revenues offset trade tax revenue losses. Sustained increases in non-trade tax revenue of the magnitude needed to offset trade revenue losses have been common and typically did not involve tax rate increases.

Contributions to the literature

This chapter contributes to the literature in several ways.

First, since 2000, the empirical academic literature on labor market effects of trade reform has focused on distributional impacts. With the exception of one study on unemployment rates (Dutt, Mitra, and Rajan 2009), aggregate impacts were at most discussed in terms of productivity outcomes, not employment outcomes. Hence, this chapter illustrates aggregate employment outcomes in an event study of past episodes of the largest tariff reductions since 1995. It also discusses major trade reforms in South Asia before 2000.

Second, because the academic literature on distributional effects finds a wide range of results, this chapter conducts a meta-regression analysis. It thus updates the landmark review of Goldberg and Pavcnik (2007), and complements the review of productivity outcomes of Irwin (2025a) and the review of spatial and informal-sector outcomes of Dix-Carneiro and Kovak (2025).

Third, this chapter is the first to illustrate the tariff protection of the workforce in a sample of 12 EMDEs, including six South Asian countries. In contrast to previous work, for example in World Bank (2024c), the chapter distinguishes between general tariffs and tariffs on intermediate inputs, and shows that this distinction materially alters the assessment of South Asia's competitiveness.

Fourth, this study is the first to explicitly model the general equilibrium effects of sequencing trade and labor market reforms for a large set of EMDEs. Similar previous modeling efforts, such as Caliendo, Dvorkin, and Parro (2019), have focused on the impact of China's trade expansion on the United States or have examined the impact of trade reform in the presence of labor market frictions, but have not examined the interaction between trade reform and the removal of frictions to labor mobility.

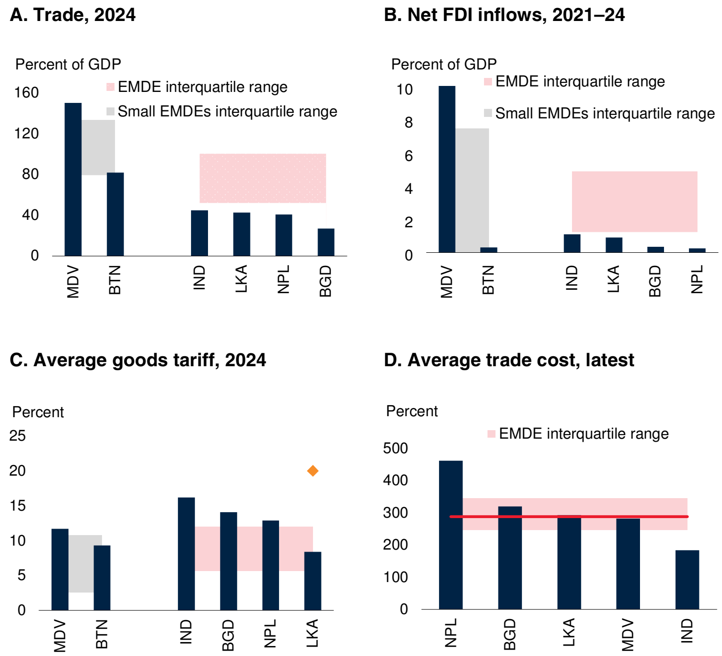
Fifth, this chapter is the first to tackle the effect of tariff cuts on government revenues—a common reason for governments' reluctance to lower tariffs. It uses the same event study that tracks the evolution of aggregate employment to track the evolution of government revenues.

Methodology and data

Methodology. The chapter relies on a wide range of approaches (annex 3.1). An event study of developments during past episodes of major trade

FIGURE 3.4 Barriers to trade

Openness to trade and foreign direct investment is unusually low in South Asia, partly because of high tariffs and non-tariff trade costs.



Sources: ESCAP-World Bank trade cost database; World Development Indicators (database); World Bank.

Note: BGD = Bangladesh; BTN = Bhutan; EMDEs = emerging market and developing economies; FDI = foreign direct investment; IND = India; LKA = Sri Lanka; MDV = Maldives; NPL = Nepal; SAR = South Asia. South Asia comprises Bangladesh, Bhutan, India, Maldives, Nepal, and Sri Lanka.

A.B. Red-shaded region shows interquartile ranges for other EMDEs, comprising 97 economies (A); 70 economies (B). Gray-shaded region shows interquartile ranges for small-state EMDEs (as defined by World Bank 2024b), comprising 10 economies (A); 15 economies (B). Bhutan and Maldives use 2023 data for trade. Bhutan and Sri Lanka use 2021–23 averages for FDI.

C. Simple average of effectively applied most-favored-nation tariffs. For Sri Lanka, the diamond shows para-tariffs in 2023 added to latest data for tariffs.

D. Trade costs are expressed as a percentage of domestic traded values. 2022 or latest year available. For each country, trade costs are calculated using a simple average of all trading partners.

liberalization is therefore conducted. A meta-regression analysis of the international evidence established in the academic literature provides evidence for the distributional impacts—the winners and losers—of trade reforms. A comparison with the particular features of South Asia's labor markets puts potential lessons from the international evidence into context. Detailed labor force survey data are linked to data on trade flows and trade restrictions through input-output tables and regression analysis to help identify the segments of the work force that may be most affected by efforts to lower import tariffs. A dynamic general equilibrium trade model with labor market frictions is used to calibrate and compare different scenarios of policy sequencing.

Data. The analysis draws on a wide variety of data sources. The literature survey of 83 studies is coded into a dataset as explained in annex 3.1. Data for aggregate, sectoral, and women's employment are drawn from the Penn World Tables, the World Development Indicators, and the International Labour Organization, and are available for 133 EMDEs and 36 advanced economies for 2000–24. The study of workers' exposure to tariff cuts uses harmonized, detailed labor force surveys from the World Bank's Global Labor Database (GLD), supplemented with national survey data for Bhutan and Maldives, tariff data from the Analytical Database of the World Trade Organization (WTO), and Multiregional Input-Output Tables from the Asian Development Bank (ADB).

Caveats. *First*, most of this chapter focuses on the potential labor market effect of tariff reductions. However, similar arguments can be made about non-tariff barriers to trade. These include quantitative restrictions, licensing requirements or para-tariffs, and also foreign exchange restrictions and exchange rate misalignments (Irwin 2025b). In fact, exchange rate reform has often accompanied trade liberalization in the past. But because comparable cross-country data on non-tariff barriers are sparse and because they are often correlated with tariffs, this chapter—with the exception of box 3.1—restricts its empirical exercises to tariffs.

Second, this chapter focuses on employment outcomes. Additional benefits from tariff reduction can materialize for consumption, productivity, or income, which could further improve aggregate labor market outcomes. Such effects go beyond the scope of this chapter but are extensively discussed in the literature.

Third, this chapter does not aim to distinguish between formal and informal employment. A substantial literature has examined the impact of trade reforms on informal employment, in part inspired by the rich research on trade liberalization in Latin America. Dix-Carneiro et al. (2025) argue that real income gains from trade reform may be higher the more informal the economy is. But because the vast majority of South Asia's employment is informal, by some estimates almost 90 percent, this chapter does not aim to isolate effects on informal employment specifically. That said, the labor force surveys underlying the empirical exercise here do include informal workers.

Fourth, the lessons from historical experience may be dampened by changes in the global economy. For the sample of EMDEs used in this chapter, all but five episodes of major tariffs cuts occurred before 2010. The period leading up to the global financial crisis of 2008–09 was a period of rapid global trade expansion, which amplified the gains from trade opening by any individual country. Since 2010, global trade has been broadly flat as a share of global GDP. In this environment, trade opening by any individual country may be less growth- and job-enhancing than it would have been before 2010.

International evidence from past trade reforms

Past episodes of major tariff reductions were typically accompanied by significant increases in employment, with benefits disproportionately rewarding skilled and young workers, and firms in the manufacturing sector. Employment or wage gains were greater after reductions of input tariffs than after general tariff reductions. In South Asia, too, past trade reforms initiated periods of faster employment growth in Bangladesh and Sri Lanka but had limited and uncertain impacts on aggregate employment in India.

Past trade reform episodes: Aggregate labor market outcomes

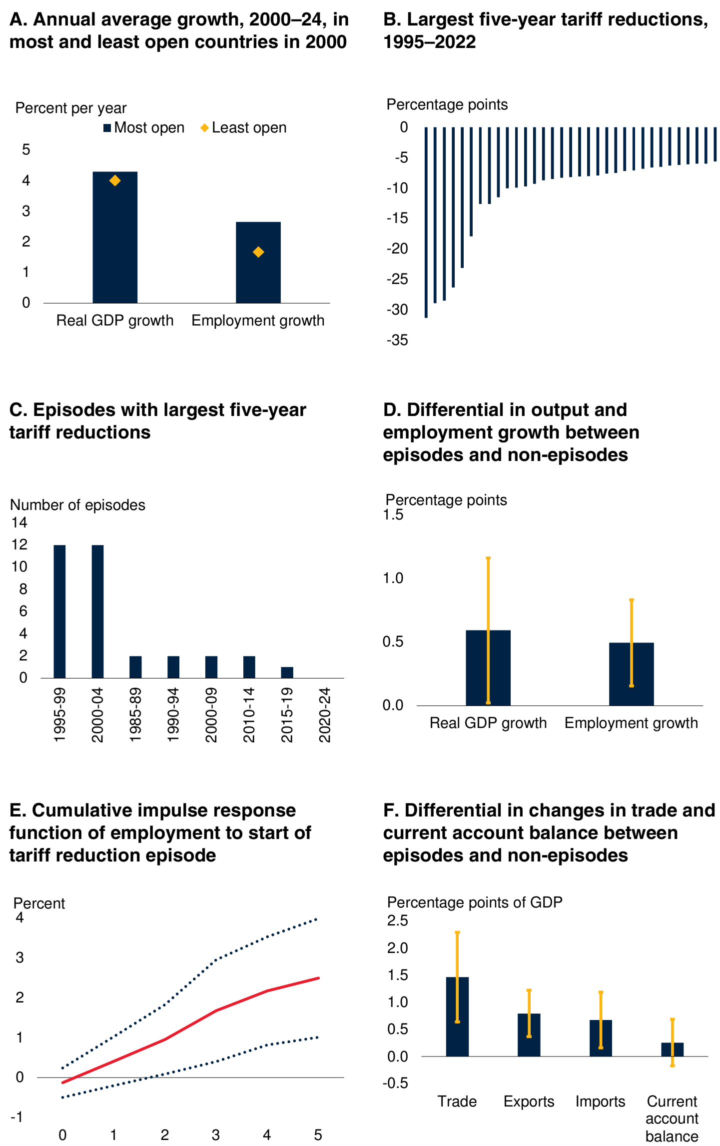
Conceptual framework. The standard endowments-based trade theory suggests that trade opening would raise incomes more for the more abundant factor—typically unskilled labor in EMDEs—than for the less abundant factor—typically human or physical capital in EMDEs (Bernhofen and Brown 2004, 2005; Eaton and Kortum 2002). For EMDEs, this effect would be amplified if trade opening also catalyzed skill-biased technological change (Attanasio, Goldberg, and Pavcnik 2004). Although these forces would predict disproportionate gains from a trade opening for skilled workers in EMDEs, they do not imply aggregate employment gains. However, aggregate employment could be expected to rise if a trade opening strengthened labor demand by triggering faster capital accumulation or broader productivity gains, for example, through enhanced competition (De Loecker et al. 2016); increasing returns to scale (Trefler 2004); access to better and cheaper inputs from abroad (Goldberg et al. 2010; Gopinath and Neiman 2014; Halpern, Koren, and Szeidl 2015); or factor reallocation through firms' exit (Pavcnik 2002).

Event study. The late 1990s and early 2000s were periods of continued trade liberalization, although at a more moderate pace than in the episodes examined in the existing literature (Dix-Carneiro and Kovak 2025; Sachs and Warner 1995; Wacziarg and Wallack 2004). Continued liberalization also contributed to 0.3–1 percentage -point faster output and employment growth in those economies that were most open in 2000 compared with those that were least open (figure 3.5). An event study illustrates the evolution of labor market outcomes after past episodes of major liberalizing trade reforms since 1995. Major trade reforms are considered those with unweighted-average reductions in import tariffs in the top decile of a sample of 122 countries (including 86 EMDEs) during 1995–2022 (annex 3.1). This results in 33 episodes in 31 countries (of which 25 are EMDEs) in which tariffs were cut by at least 5 percentage points over a five-year period and, on average, by 15 percentage points (figure 3.5). The average liberalization episode lasted seven years, with repeated tariff cuts. Most of these events took place during the late 1990s and early 2000s. Only five of these episodes occurred after the global financial crisis of 2008–09, when global trade stabilized relative to global GDP. A comparison of average output and employment growth, together with changes in trade and current account balances (in percentage points of GDP), between episodes and non-episodes, shows how outcomes differed from those in "non-reform" countries and years. A local projection model that estimates cumulative employment changes for a forecast horizon of up to five years from the start of the episodes traces out the dynamics of employment (annex 3.1).

Trade impact: Significant increases. As expected and intended, trade openness increased significantly faster during these reform episodes

FIGURE 3.5 Event study of past tariff reduction episodes

Since 2000, employment growth has been faster in the initially most open economies. Past episodes of major tariff reduction were accompanied by higher output and employment growth, larger increases in trade, but not higher current account balances. Significant employment gains materialized with a three-year lag.



Sources: IMF World Economic Outlook (database); World Development Indicators (database); World Bank.

Note: Episodes and methodology are detailed in annex 3.1. Episodes are defined as the largest decile of one-year and five-year tariff reductions among up to 122 countries during 1995–2022, with 31 countries experiencing 33 tariff reduction episodes.

A. Annual average growth rates during 2000-24 in the 16 EMDEs in the lowest trade-to-GDP quartile ("least open") and 16 EMDEs in the highest trade-to-GDPs quartile ("most open") in 2000.

D.F. Difference between the annual average during the first 5 years of episode and all years outside of episodes, derived from a fixed effects regression. Whiskers show 90 percent confidence intervals.

E. Impulse response function is from a local projection estimating of cumulative changes in log employment on a dummy variable for the start of the tariff reduction episode. Dotted lines show 95 percent confidence intervals.

than outside them: on average, trade increased by 1.5 percentage points of GDP per year faster during these episodes (figure 3.5). Both exports and imports rose significantly faster, by 0.7 and 0.8 percentage points of GDP per year, respectively. Current account balances tended to improve, but with too much variation to establish a statistically significant pattern.

Labor market impact: Significantly positive. On average during these trade reform episodes, both employment and output growth were 0.5 percentage point per year higher than outside such episodes (figure 3.5). The labor market improvements materialized with a short delay. In the year of the reform, employment outcomes were small and varied too widely to establish statistically significant results. But starting in the second year, employment rose significantly above the non-reform trend, and the gap continued to grow thereafter. This is broadly consistent with Dix-Carneiro and Kovak (2025) who show that for major trade liberalizations in a group of 18 Latin American countries in the 1980s and early 1990s, unemployment outcomes varied widely in the first few years after liberalization.

Trade reform and economic distress. About two-thirds of the trade reform events examined in this event study were implemented as part of broader reforms or during economic stress, either as part of a stabilization and adjustment program supported by the International Monetary Fund (IMF), or in the midst of crises or recessions. The event study here cannot isolate the causal impact of tariff cuts on job creation. As a robustness test, the exercise is repeated to include a dummy variable for a currency, banking, or debt crisis, an IMF-supported program, or a recession during the episode. Indeed, employment outcomes only improved significantly when there were no signs of economic stress during the episode (annex 3.1).

Evidence from the literature: Heterogeneous impact on labor market outcomes

Focus on winners and losers. Since 2000, few empirical studies or reviews have examined aggregate labor market outcomes after domestic trade reforms. Irwin (2025a) reviews the literature and finds generally positive, but highly heterogeneous productivity increases as a result of import tariff cuts. In a sample of 90 countries during 1985–2004, Dutt, Mitra, and Rajan (2009) find that an increase in trade restrictiveness was associated with significantly higher unemployment, although it may have briefly lowered unemployment in the short run. The bulk of the academic literature has focused on identifying the impacts of trade reforms by comparing outcomes between more- and less-exposed groups. Because trade may be more complementary with certain types of workers or firms—such as higher-skilled or more technologically advanced ones—or may interact with pre-existing domestic policies—such as labor market regulations—the identified impacts can be larger for some groups even with the same level of exposure. This asymmetry creates winners or losers of trade reforms. A meta-regression analysis helps synthesize the most robust results from this literature.[1]

Selection of studies. Seven widely cited studies are selected as seed studies for the review: Autor, Dorn, and Hanson (2013); Bernard et al. (2007); Caliendo, Dvorkin, and Parro (2019); Dix-Carneiro and Kovak (2019); Dutt, Mitra, and Ranjan (2009); Goldberg and Pavcnik (2007); and McCaig and Pavcnik (2018). These seed articles cover a variety of methodologies, countries, and outcome variables. Forward and backward citation chasing and related article searches based on these seed studies are used to assemble an initial set of more than 3,000 studies. These include those that are either published in top-ranked peer-reviewed journals since 2,000 or appeared in major working paper series since 2020. Of those, studies are retained if they: (i) examine specific policy changes to liberalize trade—such as tariff reduction, implementation of free trade agreements, or non-tariff barrier reductions; (ii) include labor market outcomes; and (iii) provide empirical estimates (annex 3.1). The inclusion criteria reduce the number of relevant studies to 83, of which 72 are on EMDEs. These studies cover data from 1900

[1] McLaren (2017) reviews a partially overlapping but different slice of the literature, focusing on theoretical and modeling efforts, and highlights switching costs.

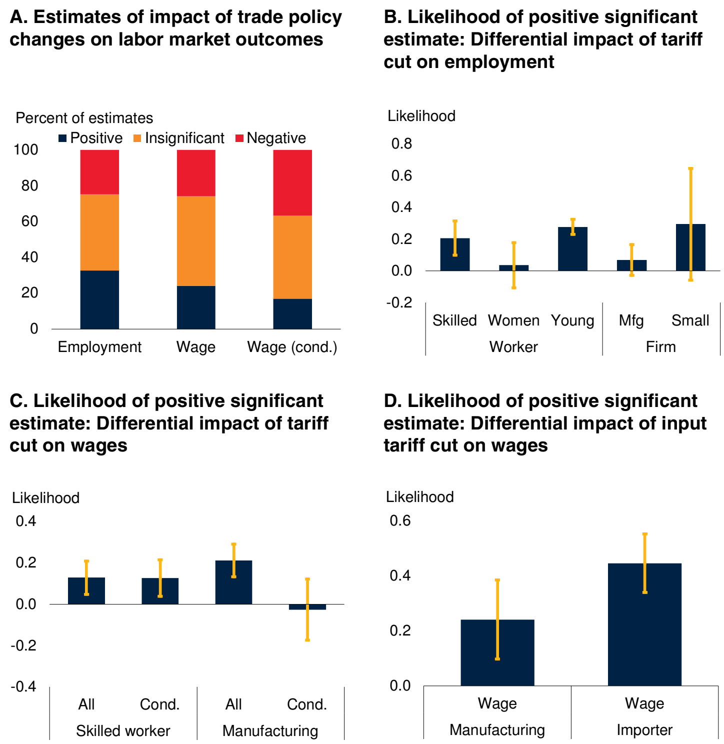
until the end of 2010s for 23 countries (of which 18 are EMDEs, mostly in Latin America and East Asia) and six studies with a group of countries.

Sample of estimates. These 83 papers offer 833 econometric estimates on labor market outcomes that constitute the sample for the meta regression analysis. Two-fifths of the estimates from these studies examine employment, one-third look at wages, and one-fifth study labor or firms' productivity. The meta-analysis focuses on employment and wage outcomes. About half of the estimates that refer to wage outcomes control for worker characteristics, either directly in the estimation, or by computing industry- or location-specific wage premiums (Krueger and Summers 1988). The other half of the estimates on wage outcomes use unconditional wages, often because of a lack of worker-level data, and capture impacts on both efficiency wage units and worker composition.

Estimation approach. The meta-regression analysis is based on ordered probit regressions with the dependent variable defined as a categorical variable that is 1 for a statistically significant estimate of higher employment or wages for more exposed firms, workers, sectors, or locations; -1 for a statistically significant negative outcome; and 0 for a statistically insignificant estimate. Two-thirds of the academic literature identified significant employment or wage effects of liberalizing trade policy reforms (figure 3.6). The independent variables are dummies for worker characteristics (skilled, women, young) and firm characteristics (manufacturing, small, importer). The employment impact is expected to differ materially by type of trade reform: general tariff cuts introduce greater import competition; tariff cuts on inputs into domestic production facilitate the import of cheaper and better-quality inputs; and FTAs include tariff cuts by trading partners that directly benefit a country's exports. Hence, a categorical variable for policy type is interacted with the independent variables to obtain separate estimates by policy type. Standard errors are clustered at the study level. This approach uncovers several robust findings of asymmetric labor market impacts in the literature. Asymmetries range across workers and firms, and depend on the type of reform.

FIGURE 3.6 Summary of the literature: Worker and firm characteristics

Two-thirds of the academic literature find significant employment or wage effects from trade policy reforms. Tariff cuts were more often associated with employment increases for skilled and young workers, and with higher wages for skilled workers and workers in manufacturing firms, the latter driven by shifts in worker composition.



Sources: Based on a review of 83 studies on the effects of trade liberalization from domestic policy changes using empirical estimates. Methodology is detailed in annex 3.1.

Note: Cond. = conditional; Mfg = manufacturing.

A. Bars show the percentage of estimates that find trade liberalization is associated with higher (positive), lower (negative) or insignificant impacts on employment, wages, and wages conditional on worker characteristics, for the affected group compared with other groups. Total number of estimates is 833.

B.–D. Bars show the estimated marginal likelihood that the impact of tariff cuts on employment or wages is statistically significantly more positive for certain workers or firms. Marginal likelihoods for conditional wages are estimated using a sample of estimates with wages as the outcome, controlling for worker-level characteristics. Whiskers show the one-standard-error band on the estimated likelihood. Standard errors are clustered at the study level. A "skilled" worker is one defined as skilled in the study, or is a white-collar or non-production worker, or has completed at least high school or upper secondary school. A "young" worker is one below the age 30. A "small firm" is defined as small in the study or has fewer than 50 workers or has a workforce size below industry median. Country-level studies are excluded. Estimates with the informal sector as the outcome variable are excluded. Marginal likelihoods are excluded from the charts where sample size is insufficient for reliable standard errors.

Skilled workers. Estimates of the impact of tariff cuts on employment and wages are significantly more likely to be positive among skilled workers than the average worker (figure 3.6). For example during the 1980s–90s, *Colombian* industries with larger tariff reductions experienced larger increases in the share of skilled workers, in part because tariff cuts induced skill-biased technological change (Attanasio, Goldberg, and Pavcnik 2004).

