OCTOBER 2026

South Asia Economic Update

Adopting AI for Growth



WORLD BANK GROUP

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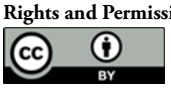
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ISBN (electronic): 978-1-4648-2365-7
DOI: 10.1596/978-1-4648-2365-7

Cover design: David Spours (Cucumber Design); Design and Creative Services, Global Corporate Solutions, World Bank Group.

The cutoff date for the data used in the report was September 23, 2026.

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Acknowledgments

This report was prepared by the Office of the Chief Economist for Asia (DECPA) in collaboration with the Prosperity Practice South Asia (ESADR). The report was managed by Franziska Ohnsorge (Chief Economist, Pacific Asia), under the general guidance of Indermit S. Gill (former Vice President and Chief Economist, Development Economics), Sarvesh Suri (Regional Vice President, Asia Pacific), and Johannes Zutt (Regional Vice President, South Asia).

Chapter 1 was written by Patrick Kirby and incorporates comments from Chetan Ghate (Indian Statistical Institute), Charles Collyns (former IMF), Phil Kenworthy, and Naotaka Sugawara (both DECPG). Box 1.1 was prepared by Lynn Hu, Elina Pradhan (HSAHN), and Zoe Leiyu Xie, and incorporates helpful comments by Charles Collyns (former IMF) and Josh Wilde (University of Oxford). Research assistance was provided by Giorgi Bokhua, Kaihao Cai, Eedo (Yiduo) Mei, Yan Wang, Julius Benedikt Alexander Wolff, and Xiao'ou Zhu.

Colleagues from Economic Policy provided country forecasts and other inputs to the country analysis in Chapter 1, including Abdoul Ganiou Mijiyawa, Anthony Obeyesekere, Arvind Nair, Aurelien Kruse, Dhruv Sharma, Jakob Engel, Kishan Abeygunawardana, Kok Zi Cheng, Mohini Gupta, Naresh Kumar, Nayan Krishna Joshi, Nazmus Sadat Khan, Ran Li, Rangeet Ghosh, Richard Walker, Ruijie Cheng, Sharmin Akter Jahan, Shruti Lakhtakia, Souleymane Coulibaly, Tanvir Malik, Udahiruni Atapattu, Vincent Belinga, and Yumeka Hirano.

Chapter 2 was prepared by Siddharth Sharma and Jonah Rexer, with inputs from Jonathan Timmis. The chapter uses inputs from a paper authored by Saher Asad (HMAPE), Jishnu Das (Georgetown University), Ali Hamza (Georgetown University), Jonah Rexer, Siddharth Sharma and Quetta Winter School Collaborative, and a paper authored by Gaurav Chiplunkar (University of Virginia), Jonah Rexer, Siddharth Sharma, and Pallavi Wats (University of Virginia). The chapter was reviewed by Ruqui Sun (University of Hong Kong), Charles Collyns and Graham Hacche (both former IMF). Helpful comments were provided by Vyjayanti Desai and colleagues from the South Asia Digital team, Gaurav Nayyar (DECWD), Shu Yu (DECPC), and colleagues from the India Economic Policy team including Vincent Belinga, Naresh Kumar, Aurelien Kruse, and Tanvir Malik. Research assistance was provided by Issac Yurui Hu and Xinyi Wang.

Syed Muhammad Shams Sadiq was responsible for the layout and typesetting. David Spours (Cucumber Design) and Design and Creative Services, Global Corporate Solutions, World Bank Group designed the graphics and layout. Graeme Littler copyedited the chapters. Maria Laura Gonzalez Canosa, Elena Karaban, Diana Ya-Wai Chung, and Trishna Thapa (all CER) coordinated the dissemination. Cecile Wodon and Narya Ou provided administrative support.

South Asia as used in this report includes Bangladesh, Bhutan, India, Maldives, Nepal, and Sri Lanka.

The data cutoff date for this report was September 23rd, 2026.

Executive Summary

South Asia's economy is maintaining strong momentum, on the back of robust domestic demand. On average during 2026-27, the region is projected to grow at 6.8 percent, retaining its status as the strongest-growing EMDE region. Growth could be slowed by a severe El Niño, by energy prices remaining persistently elevated, or by global financial market strains. Looking further ahead, the region is aging unusually rapidly, with limited financial security for older people. The creation of more and better jobs is therefore a priority for all age groups. One promising avenue for creating more, better jobs is the widespread deployment of AI. AI adoption in South Asia remains well behind that in advanced economies, but is catching up fast. Growing global value chain connections between U.S. customers and South Asian suppliers in AI-exposed sectors suggest that South Asian firms are using AI to find new market opportunities. AI adoption can be accelerated by strengthening the complementary conditions that foster firms' growth, above all workforce skills, a business-enabling environment, and reliable infrastructure, supported by measures to ease adoption barriers for small firms, foster local AI innovation, and provide a clear AI policy framework that reduces regulatory uncertainty while addressing risks.

Chapter 1. South Asia's High-Energy Growth. South Asia is suffering from high energy prices and has limited involvement in the AI-related supply chains that are currently underpinning global economic activity. Despite this, resilient domestic demand has supported rapid growth in the region and is expected to continue doing so. The region is projected to grow at 6.8 percent per year in 2026–27, on average. Growth in the region could be slowed by persistently elevated energy prices or damage caused by a severe El Niño. While a slowdown in AI investment and related financial turbulence would also weigh on growth in South Asia, the region is less exposed than other EMDE regions. Rising incomes, AI-driven energy demand, and recent oil price spikes make scaling up domestic generation capacity a priority; renewables offer the most cost-effective path for new capacity, and pricing and trade reforms can accelerate their deployment alongside reliable baseload sources. As adoption catches up to peers, AI can offer opportunities for productivity gains and the creation of higher-paying jobs. Tourism and agribusiness offer opportunities to create jobs with low entry barriers at scale if major investment needs and improvements in regulatory environments are addressed.

Box 1.1. South Asia's Compressed Demographic Transition. South Asia's demographic transition is unusually compressed: the working-age share peaks around 2034 and the region turns "aged" by 2049. Currently, aging is often neither productive nor financially secure—longer lives come with more years in poor health, older workers stay in informal, low-productivity jobs, and pension coverage is among the lowest in the world. International experience suggests that older households use a smaller share of their spending on food and clothing and a larger share for services such as health care, hospitality, and communications. Seizing the opportunities offered by an aging society requires policy actions on all fronts at once: accelerating job creation

while building old-age income support and health systems before aging pressures peak.

Chapter 2. Delivering the Promise of AI in South Asia. Artificial intelligence (AI) can transform South Asia's development prospects through several channels, including by boosting the growth of labor productivity, by increasing export opportunities, and by improving the delivery of public services. AI adoption among the region's firms is rising fast but still trails the frontier: about 23 percent of Indian firms report using AI, against 43 percent in the United States, and the gap is wider for more sophisticated uses. Global value-chain links between South Asian suppliers and U.S. customers have grown faster when suppliers and customers are in sectors that are more exposed to AI, suggesting that AI is generating new global market opportunities for the region's firms. Prospects for AI-enhanced public service delivery are mixed: evidence suggests that AI's success in this area depends on tailoring to local conditions. Access to computing power underpins AI, and local data center investment is one means to secure it. For most of the region, the greatest gains lie in adopting AI and adapting it to local conditions—including through small AI applications suited to low-resource settings. Realizing AI's promise will therefore depend on policy action to secure the analog foundations for success, by strengthening workforce skills, establishing a more business-enabling environment, and improving the physical and digital infrastructure. It will also depend on complementary measures to reduce barriers to AI adoption by small firms, foster local AI innovation, and establish a clear regulatory framework that reduces uncertainty and safeguards data security and privacy.

Abbreviations

AE	Advanced Economy
AI	Artificial Intelligence
AIIE	AI Industry Exposure
AIOE	AI Occupation Exposure Index
ASER	Annual Status of Education Report
BACI	Base pour l'Analyse du Commerce International
BAL	Balochistan
BGD	Bangladesh
BLS	U.S. Bureau of Labor Statistics
BPO	Business Process Outsourcing
BRA	Brazil
BTN	Bhutan
CAD	Current Account Deficit
CAN	Canada
CAPE	Cyclically Adjusted Price-to-Earnings Ratio
CATI	Computer-Assisted Telephone Interview
CEPII	Centre d'Études Prospectives et d'Informations Internationales
CERP	Center for Economic Research in Pakistan
CETA	Comprehensive Economic and Trade Agreement
CHN	China
DEU	Germany
EA	Euro Area
EAP	East Asia and the Pacific
ECA	Europe and Central Asia
EMDE	Emerging Market and Developing Economy
EPIC India	Energy Policy Institute at the University of Chicago, India
ESP	Spain
EU	European Union
FAO	Food and Agriculture Organization of the United Nations
FDI	Foreign Direct Investment
FRA	France
GBR	United Kingdom
GDP	Gross Domestic Product
GenAI	Generative Artificial Intelligence
GEPD	Global Education Policy Dashboard
GFS	Government Finance Statistics
GLD	Global Labor Database
GPT	Generative Pre-trained Transformer
GPU	Graphics Processing Unit
GTA	Global Trade Alert
GTED	Global Tax Expenditures Database
GVC	Global Value Chain
H100	NVIDIA H100-series AI chip

Abbreviations (continued)

ICT	Information and Communications Technology
IDA	International Development Association
IEA	International Energy Agency
IEEFA	Institute for Energy Economics and Financial Analysis
IFPRI	International Food Policy Research Institute
IMF	International Monetary Fund
IND	India
ISCO	International Standard Classification of Occupations
ISCO-08	International Standard Classification of Occupations 2008
ISIC	International Standard Industrial Classification
IT	Information Technology
ITA	Idara-e-Taleem-o-Aagahi (Centre of Education and Consciousness)
JPN	Japan
KP	Khyber Pakhtunkhwa
kWh	Kilowatt-hour
LAC	Latin America and the Caribbean
LHS	Left-Hand Side
LLM	Large Language Model
LNG	Liquefied Natural Gas
m^3	Cubic Meter
Mbps	Megabits per Second
MNA	Middle East and North Africa
MPO	Macro Poverty Outlook
NOx	Nitrogen Oxides
O*NET	Occupational Information Network
OLS	Ordinary Least Squares
OpEx	Operational Expenditures
PAL	Ports and Airports Development Levy
PM10	Particulate Matter ≤10 Micrometers in Diameter
PM2.5	Particulate Matter ≤2.5 Micrometers in Diameter
PMI	Purchasing Managers' Index
PPML	Poisson Pseudo-Maximum Likelihood
R&D	Research and Development
RCA	Revealed Comparative Advantage
RCT	Randomized Controlled Trial
resp.	respectively
RHS	Right-Hand Side
RLHF	Reinforcement Learning from Human Feedback
ROW	Rest of the World
S&P	Standard & Poor's
SAR	South Asia Region
SOC	Standard Occupational Classification
SOx	Sulfur Oxides

Abbreviations (continued)

SSA	Sub-Saharan Africa
T&T	Travel and Tourism
TIP	Targeted Instruction Program
TTDI	Travel & Tourism Development Index
TUR	Türkiye
U.S.	United States
USA	United States of America
USD	U.S. Dollar
VAT	Value Added Tax
VIX	CBOE Volatility Index
WBES	World Bank Enterprise Surveys
WBG	World Bank Group
WDI	World Development Indicators
WEO	World Economic Outlook
WTO	World Trade Organization



CHAPTER 1

South Asia's High-Energy Growth

Chapter 1. South Asia's High-Energy Growth

South Asia is suffering from high energy prices and has limited involvement in the AI-related supply chains that are currently underpinning global economic activity. Despite this, resilient domestic demand has supported rapid growth in the region and is expected to continue doing so. The region is projected to grow at 6.8 percent per year in 2026–27, on average. Growth in the region could be slowed by persistently elevated energy prices or damage caused by a severe El Niño. While a slowdown in AI investment and related financial turbulence would also weigh on growth in South Asia, the region is less exposed than other EMDE regions. Rising incomes, AI-driven energy demand, and recent oil price spikes make scaling up domestic generation capacity a priority; renewables offer the most cost-effective path for new capacity, and pricing and trade reforms can accelerate their deployment alongside reliable baseload sources. As adoption catches up to peers, AI can offer opportunities for productivity gains and the creation of higher-paying jobs. Tourism and agribusiness offer opportunities to create jobs with low entry barriers at scale if major investment needs and improvements in regulatory environments are addressed.

Summary

South Asia faces a challenging global environment. The region is a major net oil importer and must contend with elevated energy prices that have pushed inflation up more than elsewhere (figure 1.1). An unusually strong El Niño is straining the region's large agricultural sector. Strong growth in global AI-related trade and investment has largely passed over the region.

Despite these unfavorable forces, South Asia remains the fastest growing region due to strong momentum in consumption and investment. Growth has been more resilient than expected to elevated energy prices and is forecast to accelerate to 6.9 percent in 2026 and remain robust at 6.7 percent in 2027.

Part of the region's resilience may come from steps taken to compensate for lost oil supplies, drawing down inventories, importing solar panels, subsidizing energy prices, or rationing fuel. South Asia responded more intensively than the rest of the world, averaging more than twice as many measures per economy, with a greater focus on demand-side measures.

For now, the impact of energy shortages has been mitigated by a drawdown of inventories and energy subsidies, but these may not be sustainable given the pace of depletion and stretched fiscal positions in many countries. A renewed rise in energy prices may therefore be more damaging to South Asian economies than observed during the initial increase, particularly as the drag from higher inflation and tighter financial conditions grows.

In the longer term, resolving energy shortages while meeting the needs of growing, AI-enabled economies requires scaling up energy generation. This will be supported by increasingly cost-effective technologies such as solar panels and wind turbines. Speeding this process involves removing price distortions that discourage investment in renewables, mobilizing private investment, and investing in grid infrastructure.