In rural *India* during the 1990s, tariff declines were associated with more days in waged work for literate men and fewer days in waged work for illiterate men (Edmonds, Pavcnik, and Topalova 2010). In *Brazil* during 1991–2000, non-employment rose in regions that were more exposed to trade opening, but this effect was much smaller and only marginally significant for high-skilled workers (Dix-Carneiro and Kovak 2019).

Women. Estimates of the impact of tariff cuts on employment are *not* significantly more likely to be positive for women (figure 3.6). On the one hand, increased trade induces more women to join the workforce. For example, import tariff reductions following China's accession to the WTO were associated with overall increases in employment among women but not among men in *China*; men previously working in the tradable sector lost their jobs, whereas women entered the non-tradable sector to make up for household income losses (Dai, Huang, and Zhang 2021). On the other hand, rigid labor laws can interact with the effect of tariff cuts to reduce women's employment. In *India*, with import competition from general tariff cuts, firms increased the number of shifts, which reduced women's employment in the 1990s because women, but not men, were constrained by limits on the maximum number of hours of work (Gupta 2021).

Young workers. Estimates of the impact on employment are significantly more likely to be positive for workers under 30 than for older cohorts (figure 3.6). For example, in response to tariff reductions in *China* during the 2000s, employment increased more for women aged 20–29 than for older women, because employment losses in the tradable sector were concentrated among older women while both cohorts benefited equally from employment gains in the non-tradable sector (Dai, Huang, and Zhang 2021).

Manufacturing firms. Estimates of the impact of tariff cuts on wages (but not employment) are significantly more likely to be positive for manufacturing firms than among non-manufacturing firms—with both general tariff cuts as well as tariff cuts on inputs used in domestic production (figure 3.6). Overall, around half of the estimates of trade liberalization on manufacturing wages in the sample yielded positive and significant results, compared with only one-fifth of the estimates for non-manufacturing firms or for the industry average. Rising wages in manufacturing firms appear to have reflected a shift in workforce composition, rather than higher wages for the same workforce, because the impact on conditional wages (controlling for worker characteristics) in manufacturing firms was insignificant.

Small firms. The literature is split on the differential impact of trade reforms on small firms compared with larger firms (figure 3.6). In *India* during the 1990s, however, small and less productive firms exited after tariff cuts (Nataraj 2011).

Importing firms. Estimates of the impact of input tariff cuts on wages are significantly more likely to be positive for firms that use imports in their production (figure 3.6). Tariff cuts on inputs into production facilitate the import of cheaper and better-quality inputs, allowing firms to raise wages. In *Indonesia,* for example, a reduction in input tariffs during the 1990s raised wages at firms that used imported inputs more than at firms that only used domestically produced inputs (Amiti and Davis 2012).

Type of trade policy reforms. More than half of the 827 estimates focus on general tariff reductions; about 10 percent examine input tariff cuts by linking tariffs to the inputs of each industry using input-output tables. Another 10 percent of the estimates refer to FTAs, such as the U.S.-Vietnam Bilateral Trade Agreement (BTA) and the North American Free Trade Agreement (NAFTA). The number of studies using policy instruments other than tariffs is not large enough to obtain meaningful estimates for the differential impact by worker or firm characteristics.

- ***General tariffs versus tariffs on inputs for production.*** General reductions in tariffs raise import competition; tariff reductions targeted at production inputs help reduce input costs and increase input quality for domestic firms' production (Goldberg et al. 2010; Halpern, Koren, and Szeidl 2015). For example, reductions in local tariffs on production inputs in *Indonesia* during 1993–2002 were associated with higher employment and wages, but reductions in general tariffs were not (Kis-Katos and Sparrow 2015). In *Ecuador*, reductions in tariffs on inputs—but not general tariff cuts—during 1997–2007 were associated with higher skill intensity and skill premiums at the firm level, consistent with complementarity between imported inputs and skilled labor (Bas and Paunov 2021).

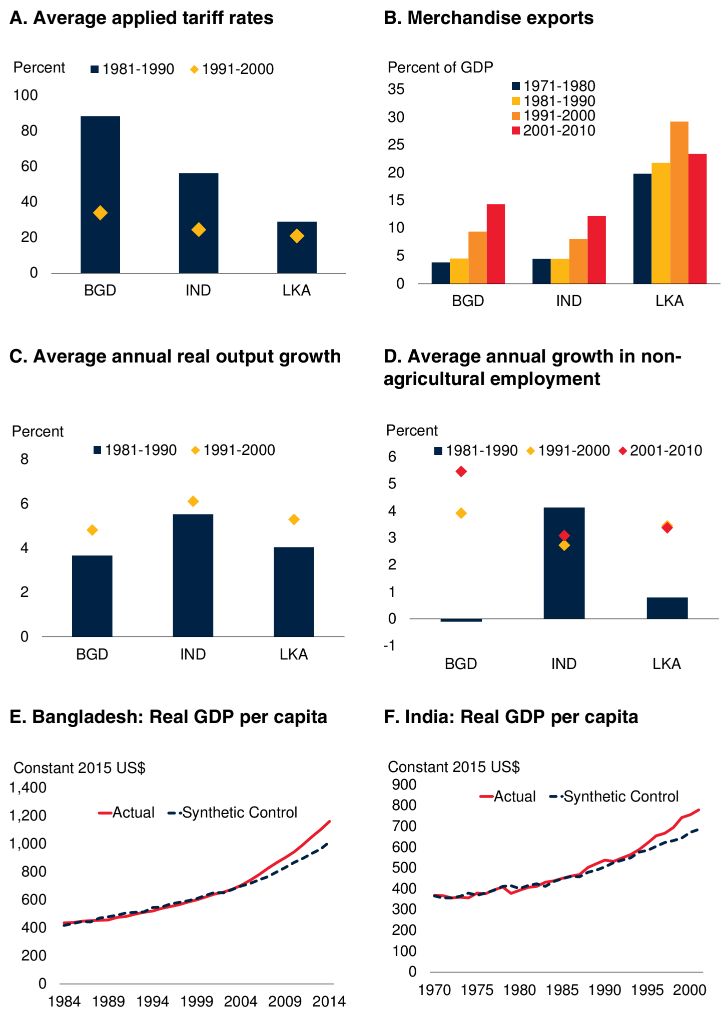
- ***Trade agreements.*** Several studies have documented the benefits of trade agreements in EMDEs. For example, export tariff reductions through the U.S.-Vietnam BTA were associated with an increase in industry-level employment in *Viet Nam* during the 2000s and 2010s, as foreign firms expanded (McCaig, Pavcnik, and Wong 2025). Trade agreements also generate distributional impacts, favoring women and the young: U.S. tariff reductions in the context of the NAFTA raised female shares of employment and the wage bill among blue-collar workers in *Mexico* during 1991–2000, because technology upgrading among exporting firms complemented female blue-collar workers (Juhn, Ujhelyi, and Villegas-Sanchez 2014). The U.S.–Vietnam BTA was associated with higher employment among workers aged 19–29 and lower employment among those aged 30–54 in *Viet Nam* (McCaig, Nguyen, and Kaestner 2022).

South Asia's past experiences with trade reform

From the 1980s until the early 2000s, several South Asian countries opened their economies significantly to international trade, including by cutting import tariffs (figure 3.7). Very few studies examine the employment impact of these reforms. The ones that do find that trade liberalization was associated with significantly faster employment growth in Bangladesh and Sri Lanka—consistent with findings from the event study—but had limited effects on aggregate employment in India.

FIGURE 3.7 South Asia's past experiences with trade reform

Bangladesh in the 1980s, India in the 1990s, and Sri Lanka during the 1970s–90s undertook reforms that significantly lowered tariff and non-tariff barriers. These reforms coincided with periods of higher exports and faster real output growth, but employment outcomes differed across countries: non-agricultural employment grew faster in Bangladesh and Sri Lanka following the reforms, but not in India.



Sources: Groningen Growth and Development Centre (GGDC) 10-sector Database; International Labour Organization; Penn World Table (database); World Development Indicators (database); World Bank.

Note: BGD = Bangladesh; IND = India; LKA = Sri Lanka.

A. Average weighted applied tariff rate of all products.

D. Non-agricultural employment is constructed by splicing aggregate employment from the Penn World Table with the sectoral shares from the ILO modeled employment series, except for 1981–90 average for India, which comes from the GGDC-10 dataset.

E. Chart shows the effect of tariff reduction on real GDP per capita using synthetic control method, which constructs a weighted combination of other countries to approximate the counterfactual of no reform. Methodology follows Abadie, Diamond and Hainmueller (2010) and Amaya (2020). Consistent with Amaya (2020), the initial set of potential synthetic control countries include Benin, Eswatini, Ghana, Fiji, Lesotho, Morocco, Mali, Malawi, Bangladesh, Guyana, Nepal, Pakistan, and Sri Lanka, and predictor variables include the investment rate (as a share of GDP), fertility rate, savings rate (as a share of GDP), and average years of schooling for individuals aged twenty-five and older, goods imports and exports and lagged GDP. The event date for Bangladesh is 2005 due to its tariff reduction from around 15 to 20 percent, which is closer to EMDE level. "Synthetic Bangladesh" includes Nepal, India and Morocco. The deviation from the synthetic control is statistically significant at the 88 percent confidence level.

F. Charts show the effect of trade reform in India on real GDP per capita, extracted from Amaya (2020). The event date is 1991. "Synthetic India" includes Nepal, Pakistan, Eswatini and Bangladesh.

Bangladesh's garment-led reform (1980s–2000s). Export promotion schemes and significant reductions in import tariffs led to a surge in Bangladesh's exports during the 1980s–2000s, especially in the ready-made garments sector. The sector also benefited from multilateral trade agreements (figure 3.7). These include the WTO Agreement on Textiles and Clothing (ATC) in 2005, which dismantled trade quotas in the ready-made garment sector, the U.S. 2009 Tariff Relief Assistance in the global clothing market, and the Generalized System of Preferences (GSP) with the European Union, which allowed Bangladesh to export ready-made garments without any tariff (Raihan 2023; Swazan and Das 2022). A synthetic control estimation suggests that, by 2014, Bangladesh's real GDP was 14 percent higher than in a synthetic control group of countries without such reforms. The expansion of the labor-intensive ready-made garment sector supported growth in non-agricultural employment during the 1990s–2000s. However, employment growth slowed during the 2010s as the sector increasingly switched to labor-saving machinery, amid technological advancements and concerns about labor safety (Galal et al. 2025; Raihan and Bidisha 2018).

Landmark reform in India (1991). As part of an IMF-supported program of reforms after the 1991 currency crisis, *India* implemented major trade liberalizing reforms. Between 1981–90 and 1991–2000, average tariffs were cut by more than 30 percentage points (figure 3.7). The reduction was larger in industries with initially higher tariffs—such as agricultural products and textiles—and, as a result, the standard deviation of tariffs fell by 30 percent during the period (Topalova and Khandelwal 2011). Non-tariff barriers were rolled back to cover 30 percent of consumer and intermediate goods, down from 90 percent before the reform. Licensing requirements were abolished and foreign investment limits lifted. The reforms contributed to higher exports and output growth (Amaya 2020; Wacziarg and Wallack 2004). Nonetheless, the reforms induced positive shifts in parts of the Indian labor market. For example, overall tariff reductions were associated with higher employment among literate adult men (Edmonds, Pavcnik, and Topalova 2010) but lower wages (Ahsan and Mitra 2014; Topalova 2010). Tariff reductions on inputs were associated with higher wages for managerial or skilled labor (Chakraborty and Raveh 2018; Leblebicioğlu and Weinberger 2021).

Sri Lanka's continued reforms (1977–1990s). Until 1977, Sri Lanka's economy was protected by high and rising import tariffs and quantitative restrictions on most imports. The reform in 1977 introduced a six-band tariff structure with rates ranging from 0 to 500 percent, with lower rates on essentials, raw and intermediate goods, and higher rates on luxury goods. A rationalization of tariffs in 1985 reduced the maximum nominal rate from 100 to 60 percent, which was further lowered in 1993 and 1995 (figure 3.7; WTO 1995). Along with lower tariff rates and quantitative import restrictions, successive reforms also realigned the exchange rate, actively promoted exports through Export Processing Zones (EPZs), and offered incentives for FDI. Merchandise exports expanded by 9 percentage points of GDP between 1971–80 and 1991–2000. The policy shift led to an increase in overall manufacturing employment, particularly in the garment industry and among women (Abeywardene et al. 1994; Sahn 1987). During 1981–2001, the overall unemployment rate fell from 17.9 to 7.6 percent, and the unemployment rate for women fell from 32 to 11.3 percent (Attanapola 2005). Between 1981–90 and 1991–2010, average annual non-agricultural employment growth accelerated from 0.8 percent to more than 3 percent. Sri Lanka's inward turn over the following two decades, however, was accompanied by a decline in exports (relative to GDP) as tariffs increased again (World Bank 2024d).

South Asia: Worker characteristics and tariffs

The international experience suggests that major tariff reductions raised aggregate employment and benefited younger and higher-skilled workers and those in manufacturing more than others. This pattern could be amplified in South Asia, because of the region's current employment structure. Currently, 39 percent of South Asia's workers are in sectors that are sheltered by tariffs above 30 percent, almost all of *them in agriculture. These workers tend to be less skilled, lower paid, and older than the average worker. A different 32 percent of South Asia's workers are in sectors (mostly services) that are protected by tariffs of no more than 5 percent but face tariffs on intermediate inputs more than twice the EMDE average excluding South Asia. These jobs in South Asia's least-protected sectors pay 16 percent higher wages than the average job, and firms in these least-protected sectors employ significantly younger and more skilled workers.*

Tariffs

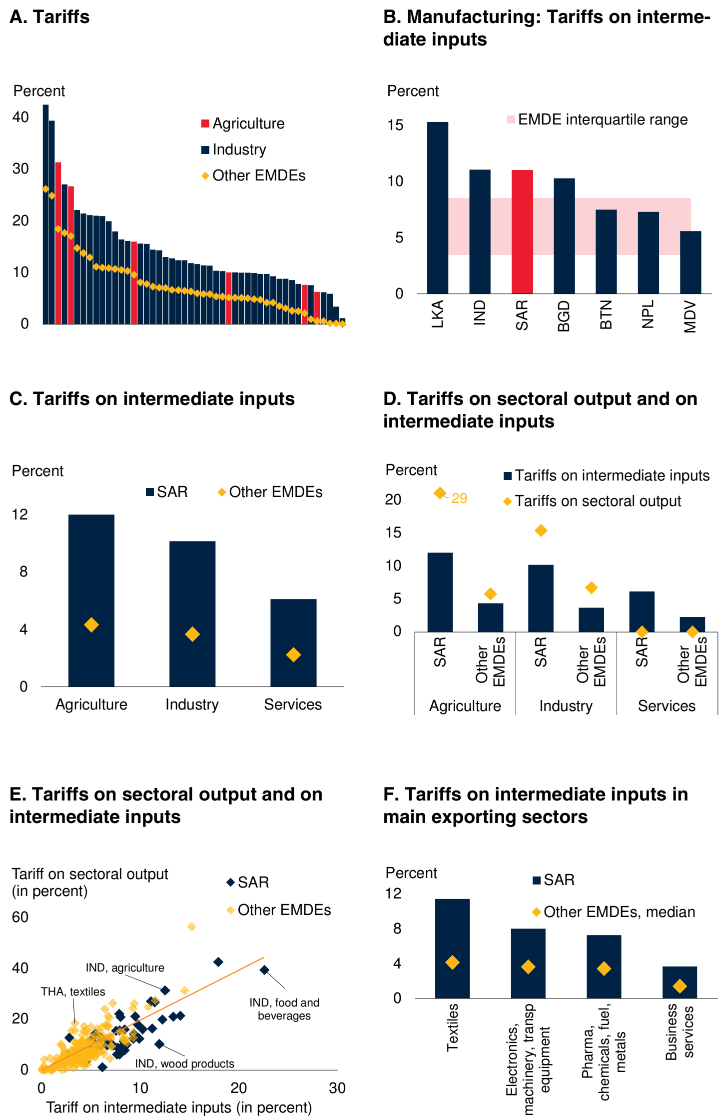
Average tariffs. At 16 percent in 2024, average tariffs in South Asia were more than twice the global average of 6 percent (figure 3.8). Across South Asian countries, average tariffs ranged from 9 to 20 percent in 2024. For agriculture, they amounted to 29 percent—five times the EMDE median. For almost every industry in every South Asian country, tariffs were higher than in the median EMDE.

Impact on intermediate input cost. South Asia's high tariffs pass through into higher costs of intermediate inputs for its firms—directly by raising import costs and indirectly by allowing domestic producers to raise prices without triggering a switch to imported inputs. For a sample of 29 EMDEs, recent input–output tables are available that allow the calculation of tariffs on intermediate inputs. Compared with the median EMDE outside South Asia, tariffs on intermediate inputs are almost three times higher for South Asia's agriculture (12 percent), industry (10 percent), and services (6 percent; figure 3.8). For services, for example, such intermediate inputs could be food and beverages (with tariff of 35 percent in South Asia and 11 percent in other EMDEs) for restaurants and hotels, or electronic equipment (with tariffs of 11 percent in South Asia and 5 percent in other EMDEs) for business services.

Unintended consequences for import protection and export competitiveness. The sectors with the highest tariffs on final goods also tend to have the highest tariffs on intermediate inputs, which can

FIGURE 3.8 Tariffs

In all South Asian countries and across most sectors, tariffs tend to be higher than in other EMDEs. Because South Asia's high tariffs pass through into input costs, tariffs on intermediate inputs are almost three times those in other EMDEs.



Sources: ADB Multiregional Input-Output Tables (database); WTO Analytical Database; World Bank.

Note: BGD = Bangladesh; BTN = Bhutan; EMDEs = emerging market and developing economies; IND = India; LKA = Sri Lanka; MDV = Maldives; NPL = Nepal; SAR = South Asia; THA = Thailand. Tariff data are the latest available (see annex 3.1), while trade and input shares use 2023 data. For Sri Lanka, data include para-tariffs.

A. Figure reports simple averages of the ad valorem most-favored-nation duties applied, mapped into the 8 goods-producing sectors described in annex table A3.1.10.

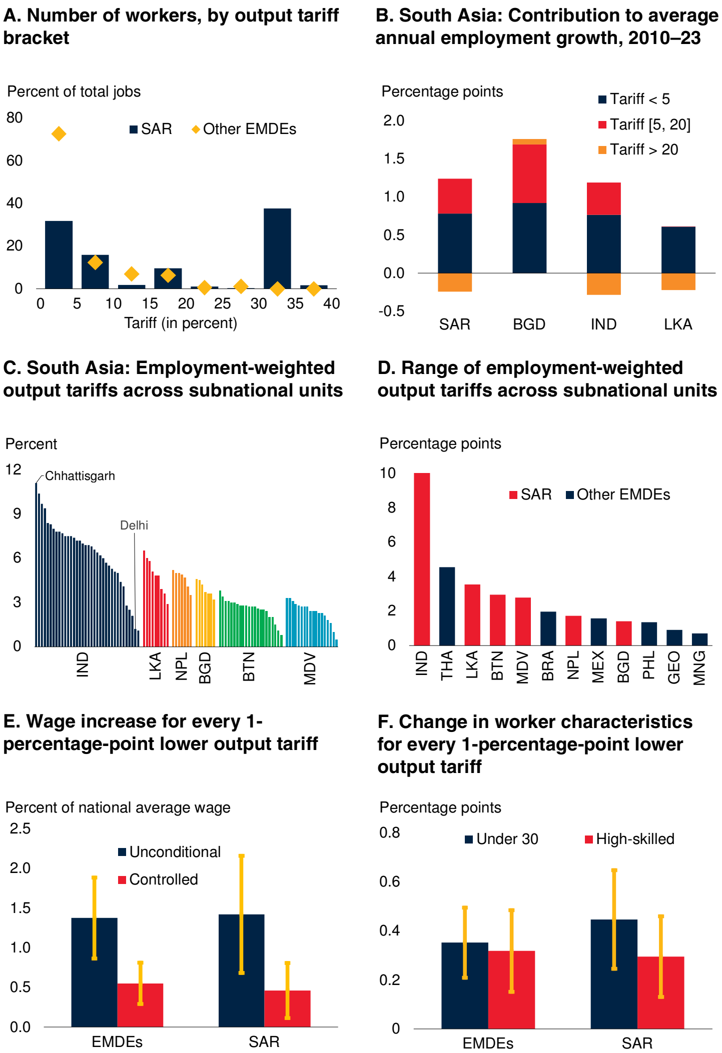
B.-F. Tariffs on intermediate inputs are calculated as the weighted average across inputs (split from HS6 product codes using the Classification by Broad Economic Categories) used in the respective sectors.

B. Red shaded area represents the interquartile range across 29 other EMDEs.

F. Diamonds represent the median across 29 other EMDEs.

FIGURE 3.9 Workers in jobs protected by tariffs on sectoral outputs

In South Asia, more than one-third of workers is employed in the least tariff-protected sectors, whereas in other EMDEs, more than three-quarters of workers work in the least-protected sectors. The least tariff-protected sectors have been the main source of employment growth since the early 2010s and tend to employ higher-wage, more skilled, and younger workers. The most tariff-protected workers are located in India's interior.



Sources: Global Labor Database; WTO Analytical Database; World Bank.

Note: BGD = Bangladesh; BRA = Brazil; BTN = Bhutan; EMDEs = emerging market and developing economies; IND = India; GEO = Georgia; LKA = Sri Lanka; MDV = Maldives; MEX = Mexico; MNG = Mongolia; NPL = Nepal; PHL = Philippines; SAR = South Asia; THA = Thailand.

A.C.E.F. South Asia comprises latest data for all 6 countries in the region, and "other EMDEs" comprise the 6 comparator countries listed in annex table A3.1.9.

B. For South Asia, sample is restricted to Bangladesh, India, and Sri Lanka due to employment data availability at the two-digit level between 2010–14 to compute growth rates for at least a decade.

C. Figure plots the employment-weighted average tariff.

D. Figure plots the difference between the highest and lowest employment-weighted average tariff across regions within countries.

E. Bars show coefficients of linear regressions with wages relative to the respective national mean as dependent variable and output tariffs as main explanatory variable. "Controlled" specification includes indicators for male, urban, less than primary education, secondary education, post-secondary education, years of experience, experience squared, and country fixed effects. Experience is defined as age minus years of education minus 6. For comparability, the sample is restricted to monthly wage earners in goods-producing sectors. Standard errors are clustered at the country-sector level. Whiskers indicate 90-percent confidence intervals. Regression results in annex table A3.1.11.

F. Bars show marginal effects of probit regressions with the respective worker characteristic as binary dependent variable. The explanatory variable is the average output tariff. Standard errors are clustered at the country-sector level. Whiskers indicate 90-percent confidence intervals. Regression results are in annex table A3.1.12.

significantly erode a sector's overall protection granted by import tariffs (figure 3.8). For example, tariffs on agricultural goods average 29 percent in South Asia, but tariffs on intermediate inputs used in agriculture (such as pesticides or seeds) average 12 percent. And high tariffs on intermediate inputs weigh on exports. Export-intensive sectors in South Asia, with export shares in sectoral gross output in the top quartile—such as business services, textiles, and other manufacturing—had tariffs on intermediate inputs that were double those of export-intensive sectors in other EMDEs.

"Effective rate of protection". The difference between average tariffs on the output produced by a sector and the average tariff on inputs (weighted by the total expenditure shares for intermediate inputs used in the sector) can be considered a proxy for an "effective rate of protection."

- ***For the services sector***, whose inputs are subject to tariffs but whose outputs are not protected by tariffs, the effective rate of protection is negative.
- ***For manufacturing***, where opportunities to substitute intermediate inputs with capital and labor are limited, the effective rate of protection in South Asian countries is only one-third to two-thirds of the average tariff on manufactured goods. While the average tariff rate on manufactured goods was 8 percentage points higher in South Asia than in other EMDEs, the "effective" tariff rate was only 4 percentage points higher.
- ***For the agricultural sector***, high tariffs on intermediate inputs have prevented substitution away from labor (and capital) toward the use of more intermediate inputs. As a result, the "effective" rate of protection in agriculture is not much less than the actual tariffs on agricultural goods.

Jobs protected by tariffs

Number of trade-protected workers. Labor force survey data can be used to match workers to sectors, and tariff schedules can be matched to sectoral outputs. More South Asian workers (39 percent) are employed in sectors (mostly agriculture) with tariffs in excess of 30 percent than workers are employed in sectors (mostly services) with tariffs of no more than 5 percent (32 percent). This is in contrast to other EMDEs, where almost three-quarters of workers are in sectors minimally protected by tariffs (figure 3.9). Protected sectors have not been the source of job creation, but unprotected sectors have been: since 2010, more than three-quarters of employment growth has been generated in sectors with average tariffs below 5 percent.

Worker characteristics for least and most trade-protected workers. Workers in South Asia's least-protected sectors tend to be higher skilled, higher paid, and younger than those in the most protected sectors (figure 3.9).

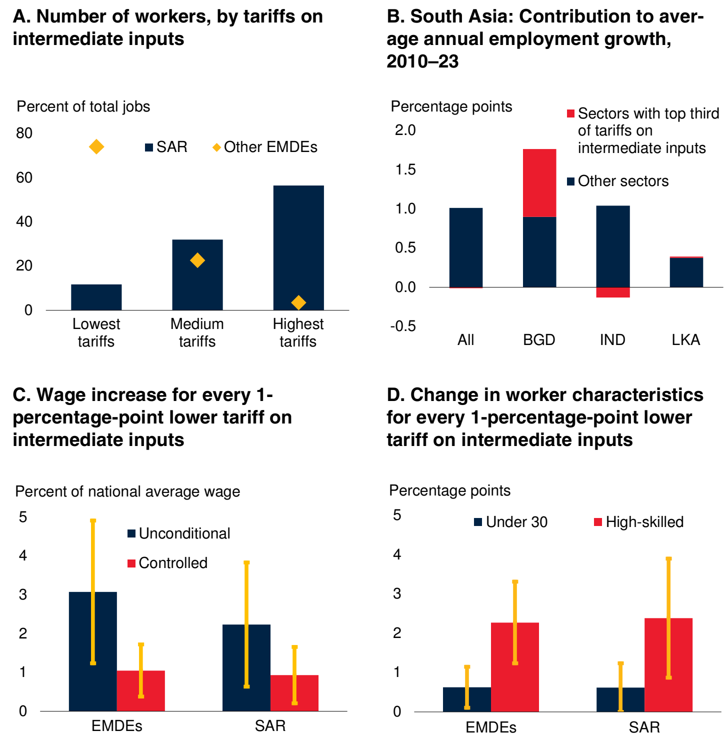
- More than one-quarter of the workers in the least tariff-protected sectors are high-skilled (compared with 3 percent in more protected sectors).
- The wages of 30 percent of the workers in the least tariff-protected sectors rank in the top wage quartile (compared with 9 percent in more protected sectors).
- Because of different sectoral compositions of their subnational economies, the protection offered by tariffs differs widely across subnational labor markets. In almost all South Asian countries, tariff protection varies across subnational regions much more widely than in other EMDEs in the sample.

Jobs encumbered by tariffs

Jobs encumbered by high tariffs. Workers can also be characterized by their exposure to tariffs on intermediate inputs by using input–output matrices to match sectors to their intermediate inputs and applying tariff schedules to these intermediate inputs. Only one-tenth of South Asia's workers are in the one-third of sectors with the lowest tariffs on intermediate inputs (4.5 percent or less), and they are mostly in services. Almost 60 percent of workers are employed in the one-third of sectors with the highest tariffs on intermediate inputs (7.7 percent or more), and they are mostly in agriculture, as well as in food manufacturing, textiles, and electronics. By contrast, in other EMDEs, about three-quarters of workers are in sectors with tariffs on intermediate inputs below 4.5 percent (figure 3.10).

FIGURE 3.10 Workers exposed to tariffs on intermediate inputs

In South Asia, only one-tenth of workers are employed in the sectors with the lowest tariffs on intermediate inputs, compared with more than three-quarters of workers in other EMDEs. The sectors with lower tariffs on inputs—which have been the main source of employment growth since the early 2010s—pay significantly higher wages and employ more skilled and younger workers.



Sources: ADB Multiregional Input-Output Tables (database); Global Labor Database; WTO Analytical Database; World Bank.

Note: BGD = Bangladesh; EMDEs = emerging market and developing economies; IND = India; LKA = Sri Lanka; SAR = South Asia. South Asia comprises the latest data for all 6 countries in the region, and "other EMDEs" comprise the 6 comparator countries listed in annex table A3.1.9.

A. "Lowest cost" refers to the third of South Asian country-sector pairs with the lowest intermediate input tariffs—that is, below 4.5 percent. "Highest cost" refers to the third of South Asian country-sector pairs with the highest intermediate input tariffs—above 7.7 percent. "Medium cost" refer to all others.

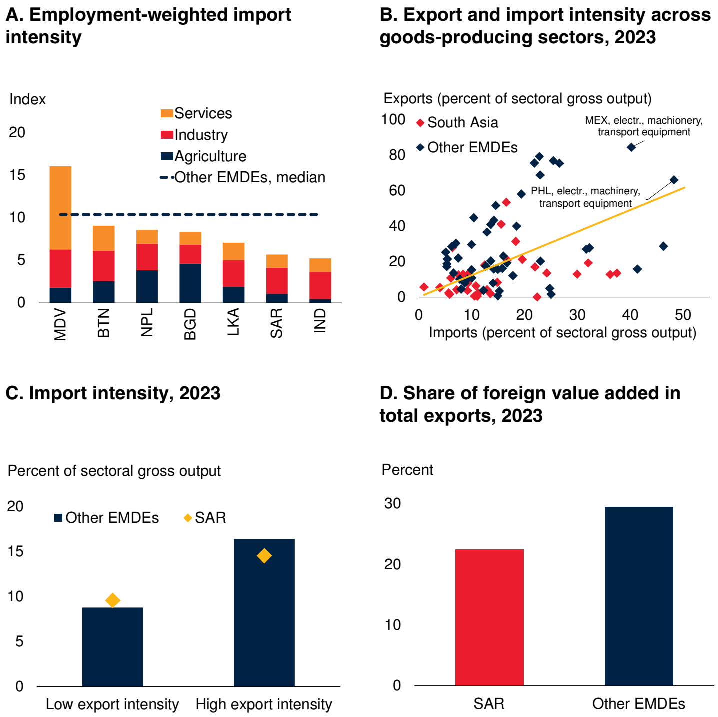
B. South Asia sample is restricted to Bangladesh, India, and Sri Lanka because of lack of data availability for other countries of employment data on the two-digit level between 2010 and 2014 to compute growth rates for at least a decade.

C. Bars show the coefficients of linear regressions with wages relative to the respective national mean as the dependent variable and intermediate input tariff rates as the main explanatory variable. "Controlled" specification includes indicators for male, urban, less than primary education, secondary education, post-secondary education, years of experience, experience squared, and country fixed effects. Experience is defined as age minus years of education minus 6. For comparability, the sample is restricted to monthly wage earners in goods-producing sectors. Standard errors are clustered at the country-sector level. Whiskers indicate 90-percent confidence intervals. Regression results are in annex table A3.1.11.

D. Bars show the marginal effects of probit regressions with the respective worker characteristic as the binary dependent variable. The explanatory variable is intermediate input tariff rates. Standard errors are clustered at the country-sector level. Whiskers indicate 90-percent confidence intervals. Regression results are in annex table A3.1.12.

FIGURE 3.11 Import-dependent and export-intensive industries

In South Asia, the share of workers employed in import-dependent activities is lower than in other EMDEs. South Asia's most export-intensive goods-producing sectors are also its most import-intensive ones, but South Asia's exports incorporate less foreign value added than exports in other EMDEs.



Sources: ADB Multiregional Input-Output Tables (database); Global Labor Database; World Bank.

Note: BGD = Bangladesh; BTN = Bhutan; EMDEs = emerging market and developing economies; IND = India; LKA = Sri Lanka; MDV = Maldives; MEX = Mexico; NPL = Nepal; PHL = Philippines; SAR = South Asia.

A. Employment-weighted import intensity is the product of sectoral employment and the corresponding import-to-gross output ratio as share of total employment.

C. Import intensity (on the vertical axis) is measured as average import-to-gross output ratio. Low export intensity refers to sectors with export-to-gross output ratios below the median across sectors and SAR countries or other EMDEs. High export intensity refers to all other sectors.

Jobs in sectors with high tariffs on intermediate inputs. High tariffs on intermediate inputs may have contributed to slow employment growth. The two-thirds of sectors with the lowest tariffs on intermediate inputs accounted for all employment growth during 2010–23, whereas employment in the one-third of sectors with the highest tariffs on intermediate inputs stagnated (figure 3.10). In South Asia, one-third of sectors with the highest tariffs includes agriculture in India, where employment contracted over this period, and in Bangladesh, where employment recently expanded sharply as economic stress reduced job opportunities in the non-agricultural sector.

Worker characteristics in sectors with the highest and lowest tariffs on intermediate inputs. On average, jobs in sectors with the lowest tariffs on intermediate inputs pay 10 percent higher wages than the average job. South Asian workers in sectors with the lowest tariffs on intermediate inputs tend to be significantly higher skilled, higher paid, and younger than those in sectors with the highest intermediate input tariffs (figure 3.10).

- ***Wages.*** For every 1-percentage-point reduction in tariffs on intermediate inputs, worker wages are about 2 percent higher relative to the national average wage. About half of this gap reflects worker characteristics. Hence, even after controlling for worker characteristics in a Mincer regression, the wage premium for every 1-percentage-point lower tariffs on intermediate inputs remains about 1 percentage point.

- ***Skills.*** High-skilled workers are more frequently in sectors with lower tariffs on intermediate inputs. For every 1-percentage-point reduction in tariffs on intermediate inputs, workers are 2 percentage points more likely to be highly skilled.

- ***Age.*** For every 1-percentage-point reduction in tariffs on intermediate input, workers are almost 1 percentage point more likely to be under the age of 30.

- ***Formality.*** In South Asia's sectors with the lowest tariffs on intermediate inputs, 23 percent of workers are employed under formal contracts—5 percentage points more than among South Asian workers in sectors with the highest tariffs on intermediate inputs.

Workers in trade-linked jobs

Number of import-dependent jobs. Tariff protection is often intended to reduce import competition and encourage the use of domestic alternatives. Indeed, South Asia's output in all economic sectors is less import-intensive than that of other EMDEs. As a result, the manufacturing sector is smaller and less productive than elsewhere: it accounts for 12 percent of South Asia's employment (compared with 15 percent in other EMDEs), 13 percent of its value added (compared with 20 percent in other EMDEs), and 36 percent of its exports (compared with 69 percent in other EMDEs). This is also reflected in labor market exposure to trade. The average job in South Asia is half as import-intensive as that in other EMDEs (figure 3.11).

Overlap between export- and import-intensive activities. South Asia's high import tariffs hurt exporting sectors most because—as in other EMDEs—the most export-intensive sectors are also the most import-dependent (figure 3.11). If South Asia were more integrated into global value chains, this link between exports and imports might be more pronounced. For now, South Asia's exports rely more heavily on domestic inputs and have a lower share of foreign value added than those of other EMDEs.

Number of export-linked jobs. Only about 13 percent of South Asia's workforce is directly or indirectly employed in export-linked jobs—less than half the share in other EMDEs (figure 3.12). In all South Asian countries except Nepal, jobs in light manufacturing and business services are about as likely to be export-linked as in other EMDEs. However, employment in agriculture and in the (small) heavy manufacturing sector is much less export-linked in South Asia than in other EMDEs.

Worker characteristics in trade-linked jobs. South Asia's workers in trade-linked jobs, whether export- or import-linked, tend to be higher paid, more skilled, and younger (figure 3.13).

- ***Wages*.** The share of workers earning wages in the national top quartile is more than twice as large in jobs with above-median export or import intensity.

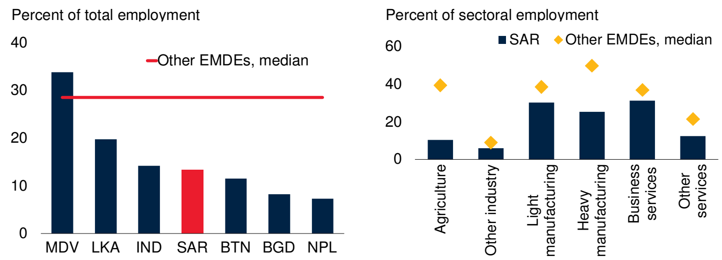
- ***Skills*.** The most distinctive characteristic is skills: the share of highly skilled workers is about seven times larger in jobs with above-median export or import intensity, while fewer than 1 percent of workers are in jobs with below-median import intensity.

FIGURE 3.12 South Asia: Export-linked employment

The share of South Asia's workforce employed in export-linked jobs is considerably smaller than in other EMDEs. The difference is largest in agriculture and heavy manufacturing, whose output does not feed prominently into South Asia's main exports.

A. Export-linked employment, aggregate economy

B. Export-linked employment: SAR



Sources: ADB Multiregional Input-Output Tables (database); Global Labor Database; World Bank.

Note: BGD = Bangladesh; BTN = Bhutan; EMDEs = emerging market and developing economies; IND = India; LKA = Sri Lanka; MDV = Maldives; NPL = Nepal; SAR = South Asia. Broad sectors are disaggregated following the International Standard Industrial Classification of All Economic Activities, revision 4, with "Agriculture" comprising section A; "Other industry" comprising sections B, D, and E (that is, mining; electricity, gas, and water supply; and construction); "Light manufacturing" comprising divisions 10 to 18 and 31 to 33 (for example, manufacture of food products, textiles, or furniture); "Heavy manufacturing" comprising divisions 19 to 30 (for example, manufacture of refined petroleum, electronics, or transport equipment); "Business services" comprising divisions 58 to 83 (for example, technical and administrative support, including IT services); and "Other services" comprising all other divisions (for example, wholesale and retail, accommodation and restaurants, and government services). "Export-linked employment" is computed in an input-output analysis following the methodology of Kruse et al. (2024) and Wolff (2003), linking trade, intersectoral linkages, and employment data.

B. SAR refers to the employment-weighted average across all 6 South Asian countries.

- ***Age*.** The share of workers under 30 years of age is 15 percentage points higher for jobs with above-median export or import intensity.

Policy implications

South Asia's high tariffs have protected the least dynamic parts of the labor market—with the most protected jobs outright reducing aggregate employment growth—and workers who are lower paid, less skilled, and older. High tariffs, by international standards, have especially handicapped manufacturing. South Asia's manufacturing sector faces average tariffs on its intermediate inputs that are more than twice those in other EMDEs. The one-third of jobs in sectors with the lowest tariffs have accounted for three-quarters of employment growth during 2013–23 and workers in these jobs have been significantly higher paid, higher skilled and younger.

BOX 3.1 Sequencing Trade and Labor Reforms

Ambitious trade reforms in South Asia could deliver substantial gains in exports and incomes, in part as a result of workers reallocating toward more productive firms, sectors, and locations. High switching costs for workers could diminish some of the potential gains. Even modest improvements in labor mobility could substantially increase the income gains from trade reform.

Introduction

International trade is widely recognized as the engine of several successful development stories in Asian emerging markets (Goldberg and Reed 2023; World Bank 2020). By lowering the cost of imported inputs and expanding access to export markets, trade integration can enhance productivity, stimulate investment, and support job creation (Maliszewska and Winkler 2024). However, realizing these gains hinges on the ability of workers and firms to respond to shifting patterns of returns to specialization. In practice, high labor market frictions—such as skill mismatches, informal employment, and limited mobility across firms, sectors, and locations—can slow reallocation, dampen wage growth, and limit the benefits of trade reform (Artuç, Chaudhuri, and McLaren 2010; Dix-Carneiro 2014).

These constraints are particularly relevant in South Asia, where average tariffs remain among the highest in the developing world and job creation falls well short of working-age population increases (World Bank 2024a, 2024b). When barriers to trade fall but workers cannot easily move to expanding sectors, potential income gains may not be fully realized. Conversely, even modest reductions in mobility frictions—such as job search costs, retraining barriers, or regulatory constraints—can substantially amplify the effect of trade reform (Coşar, Guner, and Tybout 2016; Kambourov 2009). The right combination and sequencing of trade and other reforms could therefore determine their impact in South Asia.

Questions. This box addresses the following questions.

- How do import costs in South Asia compare with those in other EMDEs?
- What are the implications of an ambitious reduction in import costs to South Asia?
- To what extent can the gains from trade liberalization be amplified if combined with reforms that lower labor mobility costs?

Contribution. This box adds to the existing literature in two ways. *First*, it provides a novel set of up-to-date, calibrated bilateral trade costs across 73 economies and 18 sectors, consistent with observed trade patterns, and comparable across goods and services sectors. Trade costs are calibrated following the approach of Lewis et al. (2022), Sposi (2019), and Sposi, Yi, and Zhang (2024), using recent data for a large set of countries. It proposes a decomposition of total trade costs into three components—tariffs, non-tariff policy barriers, and non-policy barriers—using observable data. *Second*, this box is the first to explicitly model the general equilibrium effects of sequencing trade and labor market reforms for a large set of EMDEs. Similar previous modeling efforts, such as Caliendo, Dvorkin, and Parro (2019), focused on the impact of China's trade expansion on the United States and examined trade reform in the presence of labor market frictions, but did not consider the interaction between trade reform and the removal of frictions that impede labor market adjustment.

Methodology. Total bilateral trade costs across 18 sectors (including services) and 73 economies (including a rest-of-world aggregate) in 2023 are calibrated following Lewis et al. (2022) (annex 3.1). Subsequently, total trade costs are decomposed into three components: (i) trade costs that are outside the immediate scope of trade policy (for example, exogenous factors such as geography, language differences, historical ties); (ii) tariffs; and (iii) non-tariff barriers within the scope of trade policy (for example, regulations, custom procedures, infrastructure). The sum of both policy components,

Note: This box was prepared by Erhan Artuç and Hagen Kruse.

BOX 3.1 Sequencing Trade and Labor Reforms (*continued*)

dubbed "trade policy cost", is defined as the total trade cost difference relative to an EMDE benchmark that controls for exogenous factors. The baseline trade reform scenario represents South Asian countries closing half the gap between their own trade policy costs and the EMDE benchmark. General equilibrium effects are estimated using a dynamic quantitative multi-sector open-economy model following Caliendo, Dvorkin, and Parro (2019). Labor market frictions represent mobility costs for worker reallocations across sectors and are modeled as transitional income losses when workers switch to new jobs. They are estimated following Artuç, Lederman, and Porto (2015). The baseline labor market reform scenario represents a 5-percent reduction in mobility costs. The model is calibrated in changes relative to data in 2023.

Main findings. This box presents several new findings.

First, cutting South Asia's import costs in half relative to other EMDEs would generate double-digit growth in exports and imports, and raise real per capita incomes by 1.2 percent above the baseline.

Second, the real income gains from trade liberalization could be significantly larger if combined with reforms that lower workers' moving costs to new and better jobs by just 5 percent.

Gains from reducing trade and labor mobility costs in South Asia

Potential reforms. Import costs to South Asia are 14 percent above those in the median EMDE and, for imports of light manufacturing and agricultural goods, more than 20 percent higher. For all sectors other than South Asian agriculture, non-tariff barriers are a larger source of trade costs than tariffs (figure B3.1.1).

Reform scenarios. The trade reform scenario assumes that, in each sector and each South Asian country, half of the gap in trade policy costs from the average EMDE is closed; for South Asian countries, this would reduce total import costs by 6–15 percent. Exports also use imported inputs (figure 3.11). Hence, one-third of the import cost reduction passes through into lower export costs. This makes room for wages in the export sector to rise and attracts workers into the expanding export sector. Yet, workers have a strong incentive to switch jobs only if their wage gain fully recovers or exceeds the expected cost (or transitional income loss) of reallocating across firms, sectors, or locations. The labor market reform scenario assumes a 5-percent reduction in South Asia's worker mobility costs; this would lower the average income loss upon job switching by 14 to 24 percent.

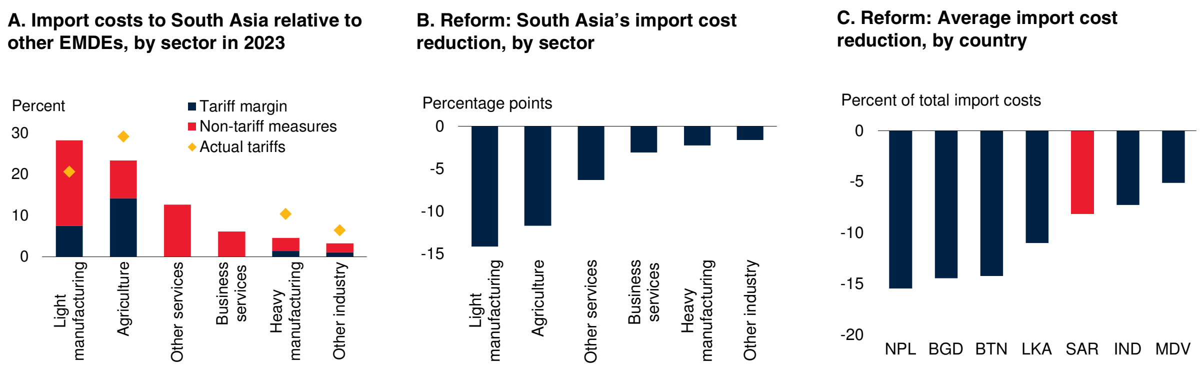
Trade reform. Even with prevailing levels of labor market frictions, cutting South Asia's import barriers by half relative to other EMDEs would markedly increase trade in South Asian countries. On average, exports would rise by 22 percent and imports by 19 percent (figure B3.1.2). Lower import barriers would broaden access to cheaper intermediate inputs which, indirectly, would also lower export costs and improve cost competitiveness. Lower import barriers in one South Asian country would generate spillovers to others, by expanding export markets. Real per-capita income would rise in all South Asian countries—on average by 1.2 percent. For comparison, these per capita income gains are on par with similarly derived estimates for the effect of the North American Free Trade Agreement (NAFTA) on Mexico. With NAFTA, Mexico cut average tariffs toward the United States and Canada by 12.5 percentage points, while U.S. and Canadian tariffs toward Mexican exports fell by 2.7 and 4.2 percentage points, respectively (Caliendo and Parro 2015).