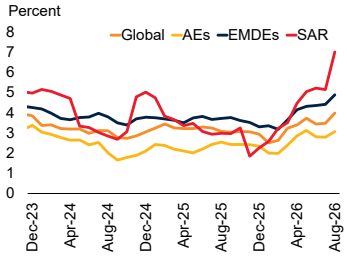
South Asian countries have many reasons to support the transition of people away from low-productivity employment in agriculture and informal activities. To be created at scale,

This chapter was prepared by Patrick Kirby (DECPA).

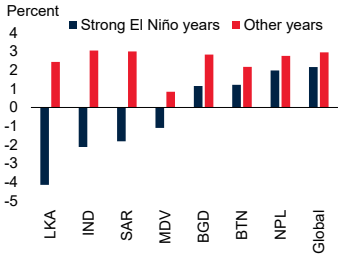
FIGURE 1.1 Summary

South Asia is contending with rising inflation due to elevated energy prices and the prospects of agricultural damage from an unusually strong El Niño. Despite this, the region is growing rapidly thanks to robust domestic demand. Governments in South Asia have taken a variety of steps to compensate for lost oil supplies. Countries can help scale up energy generation capacity by removing distortions that discourage investment in renewables, and help create better jobs by enabling workers to leave agriculture for other sectors.

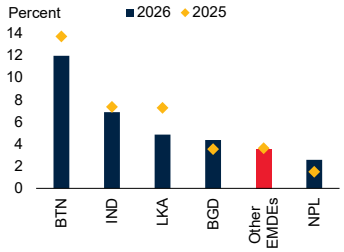
A. Median headline inflation



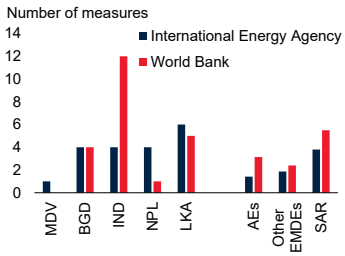
B. Crop production growth during previous strong El Niño episodes



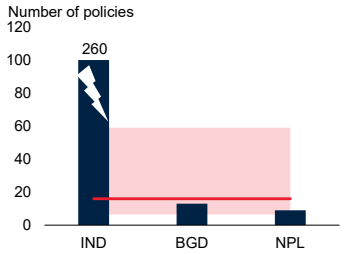
C. Domestic demand growth in South Asia



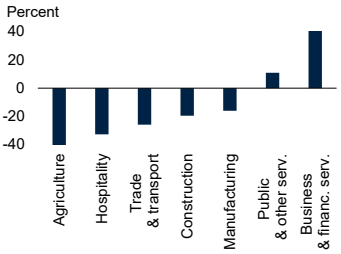
D. Policy response following the Middle East conflict



E. Restrictive policies targeting low carbon technologies



F. Wage differentials from national average



Sources: Haver Analytics; IEA 2026 Energy Crisis Policy Response Tracker; ILOSTAT; IMF Fossil Fuel Subsidies Database; National Oceanic and Atmospheric Administration (NOAA); New Industrial policy Database; WDI; World Bank Policy Tracker; World Bank Group.
A. South Asia includes Bangladesh, Bhutan, India, Maldives, Nepal and Sri Lanka. "Global" includes 138 economies, "AEs" includes 35, and "EMDEs" includes 103.
B. Bars show annualized crop production growth during strong El Niño years and other years. Strong El Niño years (1965, 1972, 1982, 1987, 1992, 1997, 2009, and 2015) are those where the Relative Oceanic Niño Index (RONI) reaches or exceeds 1.5, with five consecutive months above 0.5, with each year referring to the peak of the episode. Regional aggregates are 2010–19 real GDP-weighted. "Global" includes 186 economies; "SAR" includes 6 economies.
C. Domestic demand includes private and government consumption and investment. "Other EMDEs" is aggregated using 2015 real U.S. dollar weights. For India 2026 refers to FY 26/27.
D. Average number of measures as of 16 June 2026, drawn from the IEA 2026 Energy Crisis Policy Response Tracker, which captures energy conservation measures, and the WBG's "Tracking Global Social Policy Responses to High Energy Prices," which tracks fiscal and social protection measures in response to the energy crisis.
E. Chart shows the number of implemented restrictive industrial policies between 2009 and 2025.
F. Chart shows sectoral wages relative to national average. SAR averages are employment weighted. Data are for 2017 (Nepal), 2019 (Maldives), 2022 (Bhutan), 2024 (Bangladesh and Sri Lanka), and 2026 (India).

these jobs must be accessible, without requiring high levels of education or skill. Two sectors have particular potential to create such jobs: tourism and agribusiness. These sectors tend to have low entry barriers, low minimum scales of operation, modular and routine task structures, and labor-intensive production processes.

Across all sectors, policymakers can also spur productivity growth by increasing AI adoption and adaptation to local needs. This can be done by improving digital infrastructure, encouraging private investment that helps South Asian firms move up global value chains away from routine tasks that AI is replacing, and providing the foundational skills people need to use AI tools effectively.

Global developments and outlook

Energy market developments

Since the conflict in the Middle East, shipping through the Strait of Hormuz has been disrupted. This Strait is the world's energy chokepoint, carrying roughly 20 percent of global petroleum consumption and 20 percent of global LNG trade. Oil prices surged as a result, with the Brent oil price peaking at about $110/bbl, comparable to the increase during Russia's initial invasion of Ukraine. The price of many refined energy products, such as diesel and jet fuel, has increased by even more (figure 1.2).

Countries have taken a variety of steps to compensate for lost oil supplies. Inventories have been drawn down, with most stocks falling well below normal historical levels. Imports of solar panels, cells, and wafers have surged, particularly in EMDEs. Some countries, notably China, have reduced oil imports by switching to alternative sources of energy supply or drawing down inventories.

In general, governments have relied on four broad types of measures to cope with the energy-price shock: 1) consumer subsidies and price support, such as capping or freezing fuel and electricity prices and cutting fuel taxes, 2) demand-side measures that curb consumption directly, such as fuel rationing, driving restrictions, and work-from-home or shortened-week mandates, 3) social protection for vulnerable households, mainly cash transfers and in-kind distribution of fuel or essentials, 4) supply-security measures, such as releasing strategic reserves and trade controls.

Subsidies are by far the most common policy response among emerging and developing economies. Of 58 EMDEs tracked, 39 provided at least one new subsidy in response to the disruption of energy supplies. Many countries have also ramped up subsidies that were already in place. It is not clear how effective these policies have been, however. Countries with substantial subsidies in place generally have had smaller increases in retail gasoline prices than non-subsidizers, but this relationship weakens considerably for headline inflation.

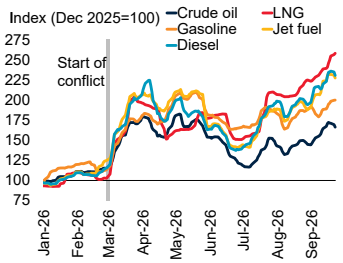
Other tools are far less universal—demand-side measures (fuel rationing, driving restrictions, work-from-home or shortened-week mandates) were adopted by only about a fifth of EMDEs, and social protection by roughly one in seven. Most developing economies thus converged on subsidies and price support, with only a minority layering on demand-side or social-protection measures.

South Asia has responded more intensively than the rest of the world, averaging more than twice as many measures per economy. The composition in South Asia differs from the global pattern, with demand-side measures accounting for close to one-third of its measures, versus roughly a tenth globally.

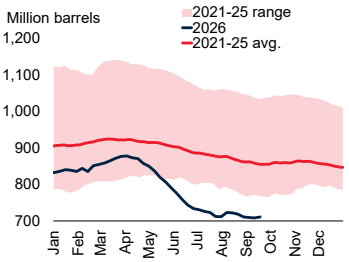
FIGURE 1.2 Energy market developments

Since the disruption of shipping in the Strait of Hormuz, prices of oil, LNG, and refined energy have risen sharply. Commercial and public oil inventories have been substantially drawn down and imports of renewable energy sources have soared. China has reduced energy imports and other countries have implemented a variety of policy measures to mitigate the impact of more expensive energy.

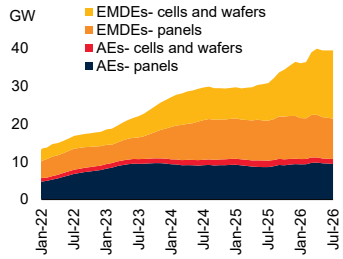
A. Crude oil, LNG, and refined-product prices



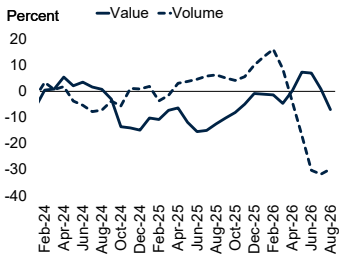
B. U.S. total crude oil inventories



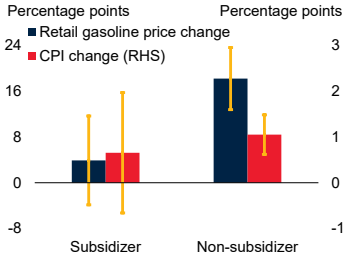
C. Solar imports by region and type, 12-month moving average



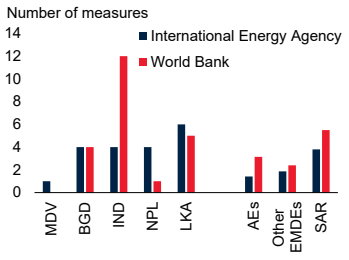
D. Crude oil import growth in China, 3-month moving average



E. Retail gasoline and CPI change, by subsidy status



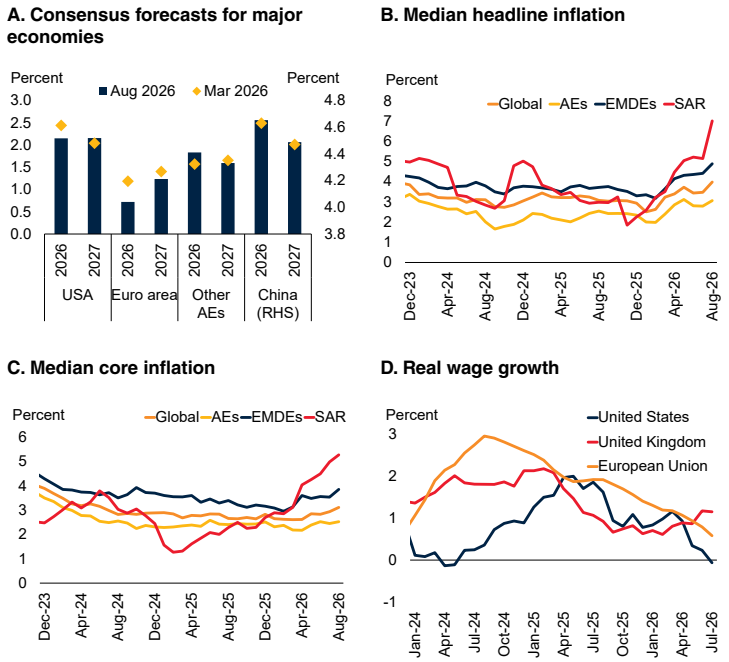
F. Policy response following the Middle East conflict



Sources: Ember; Federal Reserve Bank of St. Louis; Global Petrol Prices; Haver Analytics; IEA 2026 Energy Crisis Policy Response Tracker; U.S. Energy Information Administration; World Bank Policy Tracker; World Bank Group.
A. Lines show seven-day moving averages of prices, indexed to an average of 100 in December 2025. Crude oil refers to Brent crude oil; LNG to Platts Japan/Korea Marker (JKM) futures; gasoline to New York Harbor gasoline; diesel to the ICE Low Sulphur Gasoil continuous futures contract; and jet fuel to U.S. Gulf Coast kerosene-type jet fuel spot prices.
B. Weekly data interpolated to daily frequency and aligned by date. Shaded area shows minimum-to-maximum range across 2021–25 for each date; red line shows 2021–25 average; and blue line shows inventories in 2026. Data include the sum of the Strategic Petroleum Reserve and private crude oil stocks.
C. Area shows monthly solar imports from China. Solar panels are represented by HS code 85414300, solar cells by HS code 85414200, and solar wafers by HS code 38180019 through 2025 and 38180015 from 2026 onward.
D. The series are year-on-year growth rates of trailing 3-month moving averages.
E. Subsidizers had an explicit gasoline or diesel subsidy above 0.21% of GDP in 2024 (IMF global median); others are non-subsidizers. Gasoline price changes are latest vs. February levels. Bars show group averages; whiskers show 95% confidence intervals. Sample includes 38 EMDEs and 22 advanced economies.
F. Average number of measures as of 16 June 2026, drawn from the IEA 2026 Energy Crisis Policy Response Tracker, which captures energy conservation measures, and the WBG's "Tracking Global Social Policy Responses to High Energy Prices," which tracks fiscal and social protection measures in response to the energy crisis.

FIGURE 1.3 Global growth and inflation

The impact of lower oil supplies on economic activity has been limited thus far. The impact on headline inflation (but not core) is more apparent and has weighed on real wage growth.



Sources: CEIC; Consensus Economics; Haver Analytics; World Bank Group.
A. "Other AEs" includes 15 advanced economies.
B. "SAR" includes Bangladesh, Bhutan, India, Maldives, Nepal, and Sri Lanka. "Global" includes 138 economies, "AE" includes 35, and "EMDEs" includes 103.
C. "SAR" includes India and Sri Lanka. "Global" includes 78 economies, "AE" includes 31, and "EMDEs" includes 47.
D. Chart shows year-over-year growth rates of 6-month moving averages of real wages. Last observation is September 23, 2026.