Labor market reform before trade reform. A modest reform, to lower worker mobility costs by 5 percent, generates larger income gains than the trade reform modeled here because it would raise aggregate productivity across all sectors by allowing a more efficient allocation of workers. It would therefore not materially increase gross trade flows. If such a reform were to *coincide* with, or *precede*, trade reform, the trade impact would be broadly similar to the trade reform scenario. But the per capita income gains

BOX 3.1 Sequencing Trade and Labor Reforms (*continued*)

FIGURE B3.1.1 South Asia's import barriers and reform scenario

Import costs to South Asia relative to other EMDEs are highest in light manufacturing and agriculture, with non-tariff measures exceeding tariff costs in all sectors except agriculture. The reform scenario of closing half of the import cost gap with other EMDEs could reduce total import costs by 6 to 15 percent across South Asian countries.



Sources: ADB Multiregional Input-Output Tables (database). WTO Analytical Database; World Bank.

Note: BGD = Bangladesh; BTN = Bhutan; EMDEs = emerging market and developing economies; IND = India; LKA = Sri Lanka; MDV = Maldives; NPL = Nepal; SAR = South Asia. Broad sectors are disaggregated following the International Standard Industrial Classification of All Economic Activities, revision 4, with "Agriculture" comprising section A; "Other industry" comprising sections B, D, and E (that is, mining; electricity, gas, and water supply; and construction); "Light manufacturing" comprising divisions 10 to 18 and 31 to 33 (for example, manufacture of food products, textiles, or furniture); "Heavy manufacturing" comprises divisions 19 to 30 (for example, manufacture of refined petroleum, electronics, or transport equipment); "Business services" comprising divisions 58 to 83 (for example, technical and administrative support, including IT services); and "Other services" comprises all other divisions (for example. wholesale and retail, accommodations and restaurants, and government services). Aggregation across countries uses GDP in current US$ as weights.

A. Total bilateral trade costs κ across 18 sectors and 73 economies in 2023 are calibrated following Lewis et al. (2022). Subsequently, we decompose $\kappa = (1 + \tau + \eta) \times d$, where d refers to all trade cost that are outside the immediate scope of trade policy (such as geography, language differences, historical ties), τ refers to the tariff rate, and η to non-tariff barriers within the scope of trade policy (such as regulations, custom procedures, infrastructure). We approximate $(\tau + \eta)$ as the trade cost difference toward a regional EMDE benchmark. Finally, η is backed out as residual after accounting for observed tariff data. Annex 3.1 provides additional details.

B.C. The reform scenario represents a 50-percent reduction in trade policy barriers relative to the regional EMDE benchmark, that is, $0.5 \times (\tau + \eta)$. Figures summarize average reform magnitudes across broad sectors and countries.

would be 1.3 percentage points larger because workers are now more likely to reallocate to expanding sectors and higher-paying jobs (figure B3.1.2). Importantly, this per capita income gain excludes the even larger welfare gains from the reduced direct income losses that workers incur when switching between jobs in response to the trade reform.

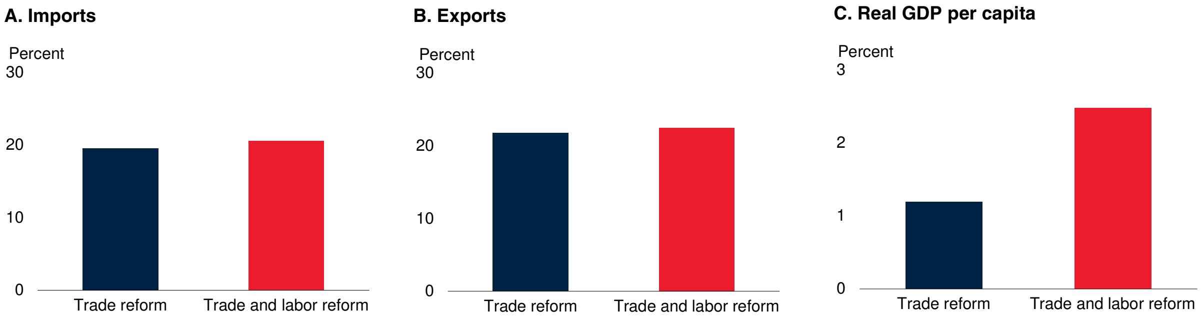
International experience: China. International experience suggests that a reduction in job switching cost for workers can yield significant output gains. By linking social benefit entitlements to workers' official place of registration, the *hukou* system represented a barrier for rural Chinese workers to move into urban jobs (Meng 2012). Between 2009 and 2012, the New Rural Pension Scheme allowed rural workers to join the non-agricultural urban sector by reducing their need to personally care for relatives. Young workers from households subject to this reform were 4.2 percentage points more likely to be employed in non-agricultural urban jobs than other young workers. On aggregate, this boost to labor mobility was estimated to have raised GDP by 2.4 percent (Gai et al. 2025).

International experience: Brazil. Job switching costs can also be lowered by boosting firms' job creation so workers spend less time searching for new jobs. The majority of small firms in EMDEs operate in the informal sector, in part due to compliance costs with labor and tax regulations (Almeida and Carneiro 2009; Ulyssea 2020). In 1996, Brazil consolidated several businesses taxes and fees into a single monthly payment that was up to 8 percent lower. This raised employment and revenues among formal firms by more than 10 percent, and this increase has been attributed to lower costs of contracting workers (Fajnzylber, Maloney, and Montes-Rojas 2011).

BOX 3.1 Sequencing Trade and Labor Reforms (*continued*)

FIGURE B3.1.2 Impact of trade and labor reforms

Besides strong increases in trade, reducing South Asia's import barriers relative to other EMDEs by half would generate per capita income gains of 1.2 percent. These gains could be significantly larger if trade liberalization were combined with a reform that lowers workers' moving costs.



Sources: ADB Multiregional Input-Output Tables (database); WTO Analytical Database; World Bank.

Notes: Each panel shows the effects on exports, imports, and GDP per capita (all three outcomes in real terms—that is, deflated by aggregate price effects) as a result of the trade policy reform (a halving of the gap with the EMDE average for trade policy costs in each country and sector) and labor reform (a 5-percent reduction in the cost of transitioning between jobs) in South Asian countries. All three general equilibrium effects are estimated using a dynamic quantitative multi-sector open-economy model following Caliendo, Dvorkin, and Parro (2019). The model is calibrated in changes relative to 2023 data for 73 economies, including a rest-of-world aggregate.

Policy implications

Lowering import tariffs in South Asia could deliver substantial gains in exports and incomes. These gains would be considerably larger if trade reform were paired with even modest improvements in labor mobility. Such improvements could be achieved by reducing barriers that hinder workers from moving between jobs, such as limited connectivity, regulatory rigidities, or insufficient skills. A reform strategy that combines tariff reductions with targeted active labor market policies, streamlined labor laws, and investments in connectivity, such as transport and housing infrastructure, could amplify gains from tariff reductions alone.

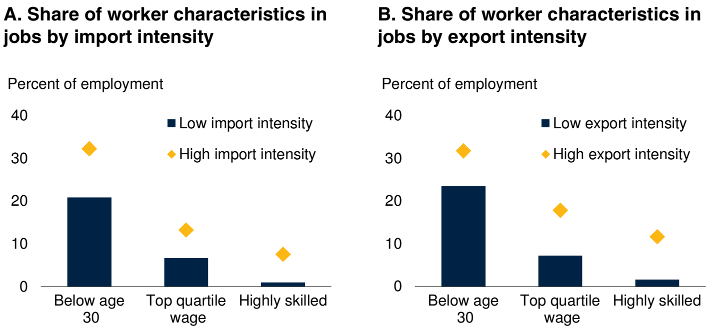
Carefully sequenced tariff cuts, starting with cuts on imported inputs, could therefore help both South Asia's manufacturing sector, as well as its labor markets. The highest tariffs that protect a large share of the workforce could be lowered more gradually by legislating a multi-year glide path toward a lower final level. This would allow the affected workers, firms, and regions time to adjust gradually in response to other opportunities arising elsewhere.

Even such a carefully sequenced and paced tariff reduction, however, is likely to catalyze labor market reallocation. The literature suggests higher employment and wages for skilled and younger workers, as well as higher employment in manufacturing firms. South Asia's most protected workers—who tend to be less skilled, lower paid, and older—may find fewer job opportunities or face slower wage growth.

Government policy can support the reallocation of workers across firms, sectors, and locations in multiple ways. One way could be to remove restrictions that impede labor market "churn" (that is, the speed of job entry and exit). The more churn the labor market can accommodate, the faster workers will find jobs in the newly competitive segments of the labor market and leave jobs in declining segments. A dynamic general equilibrium modeling exercise shows that the per capita income gains from a trade reform could be significantly larger if combined with (or even preceded by) a modest reduction in job switching costs (box 3.1).

FIGURE 3.13 South Asia: Worker characteristics in trade-linked activities

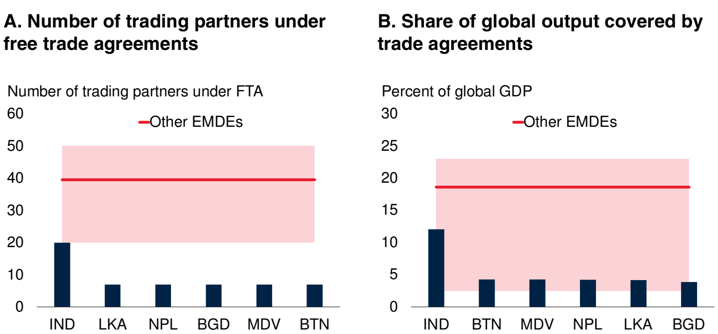
Workers in trade-linked jobs tend to be better paid, more skilled, and younger than those in jobs not linked to trade.



Sources: ADB Multiregional Input-Output Tables (database); Global Labor Database; World Bank.
Note: Export and import intensities refer to sectors with below- and above-median shares of exports or imports in sectoral gross output. Figure shows worker characteristics in goods-producing sectors only. Wage quartiles are defined within each South Asian country and across all sectors of the economy. Latest available data are used.

FIGURE 3.14 Trade agreements

South Asian countries have entered fewer trade agreements—and mostly with smaller partners—than the median EMDE outside South Asia.



Sources: World Bank Deep Trade Agreements (database); World Development Indicators (database); World Bank.
Note: BGD = Bangladesh; BTN = Bhutan; EMDEs = emerging market and developing economies; FTA = free trade agreement; IND = India; LKA = Sri Lanka; MDV = Maldives; NPL = Nepal. Free trade agreements in force in 2023. Red-shaded area denotes interquartile ranges for other EMDEs. Red line shows the median for other EMDEs.

Many factors affect the speed of job market reallocation. Labor market restrictions can discourage hiring of new workers and prevent the closure of failing firms (chapter 1). Non-transparent, illiquid, or costly housing markets, along with poor connectivity, can prevent the physical relocation of workers. A lack of general math and reading skills can hinder switching into new sectors and occupations. Size-dependent policies can slow firms' growth and job creation even in competitive sectors.

The government can help by promoting upskilling efforts, including with a focus on vulnerable workers in exposed industries, efficient housing markets, and firms' exit and entry. Size-dependent policies that discourage firms' growth beyond a threshold size could be streamlined (World Bank 2024a). To give the most adversely affected workers and firms time to adjust, the government could repurpose existing subsidies into cash transfers that provide income support without locking workers into declining activities (Muralidharan 2024).

Tariff reductions will be particularly employment-creating if they are part of broader FTAs that expand market access for South Asia's exporters and are accompanied by trade-facilitating measures beyond tariffs. Currently, South Asian countries are members of fewer trade agreements, and with smaller partner economies, than the median EMDE (figure 3.14). Negotiations are currently underway on several new agreements.

Tariff cuts could lower trade-related revenue, which accounts for 4 to 19 percent of tax revenues and 0.7 to 3.7 percent of GDP, in South Asian countries (box 3.2). However, in past episodes of major tariff cuts—on average, cuts of 15 percentage points—the impact of trade increases largely offset the tariff cuts, and trade-related revenues declined by less than 0.1 percentage point of GDP. These trade-related revenue losses were readily offset by non-trade revenue gains, mostly in consumption taxes, without increases in non-trade tax rates.

Globally, the outlook for deepening trade cooperation and reducing barriers may be muted. In South Asia, however, significant untapped potential remains. Carefully calibrated policy reforms to reduce trade barriers could unlock opportunities for the manufacturing sector, and for labor markets, although vulnerable workers in previously protected sectors may benefit from support to help them transition to expanding sectors. Such steps could help buttress job creation efforts and advance efforts to address the jobs challenge—the task of creating sufficient new employment opportunities for a growing working-age populations in the region.

BOX 3.2 No Tariffs, No Problem: Managing the Revenue Impact of Tariff Cuts

Most South Asian countries derive 4–19 percent of their government revenues, or 0.7–3.7 percent of GDP, from trade. Past episodes of major tariff cuts were, on average, accompanied by a small decline in trade revenue of less than 0.1 percentage point of GDP. Total tax revenue-to-GDP ratios stayed broadly flat during these reforms, as trade tax revenue losses were offset by gains in other tax revenues, especially from consumption taxes. These tariff reductions rarely involved tax rate increases, and typically relied on base broadening or better tax administration.

Introduction

South Asian countries are among the most closed to international trade, in part reflecting fiscal policy choices such as high tariffs and para-tariffs (chapter 3; World Bank 2024b). As countries consider lowering tariffs or para-tariffs, one major concern is the impact on government revenue.

Fiscal positions are fragile in South Asia. All South Asian countries generated lower tax revenues than the average EMDE, and all except Bangladesh had higher government debt as a percentage of GDP than the average EMDE at the end of 2024 (figure B3.2.1; World Bank 2025).

Trade revenue is a major source of tax revenue for most of South Asia's governments, accounting for 0.7–3.7 percent of GDP during 2019–23. Over this period, all South Asian countries except Bhutan derived greater shares of tax revenues, 4–19 percent, from trade taxes than the average EMDE (figure B3.2.1).

Any revenue losses from tariff cuts would therefore have to be offset by revenue gains elsewhere. This box answers the following questions:

- What was the revenue impact of past major trade reforms around the world?
- How often are offsetting non-trade revenue gains achieved without tax rate hikes?
- How can South Asia's governments manage the revenue impact of trade reform, while improving fiscal positions?

Note: This box was prepared by Zoe Leiyu Xie.

This box reports the following findings.

First, past episodes of major tariff cuts resulted in minor trade revenue losses: on average, they were associated with a decline in trade revenue of less than 0.1 percentage point of GDP. Total tax revenue-to-GDP ratios stayed broadly flat, as rising non-trade tax revenues offset trade tax revenue losses. This finding is consistent with literature, which shows that trade openness shifted tax revenue of developing countries from tariffs to value-added and income taxes (Aizenman and Jinjarak 2009), and that higher domestic revenue often made up for lower trade revenue after trade liberalization (Baunsgaard and Keen 2010).

Second, sustained increases in non-trade tax revenue of the magnitude needed to offset trade revenue losses (0.1 percent of GDP) have been common. Consumption tax revenue increases contributed to about half of the overall increase in non-trade tax revenue.

Third, increases in non-tax revenue of this order of magnitude rarely involved tax rate increases. Tax base broadening or better tax administration has helped countries achieve higher non-trade tax revenue without raising tax rates (World Bank 2025).

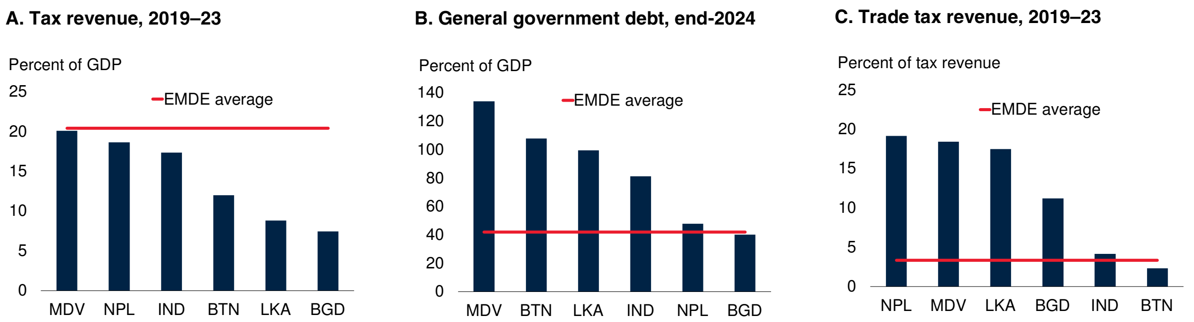
Historical episodes of major tariff cuts

The event study in the main text of chapter 3 is extended to examine revenue impacts. A major trade reform is defined as one with reductions in import tariffs in the top decile, both in the first year and over a five-year period, in a sample of 122 economies during 1980–2024 (annex 3.1). The sample consists of 33 episodes in 31 economies, including 25 EMDEs, with an average tariff cut of 15 percentage points.

BOX 3.2 No Tariffs, No Problem: Managing the Revenue Impact of Tariff Cuts (*continued*)

FIGURE B3.2.1 Fiscal challenges and reliance on trade taxes

South Asian countries face significant fiscal challenges and derive large shares of tax revenue from trade taxes, making the revenue impact of trade reform particularly salient.



Sources: Haver Analytics; IMF Government Finance Statistics (database); IMF World Economic Outlook (database); UNU-WIDER; World Bank Fiscal Survey; World Development Indicators (database); World Bank.

Note: BGD = Bangladesh; BTN = Bhutan; EMDEs = emerging market and developing economies; IND = India; LKA = Sri Lanka; MDV = Maldives; NPL = Nepal. South Asia comprises Bangladesh, Bhutan, India, Maldives, Nepal, and Sri Lanka. Tax revenue includes social security contributions and excludes grants.

A. EMDE average is the nominal GDP-weighted average of 142 EMDEs.

B. EMDE average is the nominal GDP-weighted average for 147 EMDEs. For Bhutan, about two-thirds of general government debt is in hydropower debt.

C. EMDE average is the nominal GDP-weighted average of 111 EMDEs.

Trade tax revenue loss: Significantly negative but small. Trade increases largely offset tariff cuts. As a result, despite substantially lower tariff rates, trade tax revenue was lower by less than 0.1 percentage point of GDP per year during these episodes compared with outside such episodes (figure B3.2.2). On average, trade tax revenue recovered by the fourth year after the start of tariff cuts, reflecting the delayed response in trade increases as production adjusts to lower tariff rates.

Non-trade tax revenue: Significantly positive. On average, during the first five years of the trade reform period, non-trade tax revenue was 0.2 percentage point higher per year than outside the episodes (figure B3.2.2). On average, non-trade tax revenue rose significantly—by 0.4 percentage point of GDP—in the first year after the reform and stayed at the higher level until the fourth year after the start of the reform. This reflected base broadening and tax administration rather than tax rate increases: controlling for tax rates does not materially change these results.[a]

Total tax revenue: Significantly positive. Increases in non-trade tax revenue were sufficiently large to more than offset any declines in trade tax revenue. As a result, total tax revenue during the episodes was 0.1 percentage point of GDP per year higher than outside the episodes, even after controlling for non-trade tax rates (figure B3.2.2).

Raising non-trade tax revenues

How common are non-trade tax revenue of 0.1 percentage point of GDP? A sample of country-year pairs with increases in non-trade tax revenue of 0.1 percentage point of GDP or more per year was assembled. The threshold size corresponds to a touch more than the annual average decline in trade tax revenue-to-GDP ratio during major trade reforms episodes. A sustained increase in non-trade revenue is defined as an increase of 0.1 percentage point of GDP or more in the first year, with revenue sustained at the higher level for at least three (or five) years. The sample of such episodes includes

[a] Controlling for tax rates increases the magnitude of the rise in non-trade revenue during tariff reduction episodes, both because it shrinks the sample (by around one-third; see annex figure A3.1.2) and because it corrects omitted variable bias. Consumption tax rates tend to be lower during tariff reduction episodes, and hence failure to control for tax rates lowers the impact of episodes on non-trade revenue.

BOX 3.2 No Tariffs, No Problem: Managing the Revenue Impact of Tariff Cuts (*continued*)

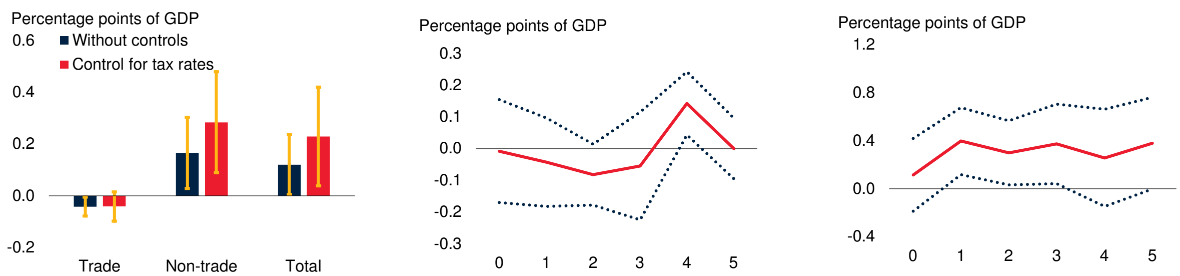
FIGURE B3.2.2 Revenue impact of past episodes of trade liberalization

Past episodes of major tariff cuts were associated with an average decline of less than 0.1 percentage point of GDP in trade tax revenue, while total tax revenue-to-GDP ratios remained broadly stable as rising non-trade tax revenue offset losses in trade tax revenue.

A. Differentials in annual revenue changes between episodes and non-episodes: Total, trade, and non-trade tax

B. Cumulative change after start of tariff reduction episode: Trade tax revenues

C. Cumulative change after start of tariff reduction episode: Non-trade tax revenues



Sources: Haver Analytics; IMF Government Finance Statistics (database); UNU-WIDER; U.S. Agency for International Development Collecting Taxes (database); Vegh and Vuletin (2015); World Bank Fiscal Survey; World Development Indicators (database); World Bank.

Note: Episodes and methodology are detailed in annex 3.1. Episodes are defined as the largest decile of tariff reductions in both the first year and over a five-year period among up to 122 countries, of which 31 countries (25 EMDEs) experienced 33 tariff reduction episodes. Tax revenue excludes social security contributions and grants.

A. Blue bars show the difference in the annual average revenue-to-GDP ratio between the first 5 years of an episode and all years outside of episodes, derived from a country fixed effects regression. Red bars show the difference after controlling for non-trade tax rates, including personal income, corporate income, and consumption (value added or goods and services) tax rates. Controlling for tax rates reduces the sample to 17 tariff reduction episodes. Whiskers indicate 90-percent confidence intervals.

B.C. Impulse response functions from a local projection estimation of cumulative changes in trade revenue-to-GDP ratio (B) and non-trade revenue-to-GDP ratio (C) on a dummy variable marking the start of the tariff reduction episode. Dotted lines indicate 90-percent confidence intervals.

117 countries (of which 81 EMDEs) for 1980–2023. The data are drawn from World Bank (2025) and the International Monetary Fund *World Economic Outlook*.

Frequency of increases: Common. Increases in non-trade tax revenue have been common since the 1980s. In more than one-half of country-year pairs, non-trade tax revenue increased by 0.1 percentage point of GDP or more, and in one-third of these instances, the revenue gain was sustained for at least five years (figure B3.2.3). Among EMDEs, non-trade revenue increases that were sustained for at least five years occurred more frequently than in advanced economies.

Magnitude of increases: Large. When non-trade revenue rose, the average increase was much larger than the 0.1-percentage-point threshold used here. On average, non-trade tax revenue increased by 0.9 percentage point of GDP, with the increase exceeding 0.6 percentage point of GDP in more than half of the events—substantially more than what would be needed to offset the average trade revenue loss during major trade reforms (figure B3.2.3). Two-fifths of that increase came from higher consumption tax revenue, one-quarter from higher corporate income tax revenue, and one-fifth from higher personal income tax revenue. Country-years with sustained increases in non-trade tax revenue for at least three or five years had an average annual increase of 0.6 and 0.5 percentage point of GDP, respectively. Even at these horizons, consumption tax revenue was still the main driver of the increases in non-trade tax revenue.

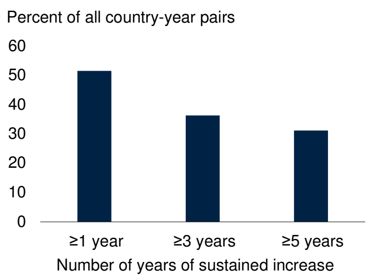
Revenue increases without tax rate hikes. In the years in which non-trade tax revenue rose by 0.1 percentage point of GDP or more, four-fifths occurred without any increases in non-trade tax rates,

BOX 3.2 No Tariffs, No Problem: Managing the Revenue Impact of Tariff Cuts (*continued*)

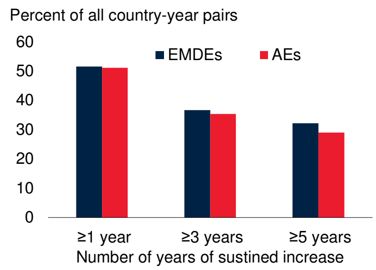
FIGURE B3.2.3 Options to raise non-trade tax revenues

Sustained increases in non-trade tax revenue of 0.1 percentage point of GDP or more have been common, with consumption tax revenue contributing about half of the overall increase. Such sustained increases rarely involved tax rate hikes. Broadening the tax base or better tax administration has been shown to help countries achieve higher tax non-trade revenue.

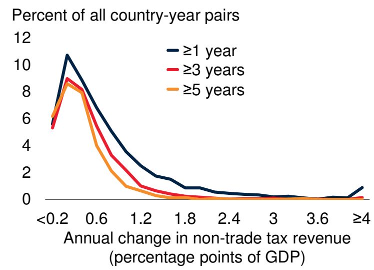
A. Frequency of sustained non-trade tax revenue increase of 0.1 percentage point of GDP



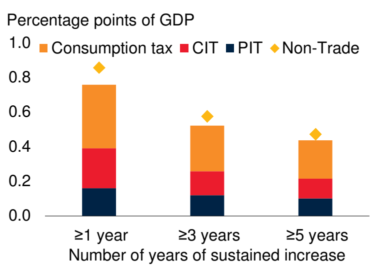
B. Frequency of sustained non-trade tax revenue increase by country type



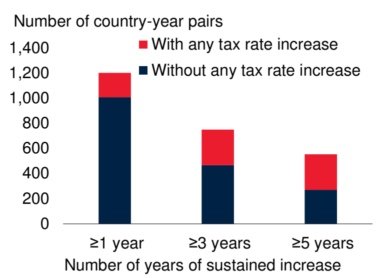
C. Frequency of annual changes of non-trade tax revenue during sustained increases, by size of change



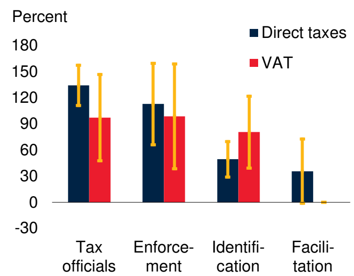
D. Average annual change of revenue during sustained non-trade tax revenue increases



E. Composition of sustained non-trade tax revenue increases, with and without non-trade tax rate hikes



F. Non-trade tax revenue increase, by type of intervention



Sources: Haver Analytics; IMF Government Finance Statistics (database); Okunogbe and Tourek (2024); UNU-WIDER; U.S. Agency for International Development Collecting Taxes (database); Vegh and Vuletin (2015); World Bank Fiscal Survey; World Development Indicators (database); World Bank.

Note: AEs = advanced economies; CIT = corporate income tax; EMDEs = emerging market and developing economies; PIT = personal income tax; VAT = value-added tax. The methodology identifies whether a country-year pair recorded an annual increase in non-trade tax revenue of 0.1 percentage point of GDP or more from the previous year. Tax revenue excludes social security contributions and grants. A revenue increase is sustained for at least 3 years if non-trade tax revenue increased by 0.1 percentage point of GDP or more between years *t-3* and *t-2*, and remained at the higher level for each year until year *t*. A revenue increase that is sustained for at least 5 years is defined analogously.

A. Bars show the frequency with which a country-year pair recorded a sustained increase in non-trade tax revenue, as a percent of all country-year pairs.

B. Bars show the frequency with which a country-year pair recorded a sustained increase in non-trade tax revenue for EMDEs and advanced economies, as a percent of all country-year pairs.

C. Lines show the frequency of sustained increases in non-trade tax revenue, as a percent of all country-year pairs, by the binned size of annual changes in non-trade tax revenue-to-GDP ratio. Bin width is 0.2 percentage point of GDP.

D. Bars show the contribution of CIT, PIT, and consumption tax revenue increases to sustained increases in non-trade tax revenue. Differences between the sum of the components and the total increase in non-trade tax revenue arise from changes in non-income direct tax revenues, including property tax and other direct taxes. Sample includes only those with data on change in each tax revenue during the sustained window.

E. Bars show the breakdown of sustained increases in non-trade tax revenue, according to whether the episode was accompanied by increases in any non-trade tax rate, including PIT, CIT, and consumption tax rates. Sample includes only those with data on change in each tax rate during the sustained window.

F. Direct taxes comprise CIT and PIT. The results of the meta-regression analysis shown here are based on estimated revenue impacts and the associated standard errors from a range of studies. The studies varied widely in their design such that the scale of interventions cannot be compared. Blue bars indicate average revenue impact of 87 interventions in 17 countries, estimated in 26 studies. Yellow whiskers indicate 95-percent confidence intervals. For details, see World Bank (2025).

BOX 3.2 No Tariffs, No Problem: Managing the Revenue Impact of Tariff Cuts (*continued*)

including personal income tax, corporate income tax, and consumption (VAT or goods and services) tax rates (figure B3.2.3). Even in episodes with sustained non-trade revenue gains for at least three or five years, three-fifths and one-half, respectively, were achieved without tax rate increases.

Options for raising non-trade tax revenues

Raising consumption taxes—most commonly value-added tax (VAT)—to offset tariff reductions can raise government revenue (Keen and Ligthart 2002). However, with pervasive informality, as in most South Asian countries, replacing trade taxes with VAT can be inefficient, especially if the VAT is poorly administered (Emran and Stiglitz 2005).

Drawing on international evidence, a review of 26 studies on the revenue impact of policy interventions suggests that governments can raise non-trade tax revenues by broadening the tax base and making tax administration more efficient (figure B3.2.3; Okunogbe and Tourek 2024; World Bank 2025). A combination of tax facilitation and better enforcement or taxpayer identification appears particularly effective. Measures to incentivize tax officials improved enforcement and raised non-trade tax revenue. Interventions to facilitate collections, such as implementing e-invoicing and measures to better identify and track taxpayers, combined with more effective enforcement, also generated significant increases in tax collection.

Annex 3.1 Methodologies and data

Event study

Definition of events. An event study tracks the evolution of labor market and trade outcomes during past episodes of major trade reforms. A major trade reform is defined as one that ranks in the top decile of (unweighted) average import tariff reductions—both in the first year and after five years—in a sample of 122 countries (including 86 EMDEs) during 1995–2022. Tariff reductions that fall into the top decile, both in the first year and over five years, but are within three years of each other, are considered part of the same episode. The sample excludes small states and fragile states. Moreover, episodes occurring during past spells of fragility are excluded. These criteria yield 33 episodes of major trade reforms in a sample of 31 countries (including 25 EMDEs; annex table A3.1.1). In these episodes, tariffs were cut by more than 5 percentage points over a five-year period. However, because the average episode lasted seven years, the average tariff cut was 15 percentage points (annex table A3.1.2).

With few exceptions, these episodes would not have qualified as trade liberalization episodes in the earlier landmark studies by Wacziarg and Wallack (2004) and Sachs and Warner (1995). Wacziarg and Wallack (2004) identify trade liberalization episodes as those in which de jure liberalization is followed by de facto liberalization, measured by at least a 5-percent increase in the trade-to-GDP ratio. De jure liberalizations are defined by Sachs and Warner (1995) as episodes in which closed economies switch to being open. Closed economies are defined as those with non-tariff barriers affecting 40 percent or more of trade, an average tariff of 40 percent or more, a black market exchange rate premium of 20 percent or more during the 1970s and 1980s, exports governed by a state monopoly, or the country had a socialist economic system.

None of the episodes identified by these authors is included in the sample here, as employment data are lacking. These authors' last episode is India in 1994, before the beginning of the sample needed here to ensure sufficient employment data coverage. For countries with data available since 1995, their methodology would exclude almost all of the episodes examined here, because only three countries in the sample were initially classified as closed under their criteria:

- Pakistan, which lowered its average tariffs by 28 percentage points, from 45 percent in 1998, and increased its trade-to-GDP ratio by one-quarter between 1998 and 2003.
- Egypt, which lowered its average tariffs by 26 percentage points, from 41 percent in 2002, and increased its trade-to-GDP ratio by more than one-half between 2002 and 2007.
- Thailand, which lowered its average tariffs by 31 percentage points, from 43 percent in 1999, and increased its trade-to-GDP ratio by one-quarter between 1999 and 2004.

Hence, the exercise conducted here can be considered an analysis of the employment effects of more modest trade liberalizations than those covered in the earlier literature.

Comparison of averages. The unweighted annual averages of employment, real GDP, and labor productivity growth, and changes in trade-to-GDP ratios and current account balance-to-GDP ratios during the first five years of major trade reform episodes are compared with the corresponding averages outside these episodes. The difference in unweighted averages is derived from a fixed effects panel regression of the outcome variable and a dummy variable, D_i, that equals 1 for the first five years of a major trade reform episode. The regression coefficient on the dummy captures the difference between the first five years of a tariff reduction episode and the sample average outside these episodes:

$$x_{it} = a_i + b \times D_i + e_{it} ,$$

where x_{it} denotes annual employment growth, annual real GDP growth, annual labor productivity growth (with labor productivity measured as the real GDP-to-employment ratio), and annual changes in the trade-to-GDP ratio and current account balance-to-GDP ratio. All growth rates are expressed in percent, and trade and current account balances are expressed in percent of GDP.

Dynamics. To trace the dynamics of employment in the first five years of major trade reform episodes, a local projection model is estimated. The regression estimates cumulative changes in log employment over forecast horizons h (up to five years) on a dummy variable that equals 1 for the first year of the major trade reform episode, controlling for one lagged change of the dependent variable, as well as country and year fixed effects:

$$\Delta_{h+t} \ln(employment_{it}) = \alpha_i + \beta_t + \gamma_h \times D_{i,t} + \lambda_h \times \Delta_{t-1}\ln(employment_{it-1}) + \varepsilon_{it} .$$

The data on real GDP, trade, and current account balances are from the IMF's *World Economic Outlook* database. The data on employment (using national data) and tariffs are from the World Bank's *World Development Indicators*.

Robustness tests. About two-thirds of the trade reform events examined in this study were not implemented in isolation. They were implemented during much broader IMF-supported stabilization and adjustment programs, sometimes amid major crises or deep recessions. Many other policy changes were implemented at the same time. Hence, at the aggregate level, it is difficult to disentangle the causal impact of trade reforms on job creation from the effects of other policy shifts or unrelated business cycle movements. Although the event study conducted here cannot establish causality, it can distinguish between trade reform episodes that were implemented during economic distress and those that were not. Four indicators of such economic distress are considered. An episode is classified as distressed if, within the five years following tariff reductions, it includes at least one year with:

- a recession (a contraction in real GDP): four of the 33 events;
- a currency crisis, banking crisis, or debt crisis or restructuring (all as defined in Laeven and Valencia 2020): seven or eight of the 33 events;
- an IMF program approval or review: 17 of the 33 events;
- any of the above: 23 of the 33 events.

The local projection estimation is adjusted to include another dummy variable that equals 1 only when the five-year period of the trade reform event coincides with an episode of economic stress. The coefficient on the dummy variable for the baseline trade event is then interpreted as the impact of trade reform in the absence of economic stress; the coefficient on the new dummy variable for the trade reform event combined with economic stress is interpreted as the impact of trade reform during economic stress.

As expected, the results suggest that employment rose statistically significantly during trade reform episodes only when these episodes were not accompanied by any type of economic stress. Employment growth during trade reform episodes was statistically significantly faster than outside episodes only when the trade reform was not accompanied by economic stress. Similarly, the cumulative employment gain five years after the start of the reform was statistically significant only when there was no economic stress during the episode (annex figure A3.1.1).

Meta regression analysis

Selection methodology. To generate a pool of potentially relevant academic studies, the review first identified seven widely cited studies on the impact of trade on labor market outcomes and firms (annex table A3.1.3). These seed articles cover a variety of methodologies (empirical estimation, structural modeling, and literature review); a range of countries (advanced economies, EMDEs, and cross-country samples); and a variety of outcome variables (employment, wage income, and productivity).

The review then conducted backward citation chasing, as well as first- and second-layer forward citation chasing and related-article searches, on these seed articles using the Scopus database. The search included economics articles published since 2000.[2] Duplicate articles that appeared in both forward (or backward) chasing and related-article search were removed.

The articles were then filtered by quality and relevance. The retained articles were published in the 250 top-ranked economics journals according to Research Papers in Economics (RePEc), and had to include two keywords in the author-chosen keyword list or abstract—one from the set "trade", "import", "export", and "globalization"; and one from the set "job", "employment", "productivity", "wage", and "labor".[3] Across the seven seed articles, this process yielded 3,026 unique articles (annex table A3.1.4). To supplement the Scopus database, which includes only published articles, an additional search and filtering using Google Scholar was conducted on each seed paper to include working papers published in the National Bureau of Economics Research (NBER) working paper series since 2020. This expanded the database to 3,056 articles.

Filtering. A review of the full text was conducted using both artificial intelligence (NotebookLM powered by Gemini 2.5 Pro) and manual reading to retain articles that (i) examine specific policy changes to liberalize trade (such as tariff reduction, free-trade agreement, non-tariff barrier reduction); (ii) include labor market outcomes (such as employment, wages, and productivity); and (iii) are published in the top 100 economics journals or had more than 100 Google citations as of June 15, 2025. In total, 111 studies were found relevant, and full-text reviews were conducted on these to extract detailed information on data coverage and structure, methodology, variable definitions, key findings, empirical estimates, and economic mechanisms. The full-text review then identified and excluded theoretical or model-based studies that did not include any relevant empirical estimates.

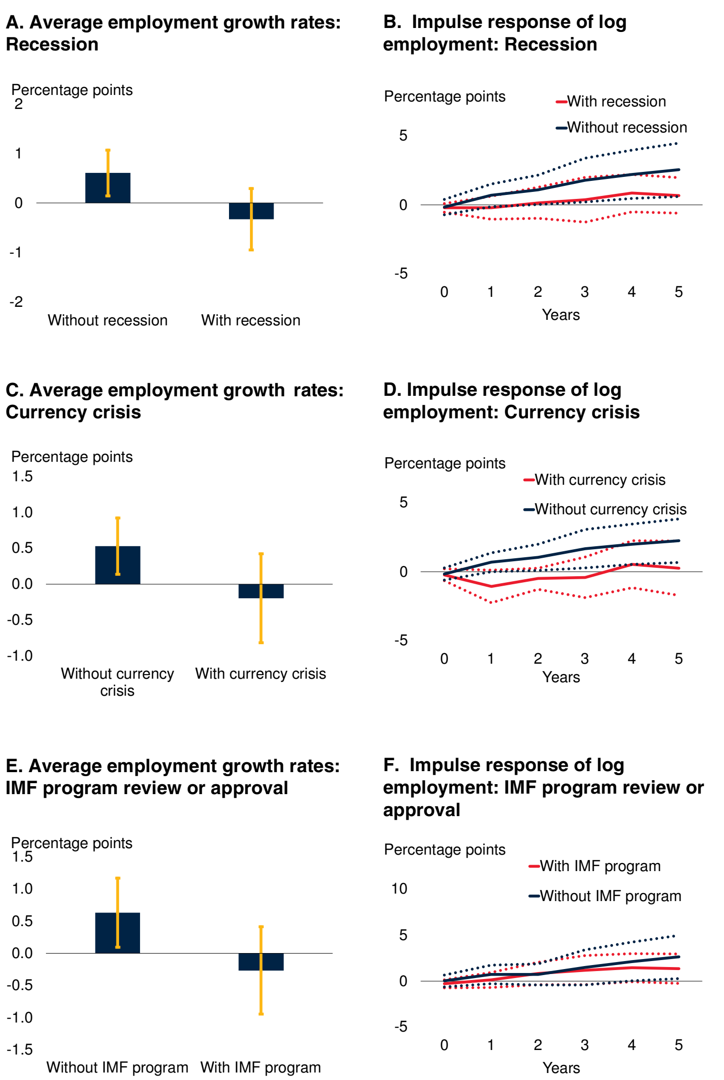
Final sample. This left 83 studies with relevant empirical estimates (72 focused on EMDEs), which form the final sample. For each reviewed study, multiple estimates were extracted based on relevance and differences with other estimates. If the same empirical analysis was conducted with additional control variables, only the final estimate with the largest number of control, or the authors' preferred specification, was recorded. Estimates on different subsamples were recorded as separate

[2] Related articles are those that share references with the seed article. Because of the large number of articles, second-layer forward searches and related-article searches from Scopus were each capped at 20,000 articles for each seed article.

[3] Keyword inclusion criteria were spot checked manually, and false inclusions of partial words (for example "important" for "import") were systematically excluded. Missing article identifiers (doi) were filled in manually.

ANNEX FIGURE A3.1.1 Robustness tests: Differences between trade reform episodes and outside such episodes

Tariff reform episodes were associated with significantly higher employment growth only when they were not accompanied by economic stress.



Sources: IMF Monitoring of Fund Arrangements (MONA, database); IMF World Economic Outlook (database); Laeven and Valencia (2020); World Development Indicators (database); World Bank.

Note: IMF programs are defined as years with IMF Executive Board action dates on IMF programs (that is, either program reviews or new program approvals). Currency crises are from Laeven and Valencia (2020). Recessions are defined as years with negative real GDP growth.

A.C.E. Charts show differences in average employment growth during 5-year periods of tariff reductions and outside such periods, based on a regression of employment growth on a dummy variable that is 1 for a trade reform period without economic stress and a dummy variable that 1 for a trade reform period with economic stress. Whiskers show 90-percent confidence intervals.

B.D.F. Charts show impulse response functions for log employment growth from local projection estimation on a dummy variable equal to 1 for a trade reform period without economic stress and a dummy variable equal to 1 for a trade reform period with economic stress. The estimation controls for country and year fixed effects as well as for lagged employment growth. Whiskers show 16–84 percent confidence intervals.

entries. The final sample included 833 relevant econometric estimates that constitute the sample for the meta-regression analysis.

Characteristics of reviewed studies. Reviewed studies were published between 2000 and 2025, covering data samples from 1900 to the 2010s (annex table A3.1.5). About one-third of the studies had samples starting in the 1990s, and about half had samples ending in the 2000s. The median study covered a sample duration of 10 years. One-fifth of the estimates from these studies were obtained at the worker level, two-fifths at the firm or plant level, and two-fifths at the sectoral or spatial level (annex table A3.1.6). The reviewed studies covered 23 individual countries, of which 18 were EMDEs—mostly in the East Asia and Pacific region and the Latin America and Caribbean region—and six studies with a group of countries (annex table A3.1.7).

About two-fifths of the estimates referred to employment outcomes, one-third to wages, and one-fifth to firms' labor or total factor productivity. Among estimates examining wage outcomes, half control for worker characteristics, either directly in the estimation or by computing industry- or location-specific wage premiums (Krueger and Summers 1988). The other half of the estimates on wage outcomes use unconditional wages, often because of a lack of worker-level data, capturing impacts on both efficiency wage units and worker composition. Estimates using unconditional wages, typically due to a lack of worker-level data, reflect both changing efficiency wage units and shifting worker composition. Half of the estimates studied general tariff changes as the main reform, one-tenth looked at input tariff changes, about one-fifth FTAs, and one-tenth other trade policies, such as export promotion campaigns or the removal of non-tariff barriers that are not part of a free trade agreement.

Estimation. The following ordered probit regression was estimated to assess the probability that the estimated impact of trade liberalization was more positive or negative for a particular group of firms and workers:

$$p_i = a + \beta_1 \times I_i^c + \beta_2 \times N_i^c + \beta_3 \times I_i^c \times P_i + \epsilon_i \,.$$

The dependent variable p_i is a categorical variable: 1 for a statistically significant estimate indicating trade liberalization is associated with higher employment, labor productivity, or wage for more exposed firms, workers, sectors, or locations; -1 for a lower outcome; and 0 for a statistically insignificant estimate.