Global economic activity

The global economic impact of lower oil supply has thus far been modest. Consensus forecasts for growth in major economies in 2026 were downgraded after the outbreak of hostilities in February and have remained stable since, with no systematic increases or decreases (figure 1.3). By contrast, the impact on prices has been rising around the world. Despite the mitigating efforts of fuel subsidies and price caps in some countries, headline inflation has sharply increased in many countries, even as core inflation has remained more subdued. Rising inflation has depressed real wage growth to around zero in major advanced economies.

Rising prices have also put an end to a global monetary easing cycle, with major central banks expected to keep rates steady in the near-term (figure 1.4). This has contributed to a steady increase in borrowing costs and substantial capital outflows from EMDEs.

Stock markets and global trade are being supported by AI-related investment. Technology stocks account for a growing share of major stock indexes, and for all of recent stock market gains—if tech stocks were excluded, most major stock index valuations would have declined thus far in 2026. The same is true for global trade: headline trade growth has been strong, but growth excluding AI-related goods has been weak or negative.

In the **United States**, private domestic demand expanded in the first half of 2026, supported by robust AI-related investment, resilient consumer spending, and additional tax breaks. However, rising inflation has weakened consumer sentiment. Going forward, tighter financing conditions and policy uncertainty are likely to slow growth. Consensus forecasts for 2026 growth have been revised from 2.4 percent in March to 2.1 percent in September. The legal framework for U.S. import tariffs has changed significantly over time, but the tariffs themselves are broadly unchanged relative to April.

In the **euro area**, growth prospects have been dampened by elevated energy prices and the tightening of monetary policy. The consensus forecast for 2026 growth has been lowered from 1.2 percent in March to 0.7 percent in August.

In **China**, the forecast for growth in 2026 is 4.5 percent, 0.3 percentage points higher than projected in April as the global surge in AI investment boosted exports and manufacturing. The impact of conflict in the Middle East has been cushioned by substantial drawdown of oil reserves, low inflation, and growing use of renewable energy. Growth has

nonetheless slowed: after rising 5 percent in 2025, the Chinese economy decelerated to 4.3 percent year-over-year in 2026Q2. With consumption slowing, the economy has increased its reliance on high-tech investment and exports.

Developments in South Asia

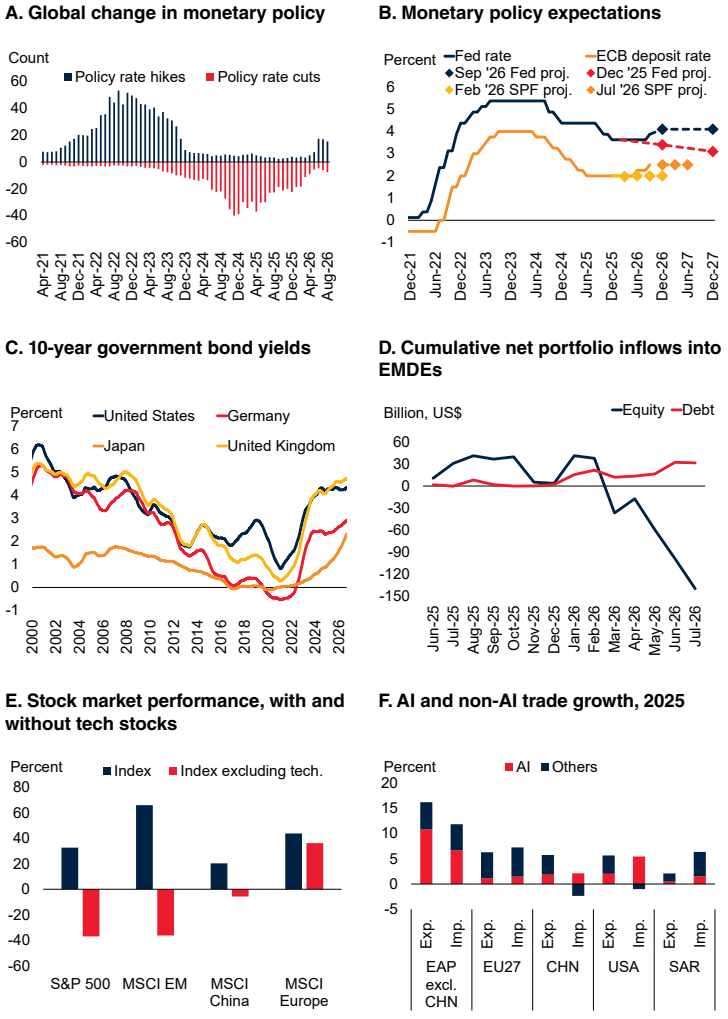
Strong domestic consumption continues to drive robust growth in South Asia (figure 1.5). Robust consumption in the region has been supported by strong remittances, despite conflicts in the Middle East, which hosts nearly half of South Asian migrant workers. In all major countries, remittances in 2026 have grown by more than 15 percent compared to the same period last year, with growth exceeding 30 percent in India and Nepal. Meanwhile, India's consumer confidence remains elevated but has been falling in 2026, reaching 3-year low in July.

Investment growth has lagged in Bangladesh and Nepal. Bhutan and Sri Lanka, however, stand out, with investment supported by post-crisis recovery in Sri Lanka and large public and hydropower-related projects in Bhutan. In India, investment has also gained momentum over the past three quarters, growing by more than 10 percent in the April-June quarter of FY2026/27.

South Asia is more dependent on energy imports than any other EMDE region and relies more heavily than other EMDEs on exporters that ship oil through the Strait of Hormuz. This left the region particularly exposed to energy supply disruptions and energy price increases resulting from the conflict in the Middle East. Since the start of the conflict, the share of oil in total imports by value has increased in all regional countries, increasing by around fifty percent in Bangladesh, Sri Lanka and Maldives. This put further pressure on regional currencies, accelerating their depreciation. The Indian and Sri Lankan rupees both depreciated by more than 6 percent in late May, before recovering modestly. Inflation was within central bank targets in 2025 in all South Asian

FIGURE 1.4 Financial markets and monetary policy

The monetary easing cycle of recent years appears to have ended, with major central banks expected to keep rates steady into 2027. Bond yields have risen and portfolio flows have left EMDEs. Stock market appreciation and international trade growth would have been weak without AI-related activity.

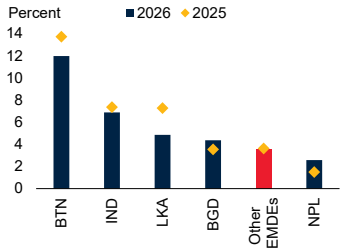


Sources: Bloomberg; Board of Governors of the Federal Reserve System; CEIC; ECB Survey of Professional Forecasters; Haver Analytics; IIF Portfolio Flow Tracker; WTO (2025); World Bank Trade Watch Database; World Bank Group.
A. Three-month moving average count of monetary policy rate hikes (above X axis) and cuts (below X axis) for 107 economies.
B. Lines show the federal funds target rate and the European Central Bank's deposit rate. Projections are year-end Federal Open Market Committee forecasts and quarterly ECB SPF modal forecasts, respectively.
C. Lines show 12-month moving averages of 10-year government bond yields for major economies. Last observation is September 23, 2026.
D. Lines show cumulative net inflows of debt and equity from June 2025 into up to 20 EMDEs. Among SAR economies, "Debt" includes only India; "Equity" includes India and Sri Lanka.
E. Chart shows total return relative to January 2025 for the index and index excluding the information technology sector (GICS definition). Last observation is September 23, 2026.
F. AI exports follow the WTO (2025) classification of AI-enabling products. "EU27" shows extra-EU trade only.

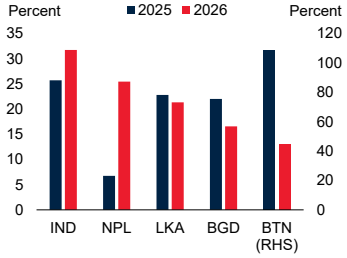
FIGURE 1.5 Regional economic activity

South Asian growth has largely been driven by consumption, supported by remittance inflows that have shown limited negative impact from conflict in the Middle East. South Asia was the region most dependent on energy flows imported through the Strait of Hormuz, and higher energy costs and significant depreciations have contributed to weak stock market dynamics.

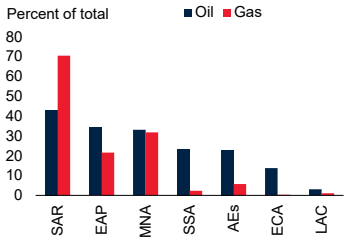
A. Domestic demand in South Asia



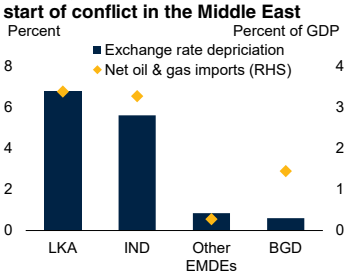
B. Remittances growth in South Asia



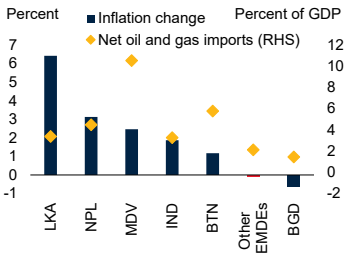
C. Share of energy imports through the Strait of Hormuz in 2024



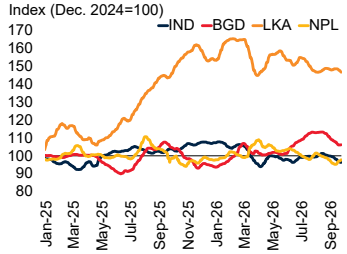
D. Energy import dependence and exchange rate depreciation since the start of conflict in the Middle East



E. Inflation change since start of the conflict in the Middle East



F. Stock market developments in South Asia



Sources: CEPII BACI; Haver Analytics; MPO; WDI; World Bank Group.
A. Domestic demand includes private and government consumption and investment. "Other EMDEs" is aggregated using 2015 real U.S. dollar weights. For India 2026 refers to FY 26/27.
B. Values for 2026 show remittance growth through June for India, through August for Nepal, and through July for other countries, compared with the same period in the previous year.
C. The import share through the Strait of Hormuz is proxied by the share of imports from Bahrain, Iran, Iraq, Kuwait, Qatar, Saudi Arabia, and the United Arab Emirates.
D. Exchange rate depreciation is measured relative to each currency's average value against the U.S. dollar in February 2026. "Other EMDEs" shows the GDP-weighted average of 70 EMDEs with moving exchange rates. Data on oil and gas imports are based on 2024 figures. Latest observation for exchange rates is as of September 23, 2026.
E. Bars show the change in inflation from the January–February 2026 average to the latest observation. "Other EMDEs" shows median values for both the change in inflation and net oil and agricultural imports, weighted by GDP.
F. Lines show 14-day moving averages, indexed such that December 2024 = 100.

countries except Bangladesh, but energy prices and currency depreciation have now pushed up inflation far more in South Asia than in other EMDEs. In Sri Lanka, for example, inflation increased from 1.4 percent in February to 8.2 percent in August, above the upper limit of the central bank's 3-7 percent target band.

The policy response of governments to higher energy prices has varied across countries, but has generally emphasized demand management over increased prices and social benefits. Sri Lanka adopted the most direct controls, including fuel rationing through a QR-code system and public-sector work restrictions, while Bangladesh relied on cooling limits, temporary closures, and fuel-price management. Nepal focused more narrowly on reducing public-sector fuel use, including limits on government vehicles. India's response combined softer conservation measures, such as remote work and reduced travel, with more medium-term measures to encourage electric vehicles and fuel switching.

South Asia's exports have grown in tandem with global trade. India's and Sri Lanka's nominal merchandise exports have grown by around 9.7 percent and 4.3 percent in 2026, respectively, compared with real global trade growth of 7.6 percent. Bangladesh's exports have steadily contracted amid weak global demand for ready-made garments. In Nepal, gross exports almost doubled in 2025 because of soybean oil exports, and have stabilized in 2026.

Exchange rate depreciation in the region has been amplified by weak capital account inflows, as global interest rates remain elevated. Foreign direct investment has been subdued across much of the region since 2025, while India, Bangladesh, and Sri Lanka have experienced moderate portfolio outflows. This is also reflected in their equity markets being largely stagnant since 2025. Sri Lanka was an exception to this, with its stock market rising sharply in late 2025 amid the country's post-crisis recovery before flattening out in 2026.

Sectoral developments

The agriculture sector remains larger in South Asia than in other EMDEs, accounting for about forty percent of employment (figure 1.6). Rising fertilizer prices and unusual weather have placed the sector under increasing strain.

The region's large economies are more dependent on fertilizer imports than other EMDEs, and a larger share of these imports passes through the Strait of Hormuz. In Bangladesh, for example, imports of fertilizer are equivalent to more than 0.4 percent of GDP—around three times the average for other EMDEs—with about 20 percent transiting through the Strait of Hormuz. Bangladesh received US$1.1 billion in emergency World Bank support—equivalent to about 0.25 percent of GDP—to strengthen food security, with a significant share expected to help finance fertilizer imports (World Bank Group 2026a). India increased its fertilizer subsidy by 12 percent relative to the previous year, while Sri Lanka also expanded financial assistance to farmers to offset higher input costs.

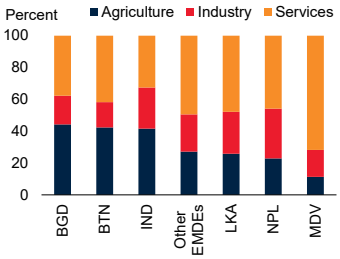
The upcoming El Niño and the associated decline in monsoon rainfall are placing further strain on the region's agriculture. In Sri Lanka, below-normal rainfall could reduce water availability during the Yala season, while in Nepal and Bhutan weaker or more erratic monsoon rains pose risks to rainfed crops. In Bangladesh, rainfall-related agricultural risks are more mixed, with dry conditions in some areas but flooding and excess rainfall affecting others.

Short-term disruptions to agricultural activity are a drag on activity. In the longer term, however, structural declines in the share of agricultural employment are associated with higher per capita growth. Bangladesh,

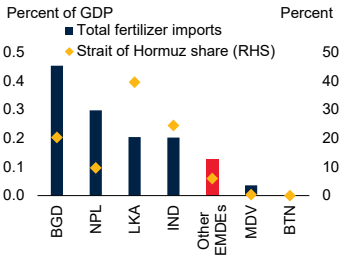
FIGURE 1.6 Sectoral developments

Agriculture remains more important in South Asia than in other EMDEs, and the sector is under strain from rising fertilizer prices and unusual weather. In the longer term, countries where the importance of agriculture has declined have grown more rapidly. Service PMIs and industrial production are still expanding but have slowed in 2026.

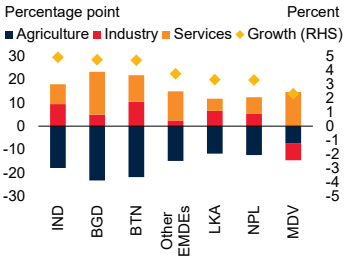
A. Employment by sector in 2025



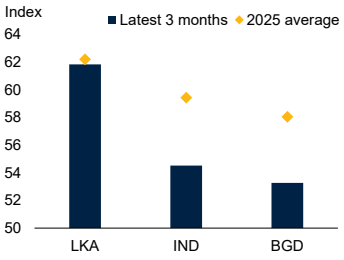
B. Fertilizer imports in South Asia, 2024



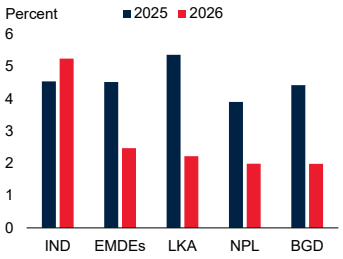
C. Change in employment share by sector and average annual GDP per capita growth 2000–25



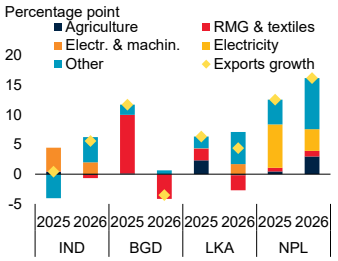
D. Service PMIs



E. Industrial production growth



F. Sectoral contributions to export growth



Sources: CEPII BACI; Haver Analytics; WDI; World Bank Group.
A. "Other EMDEs" is population-weighted average of 124 countries.
B. Fertilizer is defined as HS 2022 Chapter 31. "Other EMDEs" is a weighted average of 148 countries. Import share through the Strait of Hormuz is proxied by the share of imports from Bahrain, Iran, Iraq, Kuwait, Qatar, Saudi Arabia, and the United Arab Emirates.
C. Bars show changes in sectoral employment shares in percentage points. Diamonds indicate average annual real GDP per capita growth (RHS). "Other EMDEs" is population-weighted average of 123 countries.
D. Bars show the three-month average of service PMIs through August 2026.
E. For 2026, industrial production growth is calculated as the percent difference between the level of industrial production for the available months of 2026 versus the same period in 2025. This includes 8 months for Nepal, 5 months for Bangladesh, and 7 months for other countries. "EMDEs" is a production-weighted industrial production index that includes 45 economies.
F. For 2026, growth compares the period through August with the same period in 2025 for Nepal, through July for Sri Lanka, and June for other countries. For Nepal, soybean oil exports, which amounted to around 40 percent of total exports in the 12 months to July, are excluded from calculations.

Bhutan, and India—where agriculture's share of employment has declined the most since 2000—have grown faster than other EMDEs.

The services sector remains resilient, though surveys point to slower expansion. Service PMIs remain firmly in expansionary territory but have generally declined from their 2025 levels. In June–August 2026, service PMIs averaged 54.5 in India and 53.2 in Bangladesh, down from 59.4 and 58, respectively, in 2025. India's services exports continued to grow strongly, rising by 11.6 percent in nominal terms in the first eight months of 2026, up from 10 percent in 2025.

Higher energy prices and the associated increase in transportation costs have weighed on tourism across the region. Since the beginning of the conflict in the Middle East, tourist arrivals have declined by almost 13 percent in Maldives, 9 percent in Sri Lanka, and stagnated in India. Arrivals have increased in Nepal, reflecting a continued recovery following social unrest in 2025. Arrivals have also risen in Bhutan, supported by Indian visitors who often travel by road and are less affected by higher airfares.

On a structural level, the sector's share of employment remains below the average for other EMDEs of about 50 percent even as services have accounted for the largest employment gains across the region in recent years. Trade made a large contribution in all countries, while services employment growth in India was more diversified: information and communication technologies, finance, and professional and business services together accounted for around one-quarter of the increase. Hospitality also contributed meaningfully across the region. In Bangladesh, transport made the largest contribution, potentially reflecting rising demand for freight services and urban mobility.

Industrial activity continues to expand across South Asia, but growth has slowed in 2026 compared with 2025 in most of the region. Industrial growth has also remained below the average for other EMDEs. Higher energy prices have raised input and transportation costs, and the region's limited role in the electronics sector means it has seen little benefit from the global surge in AI-related investment.

Bangladesh's industrial production suffered a particularly sharp deceleration, slowing from about 4.4 percent in 2025 to 2 percent in 2026. Ready-made garments, which account for around 85 percent of the country's exports and drove export growth in 2025, weakened in 2026 amid sluggish demand from the European Union. The garment sector has also remained weak in Sri Lanka, although electronics and machinery have provided support to export growth. In India, electronics and machinery offset weakness in other export sectors during the trade-policy uncertainty of 2025 and have remained important contributors in 2026. Nepal, meanwhile, has benefited from rising hydropower capacity, with electricity exports to India contributing meaningfully to export growth in recent years.

On a longer time horizon, industrial employment has been growing strongly in India, Sri Lanka, and Nepal. It now accounts for around 26 percent of employment in India and Sri Lanka and 31 percent in Nepal, compared with 23 percent in other EMDEs.

Country developments

Overall output in **Bangladesh** grew by an estimated 3.4 percent in FY2025/26, marking the third consecutive year of deceleration. This slowdown was primarily driven by investment and net trade. Private investment contracted for the second consecutive year as energy sector challenges, elevated production costs, and high interest rates outweighed the benefits of reduced political uncertainty. Global demand for ready-made garments remains weak,

contributing to a steady decline in exports since the second half of 2025. Pressure on the current account from weak exports and higher import prices is being offset by strong inflows of remittances.

The banking sector remains in a state of acute vulnerability. The capital adequacy ratio fell to negative 2.6 percent in March 2026 and the nonperforming loan ratio increased to 32.8 percent in June 2026. Real private sector credit has also been contracting steadily since January 2025, weighing on investment and contributing to slowing industrial activity (figure 1.7). In June 2026, the World Bank approved a US$450 million loan to strengthen the foundations of the banking sector, including reforms of state-owned banks and improvements in Bangladesh Bank's supervisory capacity (World Bank Group 2026b).

Inflation remained elevated at 8.7 percent in FY26, above the central bank's target of 7.5 percent. Persistently high prices and job losses have eroded purchasing power: real wages of low-paid workers declined by about 0.5 percent over the year. As the South Asian economy that is most dependent on fertilizer imports, Bangladesh plans to use US$300 million from a $1.1 billion emergency World Bank support to finance imports of about 600,000 tons of fertilizer (World Bank Group 2026a).

In **Bhutan**, real GDP grew by 7.3 percent in FY25/26, driven by hydropower expansion and associated investment. The commissioning and ongoing construction of various hydropower projects supported industry growth of 10.5 percent, while higher public capital spending and a revival of tourism supported growth in domestic demand and services. Growth has also been supported by a sharp increase in remittances, which more than doubled in 2025 and rose by a further 109 percent year-on-year during January–April 2026. Real labor earnings have remained broadly unchanged since 2024, however, highlighting challenges in generating well-paying jobs.

India's economy grew by 7.8 percent in FY2025/26, slightly faster than the April forecast of 7.6 percent. Domestic demand was resilient despite heightened external headwinds, supported by recent structural reforms including labor code consolidation, GST and tariff rationalization, expanded trade agreements, streamlined business compliance requirements, and reforms facilitating private-sector finance. Services and industry expanded at a healthy pace, particularly manufacturing, construction, and power, offsetting some weakness in energy-intensive sectors such as chemicals, and weaker agricultural growth following the delayed monsoon.

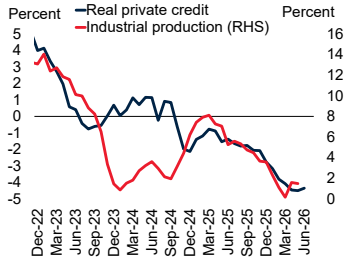
Good harvests of many food items restrained inflation in late 2025 and early 2026, but food price inflation returned to historic norms in mid-2026. Food prices could face further upward pressure as India experiences a rainfall deficit, following its fourth-driest June-August period since 1960. On the two previous occasions when monsoon rainfall between June and September was about 20 percent below normal, agricultural output fell around 4–5 percent below trend.

The current account deficit was contained at 0.6 percent of GDP in FY26. It widened in the April-June quarter relative to the previous year as higher oil imports increased the goods trade deficit, partly offset by a strong services surplus. The rupee depreciated by more than 10 percent between March 2025 and June 2026, but stabilized as oil prices eased, domestic activities remained strong, and capital flows strengthened, partially due to the Foreign Currency Non-Resident bank facility's success at attracting deposits from abroad. Foreign exchange reserves recovered to US$752 billion by end-August, covering nearly 11 months of merchandise imports.

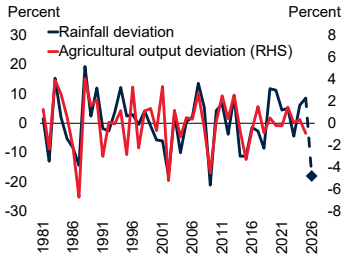
FIGURE 1.7 Country developments

Activity in Bangladesh continues to slow. Indian growth remains robust despite capital outflows, currency depreciation, and a worsening trade balance. Unusually dry weather may hamper agriculture. Tourism arrivals in the Maldives have slowed since the start of conflict in the Middle East. Nepal is benefiting from a surge in hydropower exports and remittance inflows. Sri Lanka's economy has regained its pre-crisis level thanks to strong growth in exports and consumption.

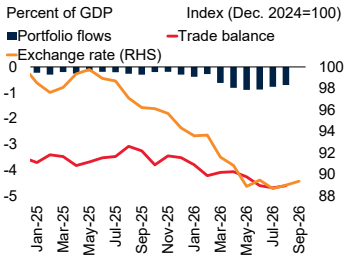
A. Growth of real private credit and industrial production in Bangladesh



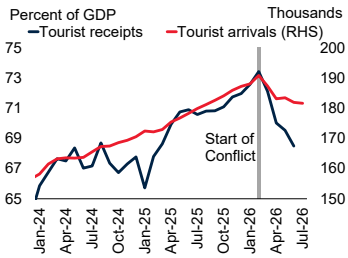
B. Rainfall deviation during Monsoon season and agriculture output gap in India



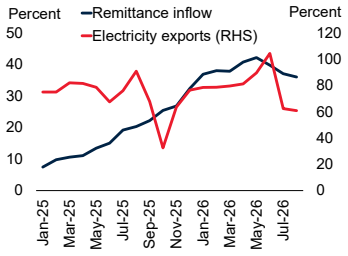
C. Portfolio flows, trade balance and exchange rate movements in India



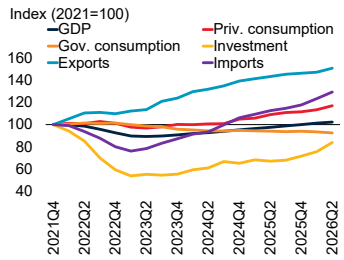
D. Tourist receipts and arrivals in Maldives



E. Electricity exports and remittance inflow growth in Nepal



F. Sri Lanka's recovery post crisis by expenditure components



Sources: Haver Analytics; Official India Meteorological Department; WDI; World Bank Group.
A. Private credit refers to the banking sector's claims on non-financial corporations, expressed in real Bangladeshi taka. Industrial production is shown as a six-month moving average.
B. The agricultural output gap measures the deviation of India's real agricultural value added from its HP-filtered trend. Monsoon rainfall deviation measures the difference between average rainfall during June–September and its 1970–2020 average. The 2026 values show June–August average.
C. Portfolio flows are cumulative net debt and equity portfolio flows since January 2025, expressed as a share of FY2025/26 GDP. The trade balance is the 12-month moving average of net exports of goods and services as a share of moving GDP. The exchange rate shows the percentage change in the monthly average exchange rate against the U.S. dollar relative to December 2024.
D. Lines show 12-month moving averages. Tourist receipts are measured as travel receipts as a share of 12-month moving GDP.
E. Lines show year-over-year growth rates of 12-month moving averages of remittance inflows and electricity exports.
F. Lines show four-quarter moving averages of each expenditure component, indexed such that the 2021 average equals 100.

Maldives' economy grew 6.2 percent in 2025, before slowing to 3.3 percent in 2026Q1. Fish production has weakened, and conflict in the Middle East has also contributed to a sharp decline in tourist arrivals from Western markets since March. Despite sharp rises in transport and food prices in 2026Q2, headline inflation remained benign at 2.6 percent thanks to administrative controls on the prices of water, electricity, and gas. Fiscal balances deteriorated in the first half of 2026 as rising subsidy costs and capital expenditure pushed spending up by 25.3 percent. The current account deficit is estimated to have widened in the first half of 2026, as the trade deficit expanded sharply amid a rising oil bill, a decline in fish exports, and contracting tourism receipts. Net reserves fell to US$118.9 million (about one week of imports) at end-June and the economy is struggling with foreign exchange liquidity shortages.