The independent variables I_i^c and N_i^c are dummies for a characteristic c associated with the estimate i. Specifically, I_i^c takes the value 1 if the estimate is obtained for workers with the characteristic c, and 0 otherwise. The characteristics include: skilled (non-production, or white-collar, or skilled by study definition, or at least high school graduate); women; young (under the age of 30); in manufacturing firms; in small firms (50 or fewer workers, or small by study definition); importer firms (importer or high import share). Variable N_i^c takes 1 for the "opposite" of I_i^c—that is, if the estimate is associated with workers who are unskilled; men; old; in non-manufacturing firms (agriculture, mining, or services); in large firms; or non-importer (non-importer or low import share) firms—and 0 otherwise.

The interaction term P_i is a categorical variable for the type of trade-liberalizing policy, including general tariff reductions, input tariff reductions, FTAs, and other policies. The constant term α captures the effect for the non-classified or mixed group. The coefficients β_1 and β_3 together capture the marginal likelihood that trade liberalization leads to a significantly higher outcome for workers or firms with characteristic c. Each characteristic is estimated separately. The estimation sample excludes estimates for only the informal sector, because the dependent variable has an ambiguous interpretation. It also excludes estimates on the country level, because those do not have specific worker, firm, or location characteristics. The estimates are clustered at the study level.

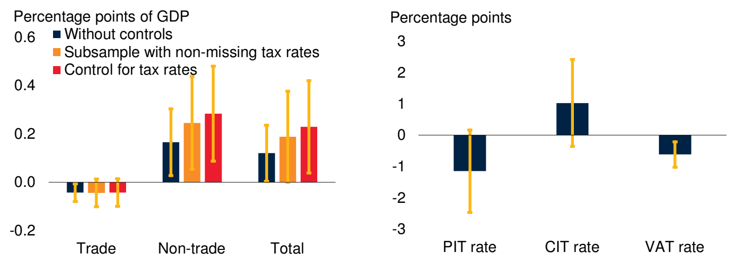
Another set of estimations is conducted to assess whether a particular type of trade reform led to significantly higher outcomes:

ANNEX FIGURE A3.1.2 Robustness for revenue impact of past trade liberalization

Subsampling and negative correlation between trade liberalization episodes and VAT rates account for the difference between estimated effects on non-trade tax revenue without and with controls for tax rates.

A. Differentials in annual revenue change between episodes and non-episodes, subsampling

B. Difference of non-trade tax rates between episodes and non-episodes



Sources: Haver Analytics; IMF Government Finance Statistics (database); UNU-WIDER; U.S. Agency for International Development Collecting Taxes (database); Vegh and Vuletin (2015); World Bank Fiscal Survey; World Development Indicators (database); World Bank.

Note: CIT = corporate income tax; EMDEs = emerging market and developing economies; PIT = personal income tax; VAT = value-added tax. Episodes are defined as the largest decile of tariff reductions in both the first year and over a 5-year period among up to 122 countries, of which 31 countries (25 EMDEs) experienced 33 tariff reduction episodes. Tax revenue excludes social security contributions and grants.

A. Blue and red bars are identical to those in figure B3.2.2A and show the difference in the annual average revenue-to-GDP ratio between the first 5 years of episode and all years outside of episodes, without or with controls for personal income, corporate income, and consumption (VAT or goods and services) tax rates. Orange bars are derived from a similar country fixed effects regression, but use the subsample of country-years with non-missing tax rates. Both the red and orange bars reduce the sample to 17 tariff reduction episodes. The difference between the blue and the orange bars reflects the effect of subsampling, while the difference between the orange and the red bars reflects the effect of controlling for tax rates. Whiskers show 90-percent confidence intervals.

B. Bars show the difference in personal income tax rates, corporate income tax rates, and VAT rates, between during and outside episodes, derived from a country fixed effects regression. Whiskers show 90-percent confidence intervals.

$$p_i = \alpha + \beta \times I_i^c + \epsilon_i \,.$$

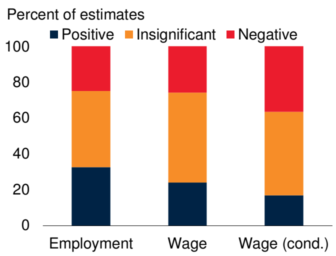
Here, the dependent variable is defined in the same way as before. The independent variable I_i^c takes 1 if the trade reform is a general tariff cut, input tariff cut, or FTA; 0 otherwise. Again, the estimation is conducted separately for each type of reform.

Annex table A3.1.8 summarizes the estimation sample by outcome type of the dependent variable and by characteristics of the independent variables. Figure 3.6 shows the marginal probabilities obtained from the ordered probit estimations. Annex figure A3.1.3 shows that the results are robust when using the subsample of studies on EMDEs only, except for small firms where the smaller, restricted sample prevents estimation of the marginal probability. The estimation model yields three sets of marginal probabilities: if estimates for a group are more likely to be (a) positive and significant, (b) negative and significant, and (c) insignificant. For brevity, the

ANNEX FIGURE A3.1.3 Robustness tests: Summary of the literature for EMDEs

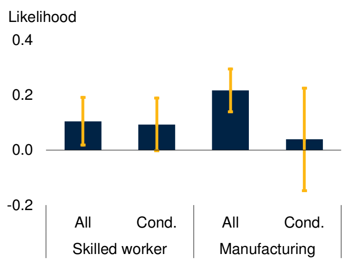
Restricting the meta-analysis sample to only studies that focus on EMDEs yields similar results as the baseline.

A. Estimates of impact of trade policy changes on labor market outcomes in EMDEs

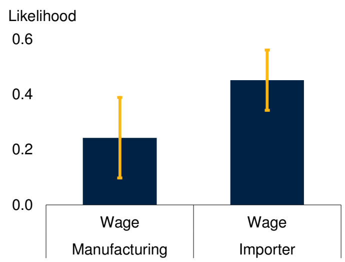


B. Likelihood of positive significant estimate: Differential impact of tariff cuts on employment in EMDEs

C. Likelihood of positive significant estimate: Differential impact of tariff cuts on wages in EMDEs



D. Likelihood of positive significant estimate: Differential impact of input tariff cuts on wages in EMDEs



Sources: Based on 72 studies on the effects of trade liberalization resulting from domestic policy changes using empirical estimates and focusing on EMDEs. Methodology is detailed in annex 3.1.

Note: Cond. = conditional; Mfg = manufacturing.

A. Bars show the percentage of estimates that find trade liberalization is associated with higher (positive), lower (negative) or insignificant impacts on employment, wages, and wages conditional on worker characteristics, for the impacted group compared with other groups. Total number of estimates 732.

B.–D. Bars show the estimated marginal likelihood that the impact of tariff cuts on employment or wages is statistically significantly more positive for certain workers or firms. Marginal likelihoods for conditional wages are estimated using a sample of estimates with wages as outcome, controlling for worker-level characteristics. Whiskers show the one-standard-error band on the estimated likelihood. Standard errors are clustered at the study level. A "skilled" worker is one defined as skilled in the study, or is a white-collar or non-production worker, or has completed at least high school or upper secondary school. A "young" worker is one below the age 30. Country-level studies are excluded. Estimates with the informal sector as the outcome variable are excluded. Marginal likelihoods are excluded from the charts where sample size is insufficient for reliable standard errors.

figures only show the marginal probabilities for positive and significant; the marginal probabilities for negative and significant show the same pattern—for example, tariff cuts on employment are more likely to be positive for skilled labor than for others, and they are also *less* likely to be *negative* for skilled labor.

Magnitude of impacts. Even when effects for different worker types predominantly move in the same direction, there are sometimes large differences in their magnitudes. Most studies are too heterogeneous—in both their definitions of exposure to trade policy changes and their labor market outcomes considered—to be comparable. A few studies, however, had sufficiently comparable methodologies to allow a comparison of magnitudes of coefficient estimates. Studies with comparable methodologies fell into two groups. Either they were specified as cross-sectional difference-in-differences regressions, estimating changes in employment or wages before and after the reform as a function of exposure to the reform interacted with a dummy variable for the type of worker or firm. Or they were specified as panel regressions that estimate employment or wages as a function of a post-reform dummy, interacted with exposure to the reform and with a dummy for the type of worker or firm. Since the regression coefficients from probit or logit models do not convey the magnitude of probabilities, studies using probit or logit models were excluded.

This left nine comparable studies, with estimates for wages (in logarithms or log changes) or employment (expressed as shares): Cisneros-Acevedo (2022) on informality in Peru; Kis-Katos and Sparrow (2015) on skilled workers in Indonesia; Ponczek and Ulyssea (2022) on labor regulations and informality in Brazil; Chamarbagwala and Sharma (2011) for labor intensity in India; Galiani and Sanguinetti (2003) on skilled workers in Argentina; Amiti and Davis (2012) on importers and exporters in Indonesia; Goldberg and Pavcnik (2003) on informal workers in Colombia and Brazil; Hasan et al. (2012) on labor market flexibility in India; and Ben Yahmed and Bombarda (2020) on informality in Mexico.

The coefficient estimates from these studies were used to derive the impact ratio, which captures the effect of trade reform on workers with a specific characteristic, such as higher skills, relative to the impact on workers without that characteristic. Being unit-free, impact ratios can be compared across studies, even if they examine different types of wages or employment. A ratio above 1 indicates that the impact on the group with the specified characteristic is greater than the impact on the group without it.

The resulting impact ratios for wages and employment are shown in annex figure A3.1.4. For the wage-related estimates, studies were dropped if they used as a dependent variable, for example, skilled-worker wages, a factor that other studies treated as a conditioning variable.

- **Employment.** Almost all studies estimating employment effect in this consistent framework focus on subgroups, typically informal and skilled workers (annex figure A3.1.4). After trade reforms, larger and less regulated firms shifted more toward both informal and skilled employment than their peers—often by multiples. In *Peru*, for example, trade-driven growth after the reforms of the 1990s and 2000s was accompanied by rapid increases in informal hiring by all types of firms. Increases were three to five times larger among larger firms than among smaller ones (Cisneros-Acevedo 2022). In *Brazil*, trade reform in the early 1990s triggered increases in informal employment up to five times larger among the unskilled in areas with less stringent labor regulations. At the same time, unemployment was lower in these areas compared with those that had stricter regulations (Ponczek and Ulyssea 2022).

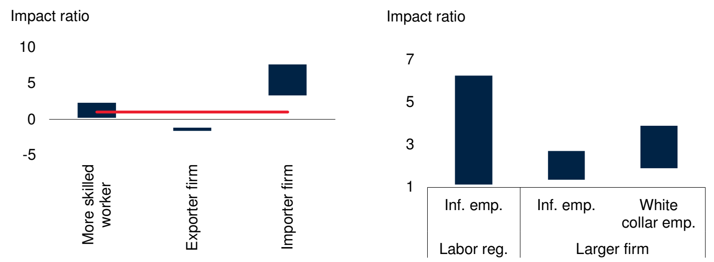
- **Wages.** After trade reforms, wage increases were much larger for skilled workers and in importing firms, but smaller in exporting firms (annex figure A3.1.4A). For example, during the trade reforms of the 1990s, skilled workers' wages rose up to as much as twice those of non-skilled workers in *Argentina's* most exposed sectors (Galiani and Sanguinetti 2003). In *Indonesia's* most exposed sectors, wages in importing firms during the 1990s rose three to four times as much as those in non-importing. For skilled workers the difference was more than 15-fold (Amiti and Davis 2012). The same study finds that wages in exporting firms declined, although less for skilled than for unskilled workers.

ANNEX FIGURE A3.1.4 Summary of the literature: Magnitude of impacts

After trade reforms, less stringent labor regulations and larger firms were associated with increases in informal employment that were two to five times those associated with more stringent regulations and smaller firms; wage increases in importing firms (and for skilled workers) were several multiples of those in non-importing firms (and for unskilled workers) and wages in exporting firms declined.

A. Estimated relative impact on wages

B. Estimated relative impact on employment



Sources: Based on a review of 9 studies that quantify the effects of trade liberalization using comparable methodologies.

Note: Inf. = informal; Emp. = employment; Reg. = regulation. Impact ratio measures the effect of trade reform on wages or employment for firms or workers with a specific characteristic in an exposed sector, relative to those without. Because it is the ratio of two impacts with the same units, the measure is unit-free. In cases of a sign reversal between groups, the sign of the coefficient for the indicated group is shown. A value above 1 indicates that a worker or firm with the relevant characteristic is more impacted by trade reform than a worker or firm without this characteristic; a value below 0 indicates that the impact is of opposite signs.

Worker characteristics

Data. Harmonized, detailed labor force surveys are available from the World Bank's Global Labor Database (GLD) for 32 EMDEs (including four South Asian countries) covering 1981–2024. The South Asian sample is expanded with data from Bhutan's 2024 labor force survey and the Maldives' 2019 household income and expenditure survey. Six-digit HS product-level tariffs are from the WTO analytical database. The ADB Multiregional Input-Output Tables provide data on exports, imports, intersectoral linkages, value added, and gross output for 35 sectors and 73 economies (including all South Asian countries). These sources provide recent data for the six South Asian economies (Bangladesh, Bhutan, India, Maldives, Nepal, and Sri Lanka), as well as a sample of six comparator EMDEs (annex table A3.1.9), covering 812 million workers. All data are mapped into a consistent set of 18 ISIC rev. 4 (two-digit) sectors. Agriculture accounts for one sector, industry for seven sectors, and services for 10 sectors (see annex table A3.1.10).

Definitions: Tariffs. Tariff measures are based on simple averages of the applied ad valorem most-favored-nation duty. Output tariffs, which measure the level of workers' tariff protection, refer to the average tariff across all products by sector. Tariffs on intermediate inputs, which capture the tariff burden imposed on firms and workers, refer to the weighted average of tariffs on intermediate inputs, derived from HS6 product codes using the Classification by Broad Economic Categories. In-text references to jobs with the highest or lowest tariffs on output or intermediate inputs refer to workers in the top and bottom third of South Asian country-sector pairs by output or intermediate input tariffs. The effective rate of protection is defined as output tariffs minus input tariffs, scaled by the expenditure share on total intermediate inputs, and weighted by the shares within intermediates and the share of intermediate inputs.

Definitions: Trade intensity. The export and import intensity of country-sector pairs is measured by the share of exports or imports in sectoral gross output. In-text references to high (low) export and import intensity refer to South Asia's goods-producing country-sector pairs with above (below) median export or import to gross output ratios. Employment-weighted import intensity is the product of sectoral employment and the corresponding import-to-gross-output ratio, expressed as a share of total employment. Export-linked employment is computed using an input-output analysis, following the methodology of Kruse et al. (2024) and Wolff (2003), linking trade, intersectoral linkages, and employment data.

Dynamic general equilibrium model

The analysis in box 3.1 employs a dynamic trade model with multiple sectors—following Caliendo, Dvorkin, and Parro (2019)—to investigate the general equilibrium effects of trade and labor market reforms in South Asia. The model features asymmetric frictions in international trade and in the allocation of workers across sectors, as well as input-output linkages. The model is calibrated to 73 economies (including a rest-of-world aggregate) and 18 sectors, using data from the ADB Multiregional Input-Output Tables (annex table A3.1.10). The calibrations examine reform scenarios relative to observed data for 2023.

Model. The dynamic, multi-country, multi-sector model by Caliendo, Dvorkin, and Parro (2019) provides all necessary features to study the general equilibrium effects of trade and labor market reforms. Countries produce and trade a continuum of sectoral varieties under Ricardian comparative advantage, with trade subject to iceberg costs and sectoral productivity draws that follow a Fréchet distribution. Production occurs in three nested layers, with goods assembled from labor and intermediate inputs using Cobb-Douglas technology. In labor markets, households are forward-looking, and workers select into sectors to maximize utility. However, when switching sectors, workers face both common and idiosyncratic mobility costs as in Artuç, Chaudhuri, and McLaren (2010). Labor market frictions limit reallocation in response to shocks, while firms choose sectors to maximize expected discounted profits. The model captures the interaction between trade and sectoral labor adjustment dynamics, and thus allows an analysis of the sequencing of policy reform.

Data. Calibrating the model requires data on sector-specific bilateral trade flows and domestic absorption, labor income across sectors, the share of intermediate inputs and value added in sectoral gross output, and intersectoral linkages in production.[4] These data come from the 2023 ADB Multiregional Input-Output Tables.

Trade barrier calibration. Total bilateral trade costs κ across 18 sectors and 73 economies in 2023 are calibrated following Lewis et al. (2022).[5] The implementation of their equation 19 for this analysis assumes price unity, such that price differences across countries are absorbed in κ. Trade elasticities are taken from the literature—Sposi (2019) for agriculture, manufacturing, and services, and Freeman et al. (2025) for mining. Subsequently, κ is decomposed as $\kappa = (1+ \tau + \eta) \times d$, where d refers to all trade costs that are outside the immediate scope of trade policy (for example, geography, language differences, or historical ties), τ refers to the tariff rate, and η to non-tariff barriers within the scope of trade policy (such as regulations, customs procedures, and infrastructure). $(\tau + \eta)$ is approximated as the

[4] As the model abstracts from capital incomes, labor income is equal to value added.

[5] The need for detailed sectoral trade costs precludes the use of the World Bank UNESCAP trade cost database, which only featured total, manufacturing, and agricultural trade costs.

difference in trade costs from an EMDE benchmark that controls for exogenous factors.[6] Finally, η is backed out as a residual after accounting for observed tariff data from the WTO analytical database.

Reforms. The trade reform scenario represents a 50-percent reduction in trade policy barriers relative to the regional EMDE benchmark, that is, $0.5 \times (\tau + \eta)$. The trade reform is an asymmetric, unilateral liberalization. To account for reform externalities from import-cost reforms—such as improved infrastructure, more efficient logistics, or trade agreements—a modest one-third spillover from import cost reductions to the trade cost faced by exporters in the same country-sector pair is assumed. Labor market frictions represent mobility costs for worker reallocations across sectors. They are modeled as transitional income losses incurred as workers switch to new jobs, and are estimated following Artuç, Lederman, and Porto (2015). Because the overall model by Caliendo, Dvorkin, and Parro (2019) is solved in changes, flows are calculated using parameters estimated by Artuç, Lederman, and Porto (2015), which are not available for the data used here. Labor-related variables are therefore converted to levels. The labor allocation problem under the baseline labor market reform scenario—a 5-percent reduction in mobility costs—is solved in levels, and the main outcome variables are converted into changes, following Caliendo, Dvorkin, and Parro (2019).

[6] The EMDE comparator group is restricted to Asian economies for this exercise, given the aim of accounting for geographic and cultural factors in the estimation of bilateral trade barriers. For Bangladesh, India, and Sri Lanka, the 25th percentile trade costs among China, Cambodia, Indonesia, the Philippines, Thailand, and Viet Nam is chosen as a benchmark, and for Bhutan, Maldives, and Nepal, the comparator group is defined as Armenia, Brunei Darussalam, Mongolia, Fiji, Lao People's Democratic Republic, and Kyrgyz Republic. The median trade cost is used because trade data are noisier for island and land-locked economies.

ANNEX TABLE A3.1.1 Episodes of major trade reforms

Country code	Year	Tariff reduction over the first five years (percentage points)	Country code	Year	Tariff reduction over the first five years
BGD	1998	-7.96	KEN	2001	-8.13
BGR	2005	-7.88	KOR	2016	-6.12
BRA	1989	-28.46	MAR	2010	-12.62
CHE	1995	-7.49	MEX	2001	-10.04
CHN	1992	-23.05	MKD	2004	-6.55
CHN	2001	-6.5	MYS	1998	-6.15
COL	2010	-6.25	NPL	1998	-6.8
CRI	1996	-5.63	NZL	1992	-9.31
CYP	1996	-8.16	PAK	1998	-28.85
DOM	2000	-9.88	PHL	1989	-7.15
DZA	2001	-6.04	PHL	1995	-12.6
EGY	2002	-26.28	RWA	2008	-7.55
IDN	1995	-5.99	SAU	2001	-8.52
IND	2001	-17.93	SVN	2001	-8.34
ISR	1999	-9.71	THA	1999	-31.29
JAM	1999	-8.7	ZMB	2004	-7.1
JOR	2000	-11.53			

Sources: World Development Indicators (database); World Bank.

Note: BGD = Bangladesh; BGR = Bulgaria; BRA = Brazil; CHE = Switzerland; CHN = China; COL = Colombia; CRI = Costa Rica; CYP = Cyprus; DOM = Dominican Republic; DZA = Algeria; EGY = Egypt, Arab Rep.; IDN = Indonesia; IND = India; ISR = Israel; JAM = Jamaica; JOR = Jordan; KEN = Kenya; KOR = Korea, Rep.; MAR = Morocco; MEX = Mexico; MKD = North Macedonia; MYS = Malaysia; NPL = Nepal; NZL = New Zealand; PAK = Pakistan; PHL = Philippines; RWA = Rwanda; SAU = Saudi Arabia; SVN = Slovenia; THA = Thailand; ZMB = Zambia.

ANNEX TABLE A3.1.2 Episodes of major trade reforms: Summary statistics

Characteristic	Value
Number of countries	31
Number of episodes	33
Number of episodes per country	1.1
Average duration (number of years between start and end of episode)	7.4
Average amplitude (percentage point tariff cut between start and end of episode)	-15.3

Sources: IMF World Economic Outlook (database); World Development Indicators (database); World Bank.

ANNEX TABLE A3.1.3 Characteristics of seed articles

Seed article	Methodology	Country coverage
Autor, Dorn, and Hanson (2013)	Empirical estimate	U.S.
Bernard et al. (2007)	Literature review	Cross-country
Caliendo, Dvorkin, and Parro (2019)	Structural model	U.S.
Dix-Carneiro and Kovak (2019)	Empirical estimate	Brazil
Dutt, Mitra, and Ranjan (2009)	Empirical estimate	Cross-country
Goldberg and Pavcnik (2007)	Literature review	Cross-country
McCaig and Pavcnik (2018)	Empirical estimate	Viet Nam

ANNEX TABLE A3.1.4 Citation chasing on seed articles using Scopus

Seed article	Scopus forward search		Scopus backward search	Scopus related-paper search	Remove cross-method duplicates	Journal filtered	Keyword filtered
	1st layer	2nd layer					
Autor, Dorn, and Hanson (2013)	1,973	20,000	70	20,000	34,437	11,509	1,788
Bernard et al. (2007)	1,223	19,966	45	19,992	32,642	9,815	1,973
Caliendo, Dvorkin, and Parro (2019)	212	2,278	51	17,165	17,827	7,851	1,500
Dix-Carneiro and Kovak (2019)	88	523	63	15,082	14,435	5,401	899
Dutt, Mitra, and Ranjan (2009)	171	1,512	28	20,000	19,681	6,474	584
Goldberg and Pavcnik (2007)	803	15,639	110	20,000	29,728	9,138	2,025
McCaig and Pavcnik (2018)	110	1,440	77	20,000	19,754	8,158	1,496

Note: Forward search pulls articles that cite the seed article (first layer) or cite the article citing the seed article (second layer). Backward search pulls articles that are in the reference list of the seed article. Related-article search pulls articles that share common references with the seed article. Because of the sheer number of articles, second-layer forward search and related-article search from Scopus are each capped at 20,000 of the most relevant articles for each seed article. Journal filtering keeps articles published in the top 250 ranked economics journals on RePEc. Keyword filtering keeps articles that include two keywords: one from the set “trade”, “import”, “export”, “globalization”; the other from the set “job”, “employment”, “productivity”, “wage”, “labor”.