Nepal's recovery from the September 2025 unrest was slowed by severe floods in August 2026. These caused devastating human and economic losses, with thousands of people killed or still missing, and damage and reconstruction needs worth billions of dollars. Most damage is concentrated in the hydropower sector, and the principal trade corridor with China has been severely damaged. Before the floods, GDP grew by 3.9 percent in FY2025/26, faster than the anticipated 2.3 percent, supported by increased hydropower generation capacity. The trade deficit widened as the oil import bill increased, reaching around 30 percent of GDP. The deficit has been fully financed by exceptionally large remittance inflows, which reached about 36 percent of GDP.

Sri Lanka's economy expanded by 4.7 percent in the first half of 2026, supported by construction, services, private demand, and reconstruction spending following cyclone Ditwah, which struck the country in

December 2025. High-frequency indicators suggest momentum has remained positive into the third quarter. However, higher energy prices pushed inflation up from 1.6 percent in February to 8 percent in August and weighed on industrial activity. The Central Bank of Sri Lanka responded in May by raising the overnight policy rate by 100 basis points to 8.75 percent, the first increase since 2023. Financial conditions have become more supportive of the recovery, as bank profitability has improved, nonperforming loans have continued to decline, and private credit has begun to increase.

Export performance remained mostly resilient despite weaker global demand and heightened trade uncertainty, with robust merchandise exports offsetting weaker tourism. The current account weakened from a surplus in January-July 2025 to a deficit over the same period in 2026, as higher energy imports and weaker tourism inflows offset remittance gains. Fiscal performance exceeded expectations in the first half of 2026, with a primary surplus driven by strong tax revenue growth from the VAT and vehicle imports.

Outlook for South Asian countries

Regional outlook

South Asia is forecast to accelerate from 6.8 percent in 2025 to 6.9 percent in 2026. The 2026 forecast has been revised up for most countries, and by 0.6 percentage points since the previous forecast, as higher energy prices have not interrupted momentum in consumption growth (figure 1.8). The main exception is Bangladesh, whose forecast has been continually downgraded in recent years.

While regional growth has not been affected as much as anticipated by high energy prices, the same cannot be said for inflation. Inflation rose rapidly across the region in 2026 and is expected to remain elevated into 2027. Despite the region's dependence on imported energy and use of policy support to buffer against higher energy prices, current account balances and fiscal balances are expected to remain generally contained.

By sector, the forecast includes a notably strong contribution from industry. Strong credit growth in India is expected to continue supporting domestic investment, while the construction of hydro megaprojects is boosting activity in Nepal and Bhutan. Agriculture, by contrast, is expected to grow weakly, restrained by the negative impacts of a strong El Niño.

Country Outlooks

In **Bangladesh,** the return of political stability was expected to lead to a rebound in economic activity, but this has not yet materialized. The forecast for growth in FY2026/27 has been revised down 1.2 percentage points to 3.4 percent. This deterioration reflects a more protracted drag from energy shortages, banking sector weakness, subdued credit growth,and tighter fiscal constraints than previously anticipated. Export growth is expected to remain weak. Exports of ready-made garments will be slowed in the short term by weak demand in the EU, and in the longer term by increased competition for market share. Inflation is projected to remain elevated at 8.6 percent, above Bangladesh Bank's target of 7.5 percent.

In **Bhutan**, the growth forecast for FY2026/27 has been revised up from 6.4 to 6.7 percent. Construction activity has exceeded expectations as hydropower megaprojects are in their most intensive build phase.

Beyond construction the outlook is more mixed. Activity in the services sector remains

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		**2025**	**2026 (f)**	**2027 (f)**	**2028 (f)**	**2025**	**2026 (f)**	**2027 (f)**
South Asia region		**6.8**	**6.9**	**6.7**	**6.7**	**-0.2**	**0.6**	**-0.2**
South Asia region, excluding India		**3.8**	**3.6**	**3.8**	**4.0**	**-0.1**	**-0.5**	**-1.1**
Maldives	January to December	6.2	2.2	4.1	4.0	0.5	1.5	-3.1
Sri Lanka	January to December	5.0	4.4	4.2	4.0	0.0	0.8	0.4
Fiscal year basis		**24/25**	**25/26 (f)**	**26/27 (f)**	**27/28 (f)**	**24/25**	**25/26 (f)**	**26/27 (f)**
Bangladesh	July to June	3.5	3.4	3.4	3.9	0.0	-0.5	-1.2
Bhutan	July to June	8.2	7.3	6.7	6.8	0.1	0.2	0.3
India	April to March	7.2	7.8	7.1	7.2	0.1	0.2	0.5
Nepal	July to June	4.4	3.9	3.7	5.2	-0.2	1.6	-0.5

Sources: World Bank Group, MPO, and staff calculations.
Note: (f) = forecast. As of July 1, 2025, Afghanistan and Pakistan have been made part of the Middle East and North Africa (MENAAP) region and are no longer grouped in the World Bank Group's South Asia region. GDP is measured in average 2010–19 prices and market exchange rates. Where quarterly data do not exist, aggregates are calculated by weighting fiscal-year data by their overlap with the calendar year.

below its pre-pandemic peak. Input prices have increased as energy costs have risen and a new 5 percent Goods and Services Tax (GST) has been put in place. Tourism growth is expected to be modest. The current account deficit is expected to worsen due to machinery imports for megaprojects, before narrowing once hydropower exports scale up. Strong inflows of remittances and FDI flows following recent liberalizing reforms are expected to continue.

In **India,** growth is expected to slow to 7.1 percent in FY2026/27, 0.5 percentage points higher than previously expected. Strong momentum in the industrial and services sectors is expected to continue. The country's growth potential remains strong, supported by a series of major reforms, such as labor code consolidation, GST reforms, tariff rationalization, the Insolvency Act, and infrastructure investments for both the real and digital economy.

Strength in the rest of the economy is expected to make up for agricultural weakness. The monsoon deficit appears to be larger than originally expected, with much of the country receiving less rain than usual. This is expected to reduce agricultural output and rural demand while increasing food inflation, adding to existing pressure from higher energy prices.

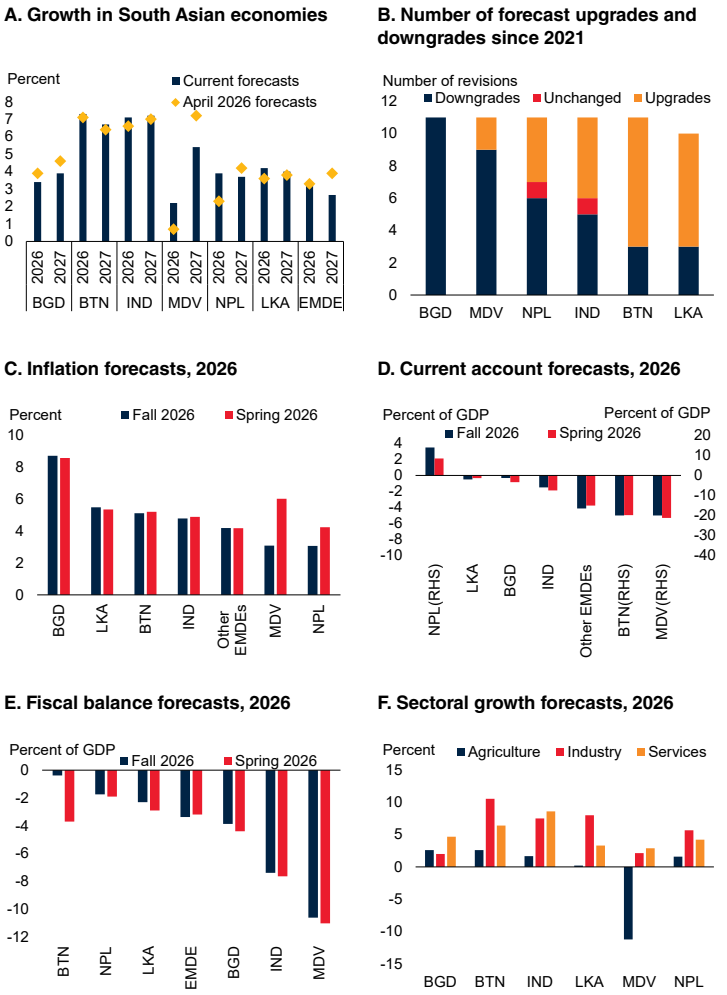
In **Maldives**, growth is expected to slow sharply in 2026, but by less than previously forecast. The growth forecast has been revised up from 0.7 to 2.2 percent as tourism has been more resilient than expected. Tourist arrivals had been expected to contract slightly in 2026 due to higher travel costs and disruptions related to conflict in the Middle East, but are now expected to grow modestly, with a slowdown in visitors from Europe more than offset by strong inflows from China and Russia. The 2027 forecast, however, has been revised down to 4.1 percent from 7.2 percent, reflecting a structurally more cautious view of medium-term growth potential. Growth in construction activity and fisheries will be weighed down by higher cost inputs, climate change, and financial sector strains.

In **Nepal**, growth is projected to slow to 3.7 percent in FY27, as flood damage to energy infrastructure weighs on industry, while disruptions to trade, transport, and tourism constrain services. Agriculture is expected to remain broadly resilient, although localized crops and livestock losses could affect livelihoods and food security. Growth is expected to rebound to 5.2 percent in FY28 as reconstruction gains momentum. The fiscal deficit is expected to widen significantly in FY27, as emergency relief and initial reconstruction raise spending, while tax relief, weaker import growth, and economic disruptions weigh on revenue. Financing is projected to rely on concessional external and domestic borrowing, with the country remaining at low risk of debt distress.

In **Sri Lanka,** the forecast has been revised up to 4.2 percent, supported by improving macroeconomic stability, private consumption, and reconstruction activity. Consumption remains robust and has been supported by robust private sector credit growth, increased energy subsidies and the cancellation of planned tax increases. Construction activity related to post-cyclone reconstruction is expected to pick up after a slow start. El Niño-related weather disruptions are expected to dampen agricultural output.

FIGURE 1.8 Outlook

The 2026 forecast has been revised up for most of the region, excepting Bangladesh. Inflation is expected to remain elevated. Current account and fiscal balances will remain generally contained. The industrial sector is forecast to contribute significantly to growth, with agriculture lagging.



Sources: MPO; World Bank Group.
Note: 2026 refers to FY25/26 for Bangladesh, Bhutan, and Nepal, and FY26/27 for India.
A. "EMDE" includes 141 economies excluding South Asia. Aggregated based on real GDP.
B. Forecast changes are measured as the difference between spring and fall forecasts for the following year from 2021 to 2026. For Sri Lanka, the 2022 Fall forecast is not available.
C-E. "Other EMDEs" includes 106 non-oil exporters and non-energy exporters.

Risks and vulnerabilities

Persistently elevated energy prices

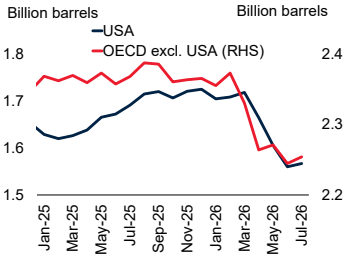
Thus far, the shortfall of oil supplies caused by conflict in the Middle East has been mitigated by a variety of factors. Governments have drawn down stocks of oil and natural gas, which were unusually full prior to the conflict but have now been substantially depleted (figure 1.9). Trade networks for crude oil and refined goods have been reconfigured. Some ships are transiting despite blockades of the Strait of Hormuz, China's oil imports have declined substantially, and U.S. exports have increased. Energy subsidies have protected many consumers from larger price increases.

Previous spikes in oil prices were not foreseen by markets, and new ones could be triggered in a variety of ways. Other oil-supplying regions could rein in recent output expansion, including due to conflict. The drawdown of oil inventories may need to be curtailed as

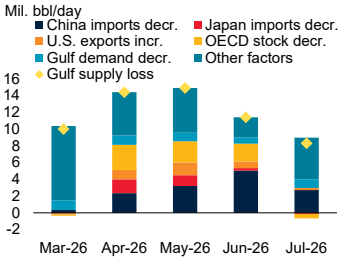
FIGURE 1.9 Risk of persistently elevated energy prices

Oil inventories have been substantially depleted, and prices remain well above pre-conflict levels, as traffic through the Strait of Hormuz remains limited. Prices for refined energy products have increased even more. Countries in SAR have put in place many policies to limit their exposure to more expensive energy imports, but it is not clear that they have been effective. A more persistent energy shortage, which could result from conflict spreading in the Middle East or another oil-producing region, would lead to larger output losses and inflation increases.

A. Oil inventories



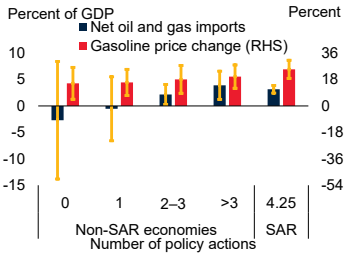
B. Changes in global oil markets following the Middle East conflict



C. Brent crude oil price and futures over time



D. Policy actions, oil imports and gasoline price change



Sources: Bloomberg; CEPII BACI; Global Petrol Prices; Haver Analytics; IEA Oil market Report; International Energy Agency; Japan Ministry of Finance, Trade Statistics of Japan; JODI-Oil World Database; U.S. Energy Information Administration; World Bank Policy Tracker; World Bank Group.

A. Lines show total stocks of oil and oil products.

B. Gulf supply losses are based on IEA Oil Market Report estimates. Changes in U.S. exports and Chinese and Japanese imports are calculated relative to the same month a year earlier. The decline in Gulf demand is proxied by the year-over-year change in refinery intake in Kuwait and Saudi Arabia, based on the JODI Oil World Database. The July value is estimated using the March-June average. OECD stock decrease shows average daily decrease in total OECD crude oil stocks based on IEA.

C. Blue line shows 1-week moving average of Brent crude oil prices. Dotted lines show oil futures curves 1 month and 1 working day before each curve's starting month, the smallest possible gap between available futures and the spot price. For example, the curve starting in July 2026 shows the oil futures curve as of May 29, 2026. Future curves are smoothed using 31 day moving average.

D. Bars show group means; whiskers show ±1 standard deviation. Gasoline price change measured from 23 February 2026 to the latest available data (retrieved July 31, 2026). Groups are arranged by the number of implemented policy actions (excluding announced-but-not-implemented measures).

reserves dwindle. Fiscal support may prove unsustainable given stretched fiscal positions in many countries. A renewed rise in energy prices may therefore be more damaging to the global economy than observed during the initial increase.

Export restrictions could compound the impact of a renewed rise in fossil fuel prices. In the most recent episode, countries that produce or refine energy products have mostly let markets match supply and demand, with the notable exception of Russia. In previous episodes of global supply disruption, however, countries have frequently resorted to export restrictions to avoid domestic shortages. These weaken market incentives and amplify scarcity during a crisis, and would amplify any increase in energy prices (Laborde, Lakatos and Martin 2019).

In the most likely, baseline scenario, oil exports from the Gulf region mostly return to pre-conflict levels by mid-2027. Should shipments remain blocked for longer, dwindling inventories will require prices to rise high enough to reduce demand by an amount equivalent to the supply shock. As inventories approach critical operational levels, physical scarcity could cause prices to spike.

Shortages of oil, fertilizers, and aluminum would weigh on the global economy: oil shortages would raise transport and logistics costs; fertilizer shortages would threaten agricultural production and food prices; and aluminum shortages would disrupt construction, transport equipment, manufacturing, and renewable energy supply chains. Given that many refined energy products, such as jet fuel, have already increased by far more than crude oil, further increases could weigh heavily on countries reliant on airborne travel or those with limited domestic refining capacity.

Further increases in energy prices would lead to disruptions in supply chains, higher inflation, and tighter financial conditions as major central banks raise policy rates. This could also trigger a deterioration of risk appetite in financial markets, leading to a substantial fall in global equity valuations, a rise in volatility, higher corporate bond spreads, and a decline in consumer and business confidence.

The impact of such a scenario of persistently higher energy price on individual countries depends on two factors: their exposure to global energy markets and their use of policies to dampen shocks. South Asian countries' policy response to the global energy market disruptions thus far has been as would be expected for a temporary shock: fiscal and exchange rate policies were used to contain temporary price pressures, while administrative measures were intended to lower consumption.

Fuel subsidies (Bangladesh, India, Sri Lanka) and fuel tax cuts (India) have slowed the pass through into consumer prices. Storage drawdowns have increased supplies and redirected fuels from industrial toward vulnerable users. Working-from-home mandates, support for efficient transportation (buses, carpooling, or EVs) and fuel rationing have reduced demand.

It is not clear how effective these measures have been, however, as South Asian countries have taken more policy actions than other EMDEs, on average, but have nonetheless seen larger increases in gasoline prices. These measures may postpone the adjustments to behavior required if the shock is persistent rather than temporary, while also imposing fiscal costs and lowering foreign currency reserves.

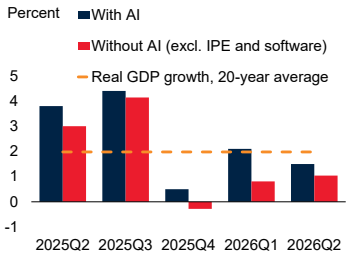
Reversal in global AI activity

Global investment in AI-related assets has risen sharply on the expectation of significant profits and productivity gains. This spending has become an important driver of global activity. Capital expenditure by the five largest U.S. hyperscalers is set to exceed US$1 trillion over 2025 and 2026, rising from 18 to 32 percent of their revenue in 2025 alone, against 7 percent for firms generally (BIS 2026). U.S. GDP growth in recent quarters would have been substantially weaker without investment in information-processing equipment and software (figure 1.10).

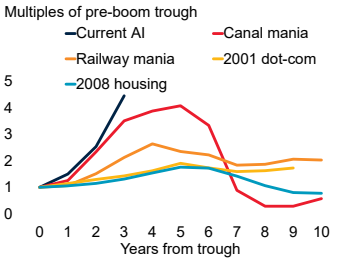
FIGURE 1.10 Reversal in AI activity

Rapid growth in AI investment is an increasingly important part of U.S. GDP and stock market valuations. This rapid growth shares some commonalities with previous increases in investment that eventually reversed. Protests against new data centers in the United States are becoming increasingly common, particularly in areas with larger increases in electricity prices.

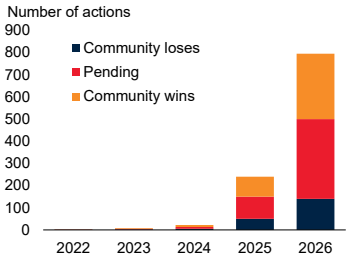
A. U.S. real GDP growth with and without IPE and software investment



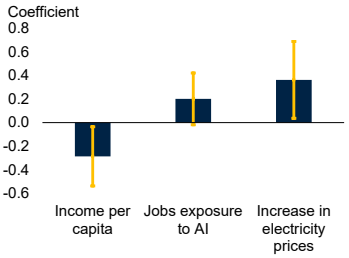
B. Change in investment around major turning points



C. Actions in U.S. against data centers



D. U.S. state-level correlates with actions against data centers



Sources: Bureau of Economic Analysis; Data Center Tracker; Federal Reserve Economic Data (FRED); Felten, Raj, and Seamans (2021); Rungcharoenkitkul (2026); U.S. Census Bureau; U.S. Energy Information Administration (2026); World Bank Group.
A. Growth excluding AI is calculated as real GDP growth less the contributions from investment in information processing equipment and software, which is used as a proxy for AI-related activity. Dashed line is average quarterly GDP growth, 2006Q2–2026Q2.
B. Investment is indexed to each episode's pre-boom trough. "Canal mania", "Railway mania", "2001 dot-com", and "Current AI" are from Rungcharoenkitkul (2026) which show U.S. canal spending (1835), British real investment (1843), U.S. information-processing equipment and software investment (1995), and capital expenditure by five U.S. AI hyperscalers (2023), respectively. AI spending for 2026 is based on guidance provided during earnings calls, not realized spending. "2008 housing" shows U.S. private residential fixed investment.
C. Chart shows the number of actions against data centers, as tracked at datacentertracker.org.
D. Regressions use standardized state-level variables. The number of actions against data centers in 2026H1 is regressed on the state-level change in electricity prices (Dec. 2024-Dec. 2025), state-level AI exposure from Felten, Raj, and Seamans (2021), and state per capita income as of May 2025. Whiskers show robust standard errors.

AI has become similarly important for global trade and financial markets. In early 2026, U.S. imports of AI-related goods rose nearly 60 percent year-over-year while imports of non-AI-related goods declined by nearly a quarter. In April, the "Magnificent 7" technology stocks accounted for 32 percent of the S&P 500 and 21 percent of the MSCI All Country World Index capitalization.

In the past, some rapid increases in sectoral investment have been followed by significant corrections. Gross AI-related capital expenditure has reached 6 percent of U.S. GDP (Armstrong 2025)—similar to the share information-technology investment reached at its peak in 2000Q4, and to the peak share that residential investment reached in 2005. After several years of accelerating investment, both episodes ended in corrections that contributed to a global downturn in 2001 and a global recession in 2008–09 (BIS 2026; Kose, Sugawara, and Terrones 2020). The current episode has risen faster than either previous cycle and is still gaining speed. As in previous episodes, a correction in AI investment would not necessarily indicate that the underlying technology had failed. Instead, it could indicate that investment had run ahead of realized demand (World Bank Group 2026c).

Such a reversal could be triggered in a few ways. The rapid growth in AI investment was supported by low interest rates and abundant liquidity, and may be slowed by the latest tightening of financial conditions. Valuations have been held up by optimism about future profits and could be lower in response to a perception that the market for AI is more competitive, and therefore less profitable, particularly for companies that are unable to ring-fence dominant market positions. New investment could be stalled by public dissatisfaction—protests against new data centers in the United States are becoming increasingly common, for example, particularly in areas with larger increases in electricity prices and lower per capita incomes.

A sharp reversal in AI investment would affect South Asia mainly through a financial channel, as a repricing of AI-related assets could prompt global risk aversion, capital outflows from emerging markets, and tighter financial conditions. How large that spillover would be depends on the type of stress transmitted and the availability of policy room to buffer shocks.

Local projections show that emerging market equities and local government bond yields respond to U.S. financial stress (as proxied by an increase in the VIX or decline in the S&P500 for equity markets, or an increase in the term premium or the MOVE index for bond markets). EMDE equities fall during both U.S. bond-market and (more substantially) U.S. equity-market stress; local government bond yields rise during bond-market stress (figure 1.11). The response in South Asia is broadly in line with those of other EMDEs (*East Asia and Pacific Economic Update*, annex 1.1).

Country vulnerabilities shape the size of these responses. Countries in the top quartile among EMDEs according to the size of their current-account deficit or external debt burdens faced larger estimated increases in local government bond yields under U.S. financial-market stress, while those with the most limited vulnerabilities—in the lowest quartile for either indicator—faced no systematic spillovers.

In South Asia, foreign financial stress would reach domestic markets through bank asset quality—the one margin on which U.S. financial stress registers in the region's markets. The exact weak points differ by country. Bangladesh's banking system is the most fragile: nonperforming loans reached 32 percent of loans in 2026Q1 and regulatory capital fell to –2.6 percent of risk-weighted assets at 2025Q4, below the Basel minimum (Bangladesh Bank 2025). Sri Lanka's nonperforming loans also remain elevated but are easing under its IMF-supported program, from 13 percent of loans in 2024Q4 to 9.9 percent at 2025Q4. In India, asset quality remains strong overall, borrower profiles have continued to improve, and foreign exchange reserves are robust.

Risks are concentrated in fast-growing, lightly supervised financial market segments such as unsecured retail credit and microfinance where the RBI has recently tightened supervision (FSB 2026; RBI 2025). External financing has also been sensitive to global conditions, with net capital inflows and foreign direct investment both muted for an extended period.

Currency mismatch is concentrated in the Maldives and Sri Lanka, where foreign-currency liabilities of banks are 32 and 12 percent of GDP, against under 6 percent in India. Only Maldives lies above the upper quartile for other emerging market and developing economies. Reserves cover 1.3 months of imports in the Maldives, 2.9 in Sri Lanka, and 3.9 in Bangladesh, against 7.9 in India, and cover has fallen since 2020 in all three. Thin buffers narrow the room to smooth a disorderly currency move—the mechanism through which these exposures would bind.

Spillover from a second channel, through the real economy, would be less pronounced than in other EMDEs. South Asia has not played a major role in the recent rapid development of global value chains for AI-related goods, which has thus far been dominated by firms in East Asia and the United States. The adoption and use of general AI tools among South Asian firms also lags the frontier (chapter 2).

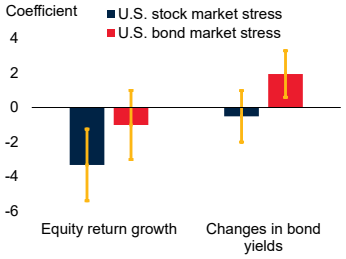
An upside risk for South Asia from AI is in the services sector, where the region could see disproportionate benefits. Fifteen percent of South Asian workers are in jobs where both exposure to AI and complementarity are high, a segment that stands to gain the most from AI-driven productivity growth. These jobs account for about 70 percent of all AI-exposed jobs in the region and 28 percent of total labor earnings, both of which are the highest shares among EMDE regions (World Bank Group 2025a). These include jobs in finance, ICT, and other professional services sectors, many of which are part of the region's successful business process outsourcing industry.

There is evidence that, rather than simply replacing routine BPO tasks and impeding the sector's growth, AI is in fact generating new global value chain opportunities in tasks adjacent to those South Asian suppliers

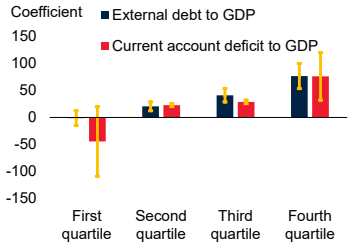
FIGURE 1.11 Reversal in AI investment, financial implications

Financial stress in the United States would propagate to EMDEs. In South Asia, foreign financial stress would reach domestic markets through bank asset quality, currency mismatches, or thin financial buffers. Given that South Asia has not played a role in AI-related production, there is also an upside risk that AI could boost growth by generating new global value chain opportunities.