ANNEX TABLE A3.1.5 Reviewed articles and estimates by publication and sample years

A. Publication year and date years

Characteristics	Count of studies/ sub-studies	Minimum	Median	Maximum
Publication year	83	2000	2014	2025
Data years				
Start year	102	1900	1991	2013
End year	102	1940	2001	2017
Number of years	102	0	10	40

Note: Several studies use more than one sample period, for which sub-studies are defined for this summary table.

B. Data decade by article and estimates

Characteristics	Pre-1980s	1980s	1990s	2000s
By data start year				
Count of studies/sub-studies	8	30	41	23
Count of estimates	42	276	380	132
By data end year				
Count of studies/sub-studies	1	4	31	51
Count of estimates	3	15	299	432

Note: Several studies use more than one sample period, for which sub-studies are defined for this summary table.

ANNEX TABLE A3.1.6 Estimates by region and level of analysis

Region	Worker	Firm	Sector	Location	Country
EMDE	149	252	124	168	2
EAP	60	45	17	76	0
ECA	0	8	0	0	0
LAC	35	109	57	61	2
MNA	0	29	0	0	0
SAR	2	63	50	31	0
SSA	52	0	0	0	0
Advanced economy	27	47	13	14	0
Mixed	0	0	8	0	27

Note: EAP = East Asia and Pacific; ECA = Europe and Central Asia; EMDEs = emerging market and developing economies; LAC = Latin America and the Caribbean; MNA = Middle East and North Africa; SAR = South Asia; SSA = Sub-Saharan Africa. Firm level includes firms and plants. Level of analysis is defined based on the level of empirical estimates. Sector level includes sectors and industries. Location level includes commuter zones, cities, counties, and other subnational geographical units.

ANNEX TABLE A3.1.7 Estimates by region and outcome or policy type

A. Outcome type

Region	Employment	Wage	Productivity
EMDE	294	228	151
EAP	96	62	38
ECA	2	0	6
LAC	98	100	66
MNA	18	0	11
SAR	46	48	30
SSA	34	18	0
Advanced economy	43	33	25
Mixed	31	0	4

Note: EAP = East Asia and Pacific; ECA = Europe and Central Asia; EMDEs = emerging market and developing economies; LAC = Latin America and the Caribbean; MNA = Middle East and North Africa; SAR = South Asia; SSA = Sub-Saharan Africa. Studies covering Korea before 1990 are counted as part of the EMDE sample. Studies covering a group of advanced economies, such as the European Union (EU-15), are counted as part of the advanced-economy sample. Twenty-four estimates with poverty as the outcome are not included in the outcome-type count.

B. Policy type

Region	Output tariff	Input tariff	FTA	Other
EMDE	397	92	101	107
EAP	81	34	46	37
ECA	1	0	0	7
LAC	170	27	44	23
MNA	0	0	11	18
SAR	93	31	0	22
SSA	52	0	0	0
Advanced economy	55	0	17	29
Mixed	3	0	0	32

Note: EAP = East Asia and Pacific; ECA = Europe and Central Asia; EMDEs = emerging market and developing economies; LAC = Latin America and the Caribbean; MNA = Middle East and North Africa; SAR = South Asia; SSA = Sub-Saharan Africa. Studies covering Korea before 1990 are counted as part of the EMDE sample. Studies covering a group of advanced economies, such as the European Union (EU-15), are counted as part of the advanced-economy sample.

ANNEX TABLE A3.1.8 Summary of sample used for the ordered probit estimation

A. Estimate count by outcome type and worker characteristics

Outcome type	Worker skill			Worker gender			Worker age		
	Skilled	Unskilled	Mixed	Women	Men	Mixed	<30	≥30	Mixed
Employment	37	25	215	52	28	197	10	22	241
Wage	61	59	152	17	1	254	0	0	271
Productivity	0	0	179	0	0	179	0	0	179

Note: A "skilled" worker is one defined as skilled in the study, or is a white-collar or non-production worker, or has completed at least high school or upper-secondary school. Country-level studies are excluded. Estimates where outcome variable focuses on the informal sector are excluded.

B. Estimate count by outcome type and firm characteristics

Outcome type	Firm sector			Firm size			Firm import		
	Manufacturing	Non-manufacturing	Mixed	Small	Big	Mixed	Importer	Non-importer	Mixed
Employment	63	12	202	4	4	267	2	20	255
Wage	93	10	169	10	10	252	4	4	264
Productivity	114	0	65	8	27	144	3	3	173

Note: A "small firm" is one defined as small in the study or as having fewer than 50 workers or fewer than the median number of workers. An "importer" is a firm that imports or has high import share. Country-level studies are excluded. Estimates where the outcome variable focuses on the informal sector are excluded.

C. Estimate count by outcome type and policy instrument

Outcome type	Input tariff	General tariff	FTA
Employment	15	161	38
Wage	29	156	47
Productivity	50	69	22

Note: FTA = free trade agreement. Country-level studies are excluded. Estimates where the outcome variable refers to the informal sector are excluded.

ANNEX TABLE A3.1.9 Country coverage and year of latest labor force survey microdata

South Asia		Comparator EMDEs	
Bangladesh	2022	Brazil	2022
Bhutan	2024	Georgia	2023
India	2023	Mexico	2023
Maldives	2019	Mongolia	2022
Nepal	2017	Philippines	2022
Sri Lanka	2023	Thailand	2021

ANNEX TABLE A3.1.10 List of sectors

Sector	ISIC Rev. 4	Short name	Broad category
n1	01-04	Agriculture	Agriculture
n2	05-09, 35-44	Non-manufacturing industry	Other industry
n3	10-12	Food and beverages	Light manufacturing
n4	13-15	Textiles	Light manufacturing
n5	16-18	Wood products	Light manufacturing
n6	19-25	Fuel, chemicals, and metals	Heavy manufacturing
n7	26-30	Electronics, machinery, and transport equipment	Heavy manufacturing
n8	31-33	Other manufacturing	Light manufacturing
n9	45-48	Trade services	Other services
n10	55-57	Accommodation and food services	Other services
n11	49-54	Transportation and storage	Other services
n12	58-63	Information and communication	Business services
n13	64-68	Finance, insurance, and real estate	Business services
n14	69-83	Technical and administrative services	Business services
n15	84	Public administration and defense	Other services
n16	85	Education	Other services
n17	86-89	Health and social work	Other services
n18	90-99	Other services	Other services

ANNEX TABLE A3.1.11 The relationship between wages and tariffs

	(1)	(2)	(3)	(4)
Panel A.	**EMDEs**	**SAR**	**EMDEs**	**SAR**
Intermediate input tariff	-3.071***	-2.232**	-1.048**	-0.933**
	(1.112)	(0.972)	(0.407)	(0.441)
Male			0.207***	0.206***
			(0.024)	(0.026)
Urban			0.114***	0.122***
			(0.011)	(0.014)
Less than primary education			-0.101***	-0.097***
			(0.025)	(0.030)
Secondary education			0.177***	0.164***
			(0.022)	(0.021)
Post-secondary education			0.654***	0.576***
			(0.062)	(0.053)
Experience			0.031***	0.030***
			(0.003)	(0.004)
Experience squared			-0.000***	-0.000***
			(0.000)	(0.000)
Number of observations	481,442	69,764	431,174	67,379
R-sq	0.011	0.014	0.244	0.325

Note: EMDEs = emerging market and developing economies. SAR = South Asia. Dependent variable is wage relative to the national mean. Experience is defined as age minus years of education minus 6. For comparability, sample is restricted to monthly wage earners in goods producing sectors. Country fixed effects and sample weights are included. Standard errors are clustered at the country–sector level. * p<0.10, ** p<0.05, *** p<0.01.

ANNEX TABLE A3.1.11 The relationship between wages and tariffs (continued)

Panel B.	(1) EMDEs	(2) SAR	(3) EMDEs	(4) SAR
Output tariff	-1.374***	-1.419***	-0.550***	-0.461**
	(0.310)	(0.449)	(0.158)	(0.211)
Male			0.201***	0.205***
			(0.021)	(0.027)
Urban			0.116***	0.121***
			(0.011)	(0.014)
Less than primary education			-0.095***	-0.097***
			(0.029)	(0.030)
Secondary education			0.178***	0.163***
			(0.023)	(0.021)
Post-secondary education			0.640***	0.573***
			(0.064)	(0.053)
Experience			0.032***	0.030***
			(0.003)	(0.004)
Experience squared			-0.000***	-0.000***
			(0.000)	(0.000)
Number of observations	479,458	69,764	431,174	67,379
R-sq	0.014	0.027	0.244	0.325

Note: EMDEs = emerging market and developing economies. SAR = South Asia. Dependent variable is wage relative to the national mean. Experience is defined as age minus years of education minus 6. For comparability, sample is restricted to monthly wage earners in goods producing sectors. Country fixed effects and sample weights are included. Standard errors are clustered at the country–sector level. * p<0.10, ** p<0.05, *** p<0.01.

ANNEX TABLE A3.1.12 The relationship between worker characteristics and tariffs

	P(high-skilled employment)		P(employed under 30)	
	(1) EMDEs	(2) SAR	(3) EMDEs	(4) SAR
Panel A.				
Output tariff	-3.654***	-0.295***	-1.047***	-0.446***
	(1.396)	(0.100)	(0.265)	(0.122)
Number of observations	906,798	237,925	991,788	263,063
Panel B.				
Intermediate input tariff	-11.193***	-2.386**	-1.790*	-0.620
	(3.552)	(0.921)	(0.941)	(0.377)
Number of observations	2,125,009	404,457	2,259,908	430,390

Note: EMDEs = emerging market and developing economies. SAR = South Asia. Dependent variable is the indicator for the probability of high-skilled employment (cols. 1–2) or the probability of employment for workers under the age of 30 (cols. 3–4). Explanatory variable is the output tariff rate (Panel A) or intermediate input tariff rate (Panel B). Probit model, with standard errors clustered at the country–sector level. Sample weights included. * p<0.10, ** p<0.05, *** p<0.01.

References

Abadie, A., A. Diamond, and J. Hainmueller. 2010. "Synthetic Control Methods for Comparative Case Studies: Estimating the Effect of California's Tobacco Control Program." *Journal of the American Statistical Association* 105 (490): 493–505.

Abeywardene, J., R. de Alwis, A. Jayasena, S. Jayaweera, and T. Sanmugam. 1994. "Export Processing Zones in Sri Lanka: Economic Impact and Social Issues." Multinational Enterprises Programme Working Paper No. 69, International Labour Organization, Geneva.

Aizenman, J., and Y. Jinjarak. 2009. "Globalisation and Developing Countries—a Shrinking Tax Base?" *Journal of Development Studies* 45 (5): 653–71.

Almeida, R., and P. Carneiro. 2009. "The Return to Firm Investments in Human Capital." *Labour Economics* 16 (1): 97–106.

Amaya, S. 2020. "The Failure of Industrial Policy: India as a Case Study." UMF Market Trends, Universidad Francisco Marroquín, Guatemala City.

Amiti, M., and D. R. Davis. 2012. "Trade, Firms, and Wages: Theory and Evidence." *Review of Economic Studies* 79 (1): 1–36.

Artuç, E., S. Chaudhuri, and J. McLaren. 2010. "Trade Shocks and Labor Adjustment: A Structural Empirical Approach." *American Economic Review* 100 (3): 1008–45.

Artuç, E., D. Lederman, and G. Porto. 2015. "A Mapping of Labor Mobility Costs in the Developing World." *Journal of International Economics* 95 (1): 28–41.

Artuç, E., G. Lopez-Acevedo, R. Robertson, and D. Samaan. 2019. *Exports to Jobs: Boosting the Gains from Trade in South Asia.* Washington, DC: World Bank.

Attanapola, C. T. 2005. "Experiences of Globalization and Health in the Narratives of Women Industrial Workers in Sri Lanka." *Gender, Technology and Development* 9 (1): 81–102.

Attanasio, O., P. K. Goldberg, and N. Pavcnik. 2004. "Trade Reforms and Wage Inequality in Colombia." *Journal of Development Economics* 74 (2): 331–66.

Autor, D. H., D. Dorn, and G. H. Hanson. 2013. "The China Syndrome: Local Labor Market Effects of Import Competition in the United States." *American Economic Review* 103 (6): 2121–68.

Bas, M., and C. Paunov. 2021. "Input Quality and Skills Are Complementary and Increase Output Quality: Causal Evidence from Ecuador's Trade Liberalization." *Journal of Development Economics* 151 (June): 102668.

Baunsgaard, T., and M. Keen. 2010. "Tax Revenue and (or?) Trade Liberalization." *Journal of Public Economics* 94 (9–10): 563–77.

Ben Yahmed, S., and P. Bombarda. 2020. "Gender, Informal Employment and Trade Liberalization in Mexico." *The World Bank Economic Review* 34 (2): 259–83.

Bernard, A. B., J. B. Jensen, S. J. Redding, and P. K. Schott. 2007. "Firms in International Trade." *Journal of Economic Perspectives* 21 (3): 105–30.

Bernard, A. B., J. B. Jensen, S. J. Redding, and P. K. Schott. 2018. "Global Firms." *Journal of Economic Literature* 56 (2): 565–619.

Bernhofen, D. M., and J. C. Brown. 2004. "A Direct Test of the Theory of Comparative Advantage: The Case of Japan." *Journal of Political Economy* 112 (1): 48–67.

Bernhofen, D. M., and J. C. Brown. 2005. "An Empirical Assessment of the Comparative Advantage Gains from Trade: Evidence from Japan." *American Economic Review* 95 (1): 208–25.

Caliendo, L., M. Dvorkin, and F. Parro. 2019. "Trade and Labor Market Dynamics: General Equilibrium Analysis of the China Trade Shock." *Econometrica* 87 (3): 741–835.

Caliendo, L., and F. Parro. 2015. "Estimates of the Trade and Welfare Effects of NAFTA." *Review of Economic Studies* 82 (1): 1–44.

Chakraborty, P., and O. Raveh. 2018. "Input-Trade Liberalization and the Demand for Managers: Evidence from India." *Journal of International Economics* 111 (March): 159–76.

Chamarbagwala, R., and G. Sharma. 2011. "Industrial De-licensing, Trade Liberalization, and Skill Upgrading in India." *Journal of Development Economics* 96 (2): 314–36.

Cisneros-Acevedo, C. 2022. "Unfolding Trade Effect in Two Margins of Informality. The Peruvian Case." *World Bank Economic Review* 36 (1): 141–70.

Coşar, A. K., N. Guner, and J. Tybout. 2016. "Firm Dynamics, Job Turnover, and Wage Distributions in an Open Economy." *American Economic Review* 106 (3): 625–63.

Dai, M., W. Huang, and Y. Zhang. 2021. "How Do Households Adjust to Tariff Liberalization? Evidence from China's WTO Accession." *Journal of Development Economics* 150 (May): 102628.

De Loecker, J., P. K. Goldberg, A. K. Khandelwal, and N. Pavcnik. 2016. "Prices, Markups, and Trade Reform." *Econometrica* 84 (2): 445–510.

Dhyne, E., A. K. Kikkawa, M. Mogstad, and F. Tintelnot. 2021. "Trade and Domestic Production Networks." *Review of Economic Studies* 88 (2): 643–68.

Dix-Carneiro, R. 2014. "Trade Liberalization and Labor Market Dynamics." *Econometrica* 82 (3): 825–85.

Dix-Carneiro, R., P. K. Goldberg, C. Meghir, and G. Ulyssea. 2025. "Trade and Domestic Distortions: The Case of Informality." NBER Working Paper 28391, National Bureau of Economic Research, Cambridge, MA.

Dix-Carneiro, R., and B. K. Kovak. 2019. "Margins of Labor Market Adjustment to Trade." *Journal of International Economics* 117 (March): 125–42.

Dix-Carneiro, R., and B. K. Kovak. 2025. "Globalization and Inequality in Latin America." *Oxford Open Economics* 4 (Supp. 1): i376–99.

Dutt, P., D. Mitra, and P. Ranjan. 2009. "International Trade and Unemployment: Theory and Cross-National Evidence." *Journal of International Economics* 78 (1): 32–44.

Eaton, J., and S. Kortum. 2002. "Technology, Geography, and Trade." *Econometrica* 70 (5): 1741–79.

Edmonds, E. V., N. Pavcnik, and P. Topalova. 2010. "Trade Adjustment and Human Capital Investments: Evidence from Indian Tariff Reform." *American Economic Journal: Applied Economics* 2 (4): 42–75.

Emran, M. S., and J. Stiglitz. 2005. "On Selective Indirect Tax Reform in Developing Countries." *Journal of Public Economics* 89 (4): 599–623.

Fajnzylber, P., W. F. Maloney, and G. V. Montes-Rojas. 2011. "Does Formality Improve Micro-Firm Performance? Evidence from the Brazilian SIMPLES Program." *Journal of Development Economics* 94 (2): 262–76.

Feng, L., Z. Li, and D. L. Swenson. 2016. "The Connection Between Imported Intermediate Inputs and Exports: Evidence from Chinese Firms." *Journal of International Economics* 101 (C): 86–101.

Freeman, R., M. Larch, A. Theodorakopoulos, and Y. V. Yotov. 2025. "Unlocking New Methods to Estimate Country-Specific Effects and Trade Elasticities with the Structural Gravity Model." *Journal of Applied Econometrics, 3133.*

Gai, Q., N. Guo, B. Li, Q. Shi, and X. Zhu. 2025. "Rural Pensions, Labor Reallocation, and Aggregate Income: An Empirical and Quantitative Analysis of China." *Econometrica* 93 (5): 1663–1696.

Galal, R., M. Schiffbauer, A. Rossignol, and G. Dexter. 2025. *Frontier Firms and Job Creation in Bangladesh.* Washington, DC: World Bank Group.

Galiani, S., and P. Sanguinetti. 2003. "The Impact of Trade Liberalization on Wage Inequality: Evidence from Argentina." *Journal of Development Economics* 72 (2): 497–513.

Goldberg, P. K., A. K. Khandelwal, N. Pavcnik, and P. Topalova. 2010. "Multiproduct Firms and Product Turnover in the Developing World: Evidence from India." *Review of Economics and Statistics* 92 (4): 1042–49.

Goldberg, P. K., and N. Pavcnik. 2003. "The Response of the Informal Sector to Trade Liberalization." *Journal of Development Economics* 72 (2): 463–96.

Goldberg, P. K., and N. Pavcnik. 2007. "Distributional Effects of Globalization in Developing Countries." *Journal of Economic Literature* 45 (1): 39–82.

Goldberg, P. K., and T. Reed. 2023. "Presidential Address: Demand-Side Constraints in Development. The Role of Market Size, Trade, and (In)Equality." *Econometrica* 91 (6): 1915–50.

Gopinath, G., and B. Neiman. 2014. "Trade Adjustment and Productivity in Large Crises." *American Economic Review* 104 (3): 793–831.

Gupta, A. 2021. "Effect of Trade Liberalization on Gender Inequality: The Case of India." *IMF Economic Review* 69 (4): 682–720.

Halpern, L., M. Koren, and A. Szeidl. 2015. "Imported Inputs and Productivity." *American Economic Review* 105 (12): 3660–703.

Hasan, R., D. Mitra, P. Ranjan, and R. N. Ahsan. 2012. "Trade Liberalization and Unemployment: Theory and Evidence from India." *Journal of Development Economics* 97 (2): 269–80.

Hoekman, B., and M. Sanfilippo. 2023. "Trade and Value Chain Participation: Domestic Firms and FDI Spillovers in Africa." *The World Economy* 46 (11): 3367–91.

Irwin, D. A. 2025a. "Does Trade Reform Promote Economic Growth? A Review of Recent Evidence." *The World Bank Research Observer* 40 (1): 147–84.

Irwin, D. A. 2025b. "Trade Policy, Exchange Rates, and the Globalization Surge of the 1990s." *Journal of Economic History* 85 (2): 303–35.

Juhn, C., G. Ujhelyi, and C. Villegas-Sanchez. 2014. "Men, Women, and Machines: How Trade Impacts Gender Inequality." *Journal of Development Economics* 106 (January): 179–93.

Kambourov, G. 2009. "Labour Market Regulations and the Sectoral Reallocation of Workers: The Case of Trade Reforms." *Review of Economic Studies* 76 (4): 1321–58.

Kathuria, S. 2018. *A Glass Half Full: The Promise of Regional Trade in South Asia*. Washington, DC: World Bank.

Keen, M., and J. E. Ligthart. 2002. "Coordinating Tariff Reduction and Domestic Tax Reform." *Journal of International Economics* 56 (2): 489–507.

Kis-Katos, K., and R. Sparrow. 2015. "Poverty, Labor Markets and Trade Liberalization in Indonesia." *Journal of Development Economics* 117 (November): 94–106.

Krueger, A. B., and L. H. Summers. 1988. "Efficiency Wages and the Inter-Industry Wage Structure." *Econometrica* 56 (2): 259–93.

Kruse, H., M. P. Timmer, G. J. de Vries, and X. Ye. 2024. "The Occupation Content of Trade." *World Bank Economic Review* 00 (0): 1–15. https://doi.org/10.1093/wber/lhae051.

Laeven, L., and F. Valencia. 2020. "Systemic Banking Crises Database II." *IMF Economic Review* 68: 307–61.

Leblebicioğlu, A., and A. Weinberger. 2021. "Openness and Factor Shares: Is Globalization Always Bad for Labor?" *Journal of International Economics* 128 (January): 103406.

Lewis, L. T., R. Monarch, M. Sposi, and J. Zhang. 2022. "Structural Change and Global Trade." *Journal of the European Economic Association* 20 (1): 476–512.

Maliszewska, M., and D. Winkler. 2024. *Leveraging Trade for More and Better Jobs*. Washington, DC: World Bank.

McCaig, B., M. Nguyen, and R. Kaestner. 2022. "Export Expansion and Investment in Children's Human Capital: Evidence from the U.S.-Vietnam Bilateral Trade Agreement." NBER Working Paper 29830, National Bureau of Economic Research, Cambridge, MA.

McCaig, B., and N. Pavcnik. 2018. "Export Markets and Labor Allocation in a Low-Income Country." *American Economic Review* 108 (7): 1899–941.

McCaig, B., N. Pavcnik, and W. F. Wong. 2025. "Foreign and Domestic Firms: Long Run Employment Effects of Export Opportunities." NBER Working Paper 30729, National Bureau of Economic Research, Cambridge, MA.

McLaren, J. 2017. "Globalization and Labor Market Dynamics." *Annual Review of Economics* 9: 177–200.

Meng, X. 2012. "Labor Market Outcomes and Reforms in China." *Journal of Economic Perspectives* 26 (4): 75–102.

Muralidharan, K. 2024. *Accelerating India's Development: A State-Led Roadmap for Effective Governance.* New York: Viking Press.

Okunogbe, O., and G. Tourek. 2024. "How Can Lower-Income Countries Collect More Taxes? The Role of Technology, Tax Agents, and Politics." *Journal of Economic Perspectives* 38 (1): 81–106.

Pavcnik, N. 2002. "Trade Liberalization, Exit, and Productivity Improvements: Evidence from Chilean Plants." *Review of Economic Studies* 69 (1): 245–76.

Ponczek, V., and G. Ulyssea. 2022. "Enforcement of Labour Regulation and the Labour Market Effects of Trade: Evidence from Brazil." *Economic Journal* 132 (641): 361–90.

Raihan, S. 2023. "Informal Institutions, the RMG Sector, and the Present Challenge of Export Diversification in Bangladesh." In *Is the Bangladesh Paradox Sustainable?: The Institutional Diagnostic Project*, edited by S. Raihan, F. Bourguignon, and U. Salam, 101-36. Cambridge, U.K.: Cambridge University Press.

Raihan, S., and S. H. Bidisha. 2018. "Female Employment Stagnation in Bangladesh." EDIG Research Paper 5, Overseas Development Institute, The Asia Foundation, and UKaid, London.

Sachs, J. D., and A. M. Warner. 1995. "Natural Resource Abundance and Economic Growth." NBER Working Paper 5398, National Bureau of Economic Research, Cambridge, MA.

Sahn, D. E. 1987. "Change in the Living Standards of the Poor in Sri Lanka During A Period of Macroeconomic Restructuring." *World Development* 15 (6): 809–30.

Sposi, M. 2019. "Evolving Comparative Advantage, Sectoral Linkages, and Structural Change." *Journal of Monetary Economics* 103 (May): 75–87.

Sposi, M., K.-M. Yi, and J. Zhang. 2024. "Deindustrialization and Industry Polarization." NBER Working Paper 29483, National Bureau of Economic Research, Cambridge, MA.

Swazan, I. S., and D. Das. 2022. "Bangladesh's Emergence as a Ready-Made Garment Export Leader: An Examination of the Competitive Advantages of the Garment Industry." *International Journal of Global Business and Competitiveness* 17 (1): 162–74.

Topalova, P. 2010. "Factor Immobility and Regional Impacts of Trade Liberalization: Evidence on Poverty from India." *American Economic Journal: Applied Economics* 2 (4): 1–41.

Topalova, P., and A. Khandelwal. 2011. "Trade Liberalization and Firm Productivity: The Case of India." *Review of Economics and Statistics* 93 (3): 995–1009.

Trefler, D. 2004. "The Long and Short of the Canada-U.S. Free Trade Agreement." *American Economic Review* 94 (4): 870–95.

Ulyssea, G. 2020. "Informality: Causes and Consequences for Development." *Annual Review of Economics* 12: 525–46.

Vegh, C. A., and G. Vuletin. 2015. "How Is Tax Policy Conducted over the Business Cycle?" *American Economic Journal: Economic Policy* 7 (3): 327–70.

Wacziarg, R., and J. S. Wallack. 2004. "Trade Liberalization and Intersectoral Labor Movements." *Journal of International Economics* 64 (2): 411–39.

Wolff, E. N. 2003. "Skills and Changing Comparative Advantage." *Review of economics and Statistics* 85 (1): 77–93.

World Bank. 2020. *World Development Report 2020: Trading for Development in the Age of Global Value Chains*. Washington, DC: World Bank.

World Bank. 2024a. *South Asia Development Update: Jobs for Resilience*. April. Washington, DC: World Bank.

World Bank. 2024b. *South Asia Development Update: Women, Jobs, and Growth*. October. Washington, DC: World Bank.

World Bank. 2024c. *India Development Update: India's Trade Opportunities in a Changing Global Context*. September. Washington, DC: World Bank.

World Bank. 2024d. *Sri Lanka Development Update: Opening Up to the Future*. October. Washington, DC: World Bank.

World Bank. 2025. *South Asia Development Update: Taxing Times*. April. Washington, DC: World Bank.

WTO (World Trade Organization). 1995. "Sri Lanka: November 1995. Trade Policy Reviews: First Press Release, Secretariat and Government Summaries." Press Release PRESS/TPRB/17, November 3, 1995. https://www.wto.org/english/tratop_e/tpr_e/tp017_e.htm.

Studies included in full-text review

Ahsan, R. N. 2013. "Input Tariffs, Speed of Contract Enforcement, and the Productivity of Firms in India." *Journal of International Economics* 90 (1): 181–92.

Ahsan, R. N., and D. Mitra. 2014. "Trade Liberalization and Labor's Slice of the Pie: Evidence from Indian Firms." *Journal of Development Economics* 108 (May): 1–16.

Amiti, M., and L. Cameron. 2012. "Trade Liberalization and the Wage Skill Premium: Evidence from Indonesia." *Journal of International Economics* 87 (2): 277–87.

Amiti, M., and D. R. Davis. 2012. "Trade, Firms, and Wages: Theory and Evidence." *The Review of Economic Studies* 79 (1): 1–36.

Amiti, M., and J. Konings. 2007. "Trade Liberalization, Intermediate Inputs, and Productivity: Evidence from Indonesia." *American Economic Review* 97 (5): 1611–38.

Arnold, J. M., B. S. Javorcik, and A. Mattoo. 2011. "Does Services Liberalization Benefit Manufacturing Firms?: Evidence from the Czech Republic." *Journal of International Economics* 85 (1): 136–46.

Attanasio, O., P. K. Goldberg, and N. Pavcnik. 2004. "Trade Reforms and Wage Inequality in Colombia." *Journal of Development Economics* 74 (2): 331–66.

Baccini, L., G. Impullitti, and E. J. Malesky. 2019. "Globalization and State Capitalism: Assessing Vietnam's Accession to the WTO." *Journal of International Economics* 119 (July): 75–92.

Bai, J., and Y. Wang. 2020. "Returns to Work, Child Labor and Schooling: The Income vs. Price Effects." *Journal of Development Economics* 145 (June): 102466.

Bas, M., and C. Paunov. 2021. "Input Quality and Skills Are Complementary and Increase Output Quality: Causal Evidence from Ecuador's Trade Liberalization." *Journal of Development Economics* 151 (June): 102668.

Ben Yahmed, S., and P. Bombarda. 2020. "Gender, Informal Employment and Trade Liberalization in Mexico." *The World Bank Economic Review* 34 (2): 259–83.

Bernard, A. B., J. B. Jensen, and P. K. Schott. 2006. "Trade Costs, Firms and Productivity." *Journal of Monetary Economics* 53 (5): 917–37.

Beverelli, C., M. Fiorini, and B. Hoekman. 2017. "Services Trade Policy and Manufacturing Productivity: The Role of Institutions." *Journal of International Economics* 104 (January): 166–82.

Bosch, M., E. Goñi-Pacchioni, and W. Maloney. 2012. "Trade Liberalization, Labor Reforms and Formal–Informal Employment Dynamics." *Labour Economics* 19 (5): 653–67.

Chakraborty, P., and O. Raveh. 2018. "Input-Trade Liberalization and the Demand for Managers: Evidence from India." *Journal of International Economics* 111 (March): 159–76.

Chamarbagwala, R., and G. Sharma. 2011. "Industrial De-Licensing, Trade Liberalization, and Skill Upgrading in India." *Journal of Development Economics* 96 (2): 314–36.

Chiquiar, D. 2008. "Globalization, Regional Wage Differentials and the Stolper–Samuelson Theorem: Evidence from Mexico." *Journal of International Economics* 74 (1): 70–93.

Choi, J., I. Kuziemko, E. Washington, and G. Wright. 2024. "Local Economic and Political Effects of Trade Deals: Evidence from NAFTA." *American Economic Review* 114 (6): 1540–75.

Cisneros-Acevedo, C. 2022. "Unfolding Trade Effect in Two Margins of Informality. The Peruvian Case." *The World Bank Economic Review* 36 (1): 141–70.

Dai, M., W. Huang, and Y. Zhang. 2021. "How Do Households Adjust to Tariff Liberalization? Evidence from China's WTO Accession." *Journal of Development Economics* 150 (May): 102628.

Defever, F., M. Imbruno, and R. Kneller. 2020. "Trade Liberalization, Input Intermediaries and Firm Productivity: Evidence from China." *Journal of International Economics* 126 (September): 103329.

Dinopoulos, E., C. Syropoulos, B. Xu, and Y. V. Yotov. 2011. "Intraindustry Trade and the Skill Premium: Theory and Evidence." *Journal of International Economics* 84 (1): 15–25.

Dix-Carneiro, R., and B. K. Kovak. 2017. "Trade Liberalization and Regional Dynamics." *American Economic Review* 107 (10): 2908–46.

Dix-Carneiro, R., and B. K. Kovak. 2019. "Margins of Labor Market Adjustment to Trade." *Journal of International Economics* 117 (March): 125–42.

Dix-Carneiro, R., R. R. Soares, and G. Ulyssea. 2018. "Economic Shocks and Crime: Evidence from the Brazilian Trade Liberalization." *American Economic Journal: Applied Economics* 10 (4): 158–95.

Dutt, P., D. Mitra, and P. Ranjan. 2009. "International Trade and Unemployment: Theory and Cross-National Evidence." *Journal of International Economics* 78 (1): 32–44.

Edmonds, E. V., N. Pavcnik, and P. Topalova. 2010. "Trade Adjustment and Human Capital Investments: Evidence from Indian Tariff Reform." *American Economic Journal: Applied Economics* 2 (4): 42–75.

Erten, B., and P. Keskin. 2024. "Trade-Offs? The Impact of WTO Accession on Intimate Partner Violence in Cambodia." *Review of Economics and Statistics* 106 (2): 322–33.

Erten, B., and J. Leight. 2021. "Exporting Out of Agriculture: The Impact of WTO Accession on Structural Transformation in China." *Review of Economics and Statistics* 103 (2): 364–80.

Erten, B., J. Leight, and F. Tregenna. 2019. "Trade Liberalization and Local Labor Market Adjustment in South Africa." *Journal of International Economics* 118 (May): 448–67.

Eslava, M., J. Haltiwanger, A. Kugler, and M. Kugler. 2013. "Trade and Market Selection: Evidence from Manufacturing Plants in Colombia." *Review of Economic Dynamics* 16 (1): 135–58.

Esquivel, G., and J. A. Rodríguez-López. 2003. "Technology, Trade, and Wage Inequality in Mexico before and after NAFTA." *Journal of Development Economics* 72 (2): 543–65.

Fernandes, A. M. 2007. "Trade Policy, Trade Volumes and Plant-Level Productivity in Colombian Manufacturing Industries." *Journal of International Economics* 71 (1): 52–71.

Gaddis, I., and J. Pieters. 2017. "The Gendered Labor Market Impacts of Trade Liberalization: Evidence from Brazil." *Journal of Human Resources* 52 (2): 457–90.

Galiani, S., and G. G. Porto. 2010. "Trends in Tariff Reforms and in the Structure of Wages." *Review of Economics and Statistics* 92 (3): 482–94.

Galiani, S., and P. Sanguinetti. 2003. "The Impact of Trade Liberalization on Wage Inequality: Evidence from Argentina." *Journal of Development Economics* 72 (2): 497–513.

Goldberg, P. K., and N. Pavcnik. 2003. "The Response of the Informal Sector to Trade Liberalization." *Journal of Development Economics* 72 (2): 463–96.

Goldberg, P. K., and N. Pavcnik. 2005. "Trade, Wages, and the Political Economy of Trade Protection: Evidence from the Colombian Trade Reforms." *Journal of International Economics* 66 (1): 75–105.

Greenland, A., and J. Lopresti. 2024. "Trade Policy as an Exogenous Shock: Focusing on the Specifics." NBER Working Paper 33127, National Bureau of Economic Research, Cambridge, MA.

Gupta, A. 2021. "Effect of Trade Liberalization on Gender Inequality: The Case of India." *IMF Economic Review* 69 (3): 682–720.

Hakobyan, S., and J. McLaren. 2016. "Looking for Local Labor Market Effects of NAFTA." *Review of Economics and Statistics* 98 (4): 728–41.

Han, J., R. Liu, and J. Zhang. 2012. "Globalization and Wage Inequality: Evidence from Urban China." *Journal of International Economics* 87 (2): 288–97.

Hasan, R., D. Mitra, P. Ranjan, and R. N. Ahsan. 2012. "Trade Liberalization and Unemployment: Theory and Evidence from India." *Journal of Development Economics* 97 (2): 269–80.

Hay, D. A. 2001. "The Post-1990 Brazilian Trade Liberalisation and the Performance of Large Manufacturing Firms: Productivity, Market Share and Profits." *The Economic Journal* 111 (473): 620–41.

Iacovone, L. 2012. "The Better You Are the Stronger It Makes You: Evidence on the Asymmetric Impact of Liberalization." *Journal of Development Economics* 99 (2): 474–85.

Jabbour, L., Z. Tao, E. Vanino, and Y. Zhang. 2019. "The Good, the Bad and the Ugly: Chinese Imports, European Union Anti-Dumping Measures and Firm Performance." *Journal of International Economics* 117 (March): 1–20.

Jamil, N., T. T. Chaudhry, and A. Chaudhry. 2022. "Trading Textiles Along the New Silk Route: The Impact on Pakistani Firms of Gaining Market Access to China." *Journal of Development Economics* 158 (September): 102935.

Juhn, C., G. Ujhelyi, and C. Villegas-Sanchez. 2014. "Men, Women, and Machines: How Trade Impacts Gender Inequality." *Journal of Development Economics* 106 (January): 179–93.

Kandilov, I. T. 2009. "Do Exporters Pay Higher Wages? Plant-Level Evidence from an Export Refund Policy in Chile." *The World Bank Economic Review* 23 (2): 269–94.

Kim, E. 2000. "Trade Liberalization and Productivity Growth in Korean Manufacturing Industries: Price Protection, Market Power, and Scale Efficiency." *Journal of Development Economics* 62 (1): 55–83.

Kim, R., and J. Vogel. 2020. "Trade and Welfare (Across Local Labor Markets)." NBER Working Paper 27133, National Bureau of Economic Research, Cambridge, MA, Cambridge, MA.

Kis-Katos, K., and R. Sparrow. 2015. "Poverty, Labor Markets and Trade Liberalization in Indonesia." *Journal of Development Economics* 117 (November): 94–106.

Kondo, I. O., Y. A. Li, and W. Qian. 2024. "Trade Liberalization and Labor Monopsony: Evidence from Chinese Firms." *Journal of International Economics* 152 (November): 104006.

Konings, J., and H. Vandenbussche. 2008. "Heterogeneous Responses of Firms to Trade Protection." *Journal of International Economics* 76 (2): 371–83.

Krishna, P., J. P. Poole, and M. Z. Senses. 2014. "Wage Effects of Trade Reform with Endogenous Worker Mobility." *Journal of International Economics* 93 (2): 239–52.

Leblebicioğlu, A., and A. Weinberger. 2021. "Openness and Factor Shares: Is Globalization Always Bad for Labor?" *Journal of International Economics* 128 (January): 103406.

Linarello, A. 2018. "Direct and Indirect Effects of Trade Liberalization: Evidence from Chile." *Journal of Development Economics* 134 (September): 160–75.

Lu, Y., Z. Tao, and L. Zhu. 2017. "Identifying FDI Spillovers." *Journal of International Economics* 107 (July): 75–90.

McCaig, B. 2011. "Exporting out of Poverty: Provincial Poverty in Vietnam and U.S. Market Access." *Journal of International Economics* 85 (1): 102–13.

McCaig, B., M. Nguyen, and R. Kaestner. 2022. "Export Expansion and Investment in Children's Human Capital: Evidence from the U.S.-Vietnam Bilateral Trade Agreement." NBER Working Paper 29830, National Bureau of Economic Research, Cambridge, MA.

McCaig, B., and N. Pavcnik. 2018. "Export Markets and Labor Allocation in a Low-Income Country." *American Economic Review* 108 (7): 1899–1941.

McCaig, B., N. Pavcnik, and W. F. Wong. 2022. "Foreign and Domestic Firms: Long Run Employment Effects of Export Opportunities." NBER Working Paper 30729, National Bureau of Economic Research, Cambridge, MA.

Mouelhi, R. B. A. 2007. "Impact of Trade Liberalization on Firm's Labour Demand by Skill: The Case of Tunisian Manufacturing." *Labour Economics* 14 (3): 539–63.

Munch, J., and G. Schaur. 2018. "The Effect of Export Promotion on Firm-Level Performance." *American Economic Journal: Economic Policy* 10 (1): 357–87.

Nataraj, S. 2011. "The Impact of Trade Liberalization on Productivity: Evidence from India's Formal and Informal Manufacturing Sectors." *Journal of International Economics* 85 (2): 292–301.

Ozler, S. 2000. "Export Orientation and Female Share of Employment: Evidence from Turkey." *World Development* 28 (7): 1239–48.

Pavcnik, N., B. Andreas, P. Goldberg, and N. Schady. 2004. "Trade Liberalization and Industry Wage Structure: Evidence from Brazil." *The World Bank Economic Review* 18 (3): 319–44.

Pavcnik, N. 2002. "Trade Liberalization, Exit, and Productivity Improvements: Evidence from Chilean Plants." *The Review of Economic Studies* 69 (1): 245–76.

Paz, L. S. 2014. "The Impacts of Trade Liberalization on Informal Labor Markets: A Theoretical and Empirical Evaluation of the Brazilian Case." *Journal of International Economics* 92 (2): 330–48.

Pierce, J. R., P. K. Schott, and C. Tello-Trillo. 2024. "To Find Relative Earnings Gains After the China Shock, Look Outside Manufacturing and Upstream." NBER Working Paper 32438, National Bureau of Economic Research, Cambridge, MA.

Ponczek, V., and G. Ulyssea. 2022. "Enforcement of Labour Regulation and the Labour Market Effects of Trade: Evidence from Brazil." *The Economic Journal* 132 (641): 361–90.

Porto, G. 2006. "Using Survey Data to Assess the Distributional Effects of Trade Policy." *Journal of International Economics* 70 (1): 140–60.

Robertson, R. 2004. "Relative Prices and Wage Inequality: Evidence from Mexico." *Journal of International Economics* 64 (2): 387–409.

Sauré, P., and H. Zoabi. 2014. "International Trade, the Gender Wage Gap and Female Labor Force Participation." *Journal of Development Economics* 111 (November): 17–33.

Schor, A. 2004. "Heterogeneous Productivity Response to Tariff Reduction. Evidence from Brazilian Manufacturing Firms." *Journal of Development Economics* 75 (2): 373–96.

Tanaka, M. 2020. "Exporting Sweatshops? Evidence from Myanmar." *The Review of Economics and Statistics* 102 (3): 442–56.

Topalova, P. 2010. "Factor Immobility and Regional Impacts of Trade Liberalization: Evidence on Poverty from India." *American Economic Journal: Applied Economics* 2 (4): 1–41.

Topalova, P., and A. Khandelwal. 2011. "Trade Liberalization and Firm Productivity: The Case of India." *Review of Economics and Statistics* 93 (3): 995–1009.

Trefler, D. 2004. "The Long and Short of the Canada-U.S. Free Trade Agreement." *American Economic Review* 94 (4): 870–95.

Wacziarg, R., and J. S. Wallack. 2004. "Trade Liberalization and Intersectoral Labor Movements." *Journal of International Economics* 64 (2): 411–39.

Yu, M. 2015. "Processing Trade, Tariff Reductions and Firm Productivity: Evidence from Chinese Firms." *The Economic Journal* 125 (585): 943–88.

Zhang, J., and K. Zhou. 2023. "Quota Removal, Destination-Specific Export Shocks, and Skill Acquisition in China." *Journal of Development Economics* 165 (October): 103149.

Zhou, S., B. He, H. Ni, and S. Pang. 2022. "Trade Liberalization and Regional Labor Market Dynamics: Evidence from China's WTO Accession." *Journal of International Money and Finance* 125 (July): 102635.

South Asia Development Update: Selected Topics, 2018–25

Growth	
Mind the side effects: Remittances and economic structure	Fall 2024, Spotlight 2
Accelerating private investment	Spring 2024, Box 1.1
Private cities: Outstanding examples from developing countries and their implications for urban policy	Urban Development Series, May 2023
Fiscal space and disaster resilience	Spring 2023, Box 2.3
Rising interest-growth differentials and what it means for developing economies	Fall 2022, Box 2.1
COVID-19 vaccination and economic activity in South Asia	Spring 2022, Box 1.1
Financial markets post-lending support measures	Spring 2022, Box 1.3
Shifting gears: Digitization and services-led development	Fall 2021, Chapter 3
Rethinking tourism: Seizing on services links post-COVID	Fall 2021, Box 3.2
Digital technologies can also aid agricultural production	Fall 2021, Box 3.4
The pandemic has exacerbated the difficulties in measuring GDP in South Asia	Spring 2021, Box 1.1
What does a model based on macro trends predict about remittance growth in 2020, and what does it miss?	Spring 2021, Box 1.2
Without immediate action, learning losses and the resulting economic losses in South Asia could be catastrophic	Spring 2021, Box 2.4
Both the spread of COVID-19 and related containment measures contributed to GDP losses	Fall 2020, Box 1.1
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Note: The *South Asia Development Update* was called *South Asia Economic Focus* through Spring 2023.

Growth in South Asia is on track to exceed earlier expectations and reach 6.6 percent in 2025, but is expected to slow to 5.8 percent in 2026, in part as a result of higher-than-expected tariffs on India's exports to the United States. While this short-term outlook is subject to downside risks, over the longer term, artificial intelligence (AI) could promote growth by boosting productivity especially among those 15 percent of South Asian workers who are in jobs where AI strongly complements human labor. Such a growth dividend could be amplified by trade reforms. Carefully sequenced tariff cuts, especially in conjunction with broader free trade agreements, would encourage private investment and job creation in trade-related activities, which disproportionately employ South Asia's younger and higher-skilled workers and have accounted for most of South Asia's employment growth over the past decade. This could particularly benefit manufacturing, where elevated tariffs on production inputs currently diminish competitiveness. South Asia's governments can support the adjustment of labor markets to new technologies and trade opportunities by proactively removing obstacles to workers' reallocation to new firms, occupations, and locations. Simultaneously, they could protect vulnerable workers during this period of change by streamlining and strengthening safety nets.

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