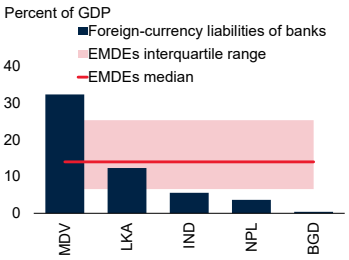
A. Spillovers to EMDE assets from U.S. financial market stress



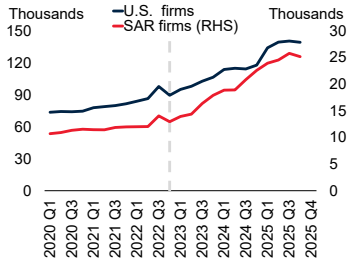
B. Estimated change in domestic bond yields in response to U.S. financial stress, by external debt and current account position



C. Foreign currency-denominated liabilities of banks in 2025



D. Total GVC connections

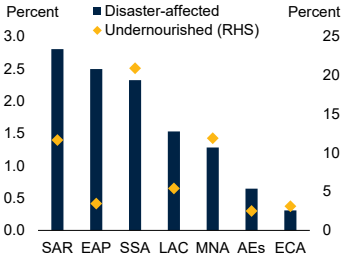


Sources: Chiplunkar et al. (2026); FactSet; Felten, Raj, and Seamans (2021); Haver Analytics; Lightcast; United States International Trade Commission; WDI; World Bank IDS (database); World Trade Organization (2025); World Bank Group.
A. Bars show the average response of emerging market equity returns and local government bond yields in the first month following an episode of U.S. financial stress, estimated by local projections. "Equity returns growth" is in percent; "Changes in bond yields" is in tens of basis points. Whiskers denote 95 percent confidence intervals.
B. Bars show the midpoint of the estimated first-month bond yield response, in basis points, within each quartile of the EMDE market vulnerability distribution. The sample covers 1997–2025 and excludes country-year observations for which external debt or the absolute current account balance exceeds 100 percent of GDP. The total effect is computed as the sum of the bond-stress coefficient and the interaction coefficient multiplied by the vulnerability level. Whiskers show the range of estimated responses within each quartile.
C. Line shows the median of 58 non-SAR EMDEs; the shaded area shows the range of the 25th to the 75th percentiles. Bars show foreign currency liabilities of deposit takers: all liabilities denominated in, or with payments linked to, a currency other than the domestic one. These include resident foreign currency deposits, borrowing from abroad, interbank funding, and debt securities issued in foreign currency.
D. Figure plots the quarterly number of U.S. and SAR firms' international connections. Vertical dashed line marks the release of ChatGPT.

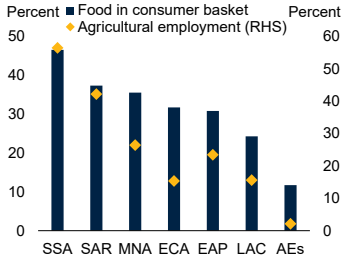
FIGURE 1.12 Food insecurity and natural disasters

South Asia is highly exposed to natural disasters. The region also has a high share of food in the consumption basket and a large share of the population employed in agriculture. This makes it vulnerable to increases in the price of agricultural inputs such as fertilizer and energy. These dynamics could be worsened by a disruptive El Niño. The warming current is expected to be one of the strongest on record this year, bringing heatwaves, droughts, and floods. Previous strong El Niños have caused a sharp decline in regional crop yields.

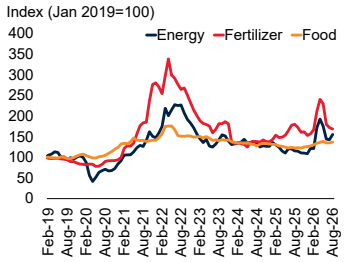
A. Share of population affected by natural disasters and undernourishment, since 2011



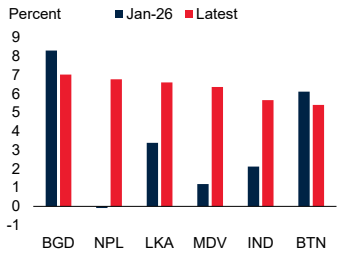
B. Share of food in the consumer basket and agricultural employment



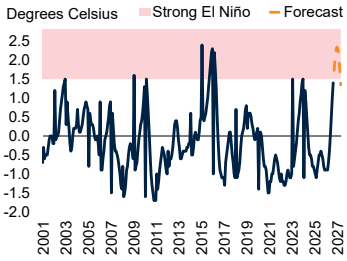
C. Commodity price indices



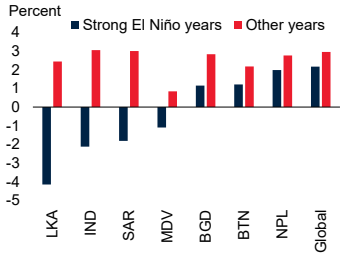
D. Food price inflation in SAR



E. Relative Oceanic Niño Index



F. Crop production growth during strong El Niño episodes



Sources: Consumer Price Index (database); Haver Analytics; IMF, United Nations, Our World in Data (database); NOAA; WDI; World Bank Group.
A. Bars show the annual average share of the population affected by natural disasters since 2011, by region. Diamonds show the share of the population that was undernourished in 2023.
B. Bars show the share of food and non-alcoholic beverages in the latest consumer price index basket. Regional averages are population-weighted averages. Diamonds show employment-weighted share of agricultural employment.
C. Lines show World Bank commodity price indices for emerging markets, indexed to January 2019 = 100.
D. Bars show food price inflation. Latest value is June for Bhutan, July for Maldives, and August for other countries.
E. Chart shows the Relative Oceanic Niño Index (RONI), measured as the 3-month average sea-surface temperature anomaly in the Niño 3.4 region relative to the tropical mean. Values above 1.5°C indicate strong El Niño conditions. Orange dashed line shows the forecast period, based on NOAA probabilities as of June 2026 for different Niño index ranges. For visualization purposes, open-ended range of "2.0°C+" is shown as 2.5°C.
F. Bars show annualized crop production growth during strong El Niño years and other years. Strong El Niño years (1965, 1972, 1982, 1987, 1992, 1997, 2009, and 2015) are identified using RONI ≥ 1.5 with 5 consecutive months above 0.5. Regional aggregates are 2010–19 real GDP-weighted. The global aggregate includes 186 economies; "SAR" includes 6 economies.

already perform. Firms in AI-exposed sectors on both sides are best placed to capture such opportunities and could contribute to a new phase of export-led services growth.

Food insecurity and natural disasters

Rising global temperatures are amplifying El Niño-related extremes, making associated heatwaves more intense, droughts more persistent, and heavy rainfall and floods more severe (WMO 2026). Many people in EMDEs have limited ability to adjust and fiscally constrained governments often have limited capacity to protect vulnerable populations.

South Asia is already the EMDE region most vulnerable to the effects of climate change, with the largest share of its population affected by natural disasters and some of the world's highest rates of malnutrition and food insecurity (figure 1.12; FAO et al. 2025). Food accounts for 37 percent of the consumption basket and 42 percent of workers are in agriculture. Water supplies are prone to disruption, as groundwater buffers are already stressed. Much of the farmland is rainfed in some countries—for example 41 percent of sown area in India (Government of India 2024). This means that disruptions to food production have major, widespread consequences for wellbeing.

The effect of extreme weather events on agricultural production could be compounded by rising fertilizer prices. The interruption of traffic through the Strait of Hormuz briefly sent prices soaring for fertilizer alongside energy. The World Bank Group's fertilizer price index rose by more than 50 percent above its 2025 average in April as the price of urea doubled, before declining alongside a rise in exports from China.

Higher input costs have contributed to increasing food prices in most South Asian countries. Food price inflation rose from -0.1 percent in January to 6.8 percent in

August in Nepal, for example, and from 2.1 to 5.7 percent in India. Estimates suggest that an extended conflict keeping oil prices above $100/bbl this year could push up to 45 million more people into acute food insecurity globally, with the largest increase in food insecurity (24 percent) in Asia (WFP 2026).

Over-stretched farmers now face El Niño conditions strengthening rapidly over the 2026 monsoon season. As of mid-2026, El Niño conditions have been established in the equatorial Pacific. By the end of the year, the probability of a very strong El Niño—with the relative Oceanic Niño Index exceeding 2°C—is above 90 percent. If realized, this would be one of the strongest El Niño episodes in this century. The previous very strong El Niño episode in 2015–16 hurt the livelihoods of more than 60 million people worldwide (UN.ESCAP 2017).

Global crop production is not systematically affected by strong El Niños, but the same is not true for South Asia: crop production during previous strong El Niño years were substantially weaker than normal. In South Asia, the impacts were felt through weaker monsoon rainfall and prolonged drought, with India's 2015 monsoon rainfall about 14 percent below normal, damaging crops, increasing water stress, and pushing up food prices. The weaker-than-average monsoon was followed by severe flooding in southern India that displaced 1.8 million people. Bangladesh and Sri Lanka also faced severe flood and cyclone-related disruptions, with Cyclone Roanu affecting about 1.2 million people in Bangladesh and causing estimated damages of US$1.2–2.0 billion in Sri Lanka.

Policy challenges

Scaling up energy generation

The need to scale up energy generation in South Asia has been magnified by two recent developments. First, the rapid expansion of AI infrastructure will require substantial energy inputs—global electricity demand from data centers alone is forecast to double from its current level by 2030 and triple by 2035, accounting for as much as 4 percent of total production (figure 1.13; IEA 2026a). These new demands are in addition to the pre-existing challenge of generating sufficient energy in a rapidly growing region—India is expected to nearly double its electricity generation capacity over the next 10 years, and even at that rapid pace the country's energy generation capacity will still only be one-sixth of the advanced-economy average.

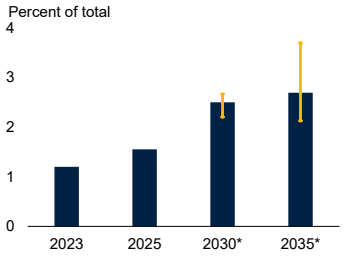
Second, recent increases in energy prices have highlighted the costs and risks of depending on imported fossil fuels. South Asia's vulnerability has been illustrated by the many disruptions caused by the interruption of energy flows through the Strait of Hormuz, including shortages of key goods, slower growth, higher inflation, and currency volatility. Many countries have imposed short-term policies to mitigate these harms, but reducing this vulnerability in the longer term requires countries to invest significantly in new generation capacity.

Renewable energy sources such as solar panels and wind turbines are increasingly the most cost-effective option for expanding electricity generation, while also causing fewer negative externalities, such as air pollution, than other energy sources. This combination has made them an increasingly compelling choice: Last year marked the first year where incremental global electricity demand—including in South Asia—was fully met by new renewable generation.

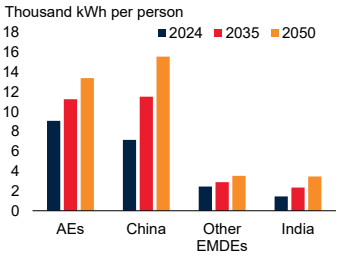
FIGURE 1.13 Scaling up energy generation

South Asia's growing economies are increasing energy demand. Last year was the first in which incremental global electricity demand was fully met by new renewable generation. Many countries in the region have a high or growing share of renewables, but others lag behind. Investments in renewables are being slowed by subsidies for fossil fuels and import restrictions on renewable energy.

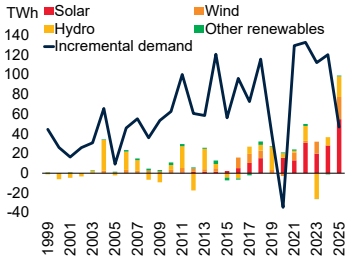
A. Global data center electricity consumption as a share of global electricity consumption



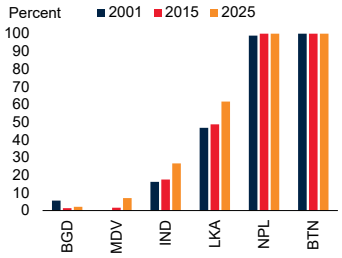
B. Electricity production projections per person



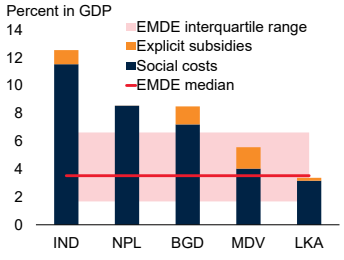
C. Incremental electricity demand and additional renewable energy production in South Asia



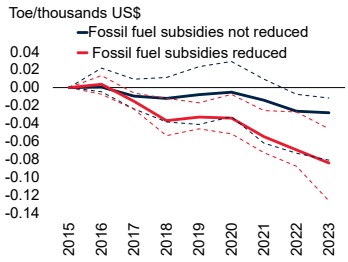
D. Share of renewable energy sources in electricity production



E. Social costs of energy support: Implicit and explicit, 2025



F. Change in energy intensity: by reduction in energy subsidies



Sources: IMF Fossil Fuel Subsidies Database; International Energy Agency (IEA); OECD Green Growth Database; United Nations, Our World in Data (database); World Bank Group.
A. Bars show projected data center electricity consumption as a share of global electricity production, based on IEA projections. Whiskers indicate the high and low cases.
B. Bars show electricity consumption per capita. Electricity projections are from the IEA and population projections are from the United Nations. "AEs" includes the United States, the European Union, and Japan.
C. Bars show additional global electricity generation capacity from each renewable source. Line shows increase in global electricity consumption compared with the previous year.
D. Bars show the share of renewable energy in total electricity production.
E. "Explicit subsidies" reflect retail prices below fuel supply cost because of direct financial transfers, tax breaks, or price controls. "Social costs" measure the difference between the price paid by the fuel user and the fuel's full social cost, including supply costs and negative externalities such as local air pollution and broader externalities related to driving. EMDE interquartile range is based on the distribution of total fossil fuel explicit subsidies and social costs as a share of GDP in 2025 among 99 non-energy exporting and non-oil exporting EMDEs.
F. Chart compares the change in energy intensity between economies that reduced fossil fuel subsidies between 2015 and 2023 and those that did not. Dotted lines show the interquartile range.

Fossil fuels still account for more than 75 percent of global energy consumption, however, and remain essential to the energy mix (World Bank Group 2024a). Sufficient baseload capacity from fossil fuels, nuclear power, or hydro power is important to compensate for the inherent intermittency of solar and wind power. In South Asia, the degree of reliance on fossil fuels is close to the global average but with wide dispersion: Nepal and Bhutan generate all their electricity using renewables (specifically hydropower), while Bangladesh is almost entirely dependent on fossil fuels.

One major obstacle to investments in renewable energy generation and complementary efforts to improve energy efficiency is the widespread use of fossil fuel subsidies. As in many other EMDEs, fossil fuels are underpriced across South Asia. Retail fossil fuel prices also typically fail to reflect the negative externalities of fossil fuel use, including pollution, congestion, and health costs, resulting in an implicit subsidy on top of more explicit price support (Black et al. 2025; Damania et al. 2023). Total fossil fuel subsidies as a share of GDP in India rank among the top quartile of EMDEs.

Studies covering EMDEs between 2010 and 2021 find that fossil fuel subsidies discourage investment in renewables (Diallo, Ouoba and Gatete 2024; Parashar and Jaiswal 2026), while phasing out fossil fuel subsidies and introducing environmental taxes accelerates renewable adoption (Chavda and Mehta 2025). Consistent with this literature, between 2015 and 2023, fossil fuel subsidies have been significantly associated with higher energy intensity, and EMDEs that reduced fossil fuel subsidies between 2015 and 2023 saw faster reductions in energy intensity than those that did not.

Muted price signals also discourage the adoption of renewable energy. Many distortive

trade measures increase the price of imports of renewable energy generation products. Because the global production network for renewable energy spans multiple stages across national borders, trade friction at any one stage can cascade through the supply chain (World Bank Group et al. 2017). Ferrantino (2012), for example, finds that an average ad valorem trade cost of 10 percent compounds to an effective tariff equivalent of 34 percent by the end of a five-stage supply chain. Such distortive trade measures erode the competitiveness of renewable energy relative to fossil fuels (UNCTAD 2014).

Reforming energy pricing and removing trade barriers are critical steps to accelerate investment in new generation capacity. Subsidy reform is most politically durable when it is sequenced carefully: reforms that recycle savings toward targeted cash transfers or energy vouchers for vulnerable households have been more successful in building and maintaining public support than those framed purely as fiscal consolidation (Damania et al. 2023).

Governments also play a role in ensuring that the underlying infrastructure can absorb and transmit the electricity that new capacity produces. Grid modernization is among the most capital-intensive and time-sensitive investment priorities facing South Asian countries. By 2050, developing economies worldwide will need to add or upgrade more than 73 million kilometers of power lines—a total exceeding all power lines built globally in the past century (IEA 2023). For many South Asian countries, reforms to state-owned utilities—including unbundling generation, transmission, and distribution functions—can introduce competitive pressures to reward efficiency and innovation (IFC 2024).

Scaling up investment in generation and grid infrastructure requires mobilizing private capital alongside public finance. Annual investment in electricity generation in developing countries needs to more than double by 2035—from around USD 280 billion to USD 630 billion—with more than half of that increment needing to come from the private sector (Banga 2025). Yet EMDEs currently attract only about one-fifth of global electricity investment, reflecting higher perceived political and regulatory risks.

Closing this gap requires a suite of complementary measures that reduce the cost of capital for private investors (IEA 2026b; IFC 2025; World Bank Group 2024b). For South Asia, combining grid modernization support with de-risking instruments for private renewable developers could accelerate deployment. Sri Lanka's ongoing energy sector restructuring illustrates this potential: blended finance and institutional reform have begun to attract foreign investors to a market that was previously considered too risky (World Bank Group 2025b).

Strengthening cross-border interconnections offers a further multiplier: expanded regional grids allow countries to exchange surplus renewable power—particularly from solar- or hydro-rich but demand-limited economies—reducing the need for back-up capacity and lowering system-wide costs. The Dorjilung Hydropower Project in Bhutan—developed with WBG funding is catalyzing roughly US$900 million in private capital—demonstrates how a small, resource-rich country can harness hydropower for domestic energy security and fiscal revenues while simultaneously helping a larger neighbor decarbonize its grid (World Bank Group 2025c).

Global overcapacity in the production of solar panels, wind turbines, and batteries provides a historical opportunity for countries in South Asia. Unit costs have declined dramatically and created a historically favorable window for

FIGURE 1.14 Creating jobs at scale in tourism

Self-employed farmers make up a large share of employment and receive below-average wages for their work. Manufacturing was once an important rung in the ladder to better jobs, but its ability to create jobs at scale has diminished over time. Tourism already employs many workers and has shown the ability to move large numbers to higher-wage work in the formal sector.



Sources: Global labor database; ILOSTAT; Informal Economy Database; Viet Nam Labor Force Survey (database); WDI; World Bank Group.
A. Self-employment data are from 2010–20. "SAR" includes five countries. "Other EMDEs" includes 65 economies. Shares are simple averages.
B. Chart shows sectoral wages relative to the national average. SAR averages are employment-weighted. Data are for 2017 (Nepal), 2019 (Maldives), 2022 (Bhutan), 2024 (Bangladesh and Sri Lanka), and 2026 (India).
C. Bars show median GDP per capita in constant U.S. dollars in the year of peak industrial employment, while whiskers show the interquartile range across economies. Sample includes 58 economies that reached their peak industrial employment share between 1995 and 2019, grouped into 5-year periods. GDP per capita is measured in thousands of constant 2015 U.S. dollars.
D. Bars show tourism as a share of total employment. Yellow whiskers show the interquartile range. "Other EMDEs" includes 23 economies; the latest data available are for 2017–24.
E. Bars show the percentage of tourism workers who are paid employees as a proxy for formality, who are young defined as those under 25 years of age, and those with tertiary education.
F. Bars show percentage-point changes in the share of workers entering and exiting tourism, categorized by employment type. "Salaried – informal" refers to salaried workers with temporary contract (less than one-year) or without contract. "Salaried – formal" refers to salaried workers with long-term contract. The analysis sample includes workers surveyed twice within a year in Viet Nam LFS intra-year during 2013–22, who reported switching industries into or out of tourism.

developing economies to acquire clean energy hardware at low cost.

Creating jobs with low entry barriers at scale

Many countries in South Asia have large numbers of people in low-productivity employment. South Asia faces an acute job-creation challenge. The region must absorb tens of millions of young workers each year, yet private sector employment growth has lagged behind working-age population growth and economic output (World Bank Group 2024c, 2024d, 2025a).

Agriculture employs more than 40 percent of the workforce in South Asia including nearly half in Bangladesh, Bhutan and India. Farmers often operate informally on a small scale, generally being self-employed or working with family members (figure 1.14). These jobs are typically less than half as productive as the economy's average (Ohnsorge and Yu 2022). Finding more productive employment for these workers is critical if the region is to grow rich before growing old (box 1.1).

Many existing, low-productivity jobs are subsistence level and would not be chosen if it were possible to earn a higher wage through a formal job in another sector. They are often chosen because the barriers to entry are small, and because other options are closed. Formal employment is weak because South Asia's small average firm size, slow firm growth, lack of product market flexibility, limited openness to trade, and lower literacy rates (World Bank Group 2024c).

While jobs in agriculture have the lowest wage premium, the jobs with the highest wage premium are in business and financial services. These jobs also have significant barriers to entry, requiring high levels of education and skills.

BOX 1.1 South Asia's compressed demographic transition

South Asia's demographic transition is unusually compressed: the working-age share peaks around 2034 and the region turns "aged" by 2049. Currently, aging is often neither productive nor financially secure—longer lives come with more years in poor health, older workers stay in informal, low-productivity jobs, and pension coverage is among the lowest in the world. International experience suggests that older households use a smaller share of their spending on food and clothing and a larger share for services such as health care, hospitality, and communications. Seizing the opportunities offered by an aging society requires policy actions on all fronts at once: accelerating job creation while building old-age income support and health systems before aging pressures peak.

Introduction

Demographic trends in South Asia shape global demographic trends. One in five workers worldwide lives in the region, and its 1.17 billion working-age people account for 22 percent of the world's labor force. South Asia is approaching a turning point in its demographic transition as the tailwinds that have supported above-average growth for decades begin to fade.

Against this backdrop, this box answers three questions.

- Where does South Asia stand in its demographic transition?
- What are the implications for growth prospects?
- What are the policy implications?

Findings. The box documents the following findings.

First, working-age population growth is projected to fall from 2.2 percent a year during 1960–2023 to 0.6 percent a year during 2024–50. The working-age share will peak around 2034, and just 15 years later the region will cross into "aged" status—seven years faster than the average emerging market and two decades faster than the average advanced economy.

Second, even if South Asia can sustain the growth rates it achieved over the past decade, it is likely to grow old before it grows rich. It is currently on track to end the transition from an "aging" to an "aged" population with per capita incomes that are below those at which other countries started similar transitions.

Third, this compressed timeline implies that staggered policy efforts—the practice of countries that went through this demographic transition earlier—are less likely to be effective than policy action on all fronts.

Contribution to the literature. This box—and the underlying study (World Bank Group forthcoming)—makes two contributions. First, it places South Asia's experience in global comparative context, building on canonical work linking age structure to economic growth (Bloom, Canning, and Sevilla 2003; Bloom and Williamson 1998; Mason and Lee 2006) and extending beyond earlier studies focused on individual countries (Navaneetham and Dharmalingam 2012). Second, it reframes the policy challenge by treating workforce expansion and aging preparation as simultaneous rather than sequential priorities—a distinction the existing

This bos was prepared by Lynn Hu (DECPA), Elina Pradhan (South Asia Health Global Practice), and Zoe Xie (DECPA).

BOX 1.1 South Asia's compressed demographic transition

literature recognizes in principle (ADB 2019, 2024; Lee and Mason 2010; Mason and Lee 2006; World Bank Group 2015) but rarely translates into operationally differentiated action. As a result, policy priorities for both transitions are articulated through the lens of more and better jobs, while remaining anchored in the more traditional approach of growth and fiscal sustainability.

Rapid aging in South Asia

South Asia's demographic tailwinds are beginning to fade. Working-age population growth is set to slow sharply, from 2.2 percent a year during 1960–2023 to 0.6 percent a year during 2024–50 (figure B1.1.1). The working-age share, about 68 percent in 2026, will peak at around 69 percent in 2034—six years after the global peak—before declining. In 2049, just 15 years after the working-age share peaks, the region will cross into "aged" status, when 14 percent of the population will be 65 years or older. The transition from "aging" to "aged" status—when the share of the population aged 65 years or older rises from 7 to 14 percent—will take only 25 years on average, compared with 32 years in other EMDEs and 46 in advanced economies. It is moving faster still in Bhutan, Maldives, and Sri Lanka.

Impact on consumption

Level of consumption expenditure. In other countries where aging is more advanced than in South Asia, consumption levels have followed a hump-shaped pattern: consumption expenditure rose steeply with the household head's age and peaked when the household head reached their late 40s, before falling steeply as the household head aged into retirement (Gourinchas and Parker 2002). In South Asia, by contrast, there is evidence that this pattern may be less pronounced. For India, for example, Bairoliya et al. (forthcoming) show that the consumption-age profile is roughly flat—household consumption does not rise or fall significantly with the age of the household head.

Composition of consumption expenditure. In countries with more aged populations, consumption patterns shifted over the course of the household head's lifetime: households with older household heads consumed fewer nondurable goods—such as food, nondurable transportation, and clothing—and instead spent a larger share of their expenditures on services such as dining and hotels, communications, and health care (Aguiar and Hurst 2013; Cravino, Levchenko, and Rojas 2022). Similarly, in India, consumption shifts away from food and transportation and toward services (health care and education) as the household head ages (figure B1.1.2; Bairoliya et al. forthcoming).

Growing old before growing rich

During 2000–23, rapid working-age population growth contributed about 0.4 percentage point per year to average annual GDP growth of 4.3 percent in South Asia. On average during 2024–50, the mechanical contribution of demographics to GDP growth is expected to be one-quarter as large as in 2000–23. Even if the region sustains the per capita growth rates of the past decade, most South Asian countries will reach aged status at per capita incomes that are at or below levels at which the average EMDE began the same transition (figure B1.1.1).

In South Asia, aging is often neither productive nor financially secure.

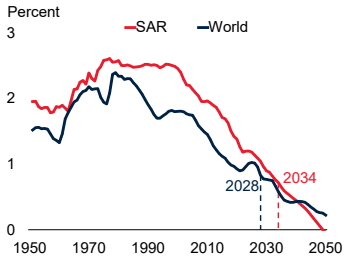
- **Productive aging.** People are living longer in South Asia, but many are not in good health. In 2023, life expectancy at birth was 72 years, but healthy life expectancy

BOX 1.1 South Asia's compressed demographic transition

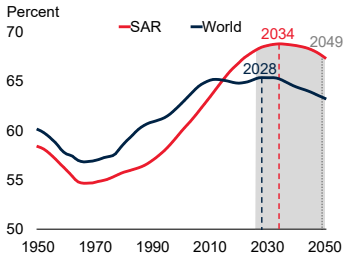
FIGURE B1.1.1 South Asia's demographic trends

South Asia's demographic transition is unusually compressed. The working-age population share is expected to peak around 2034, and the region is expected to turn "aged" by 2049, raising the risk that it grows old before it grows rich.

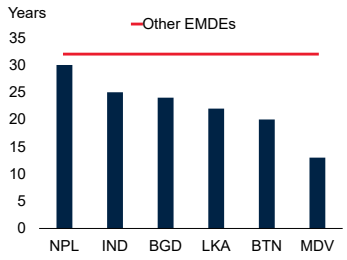
A. Annualized working-age population growth



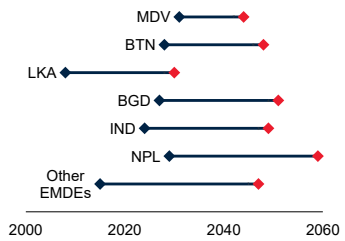
B. Share of working-age population: SAR and the World



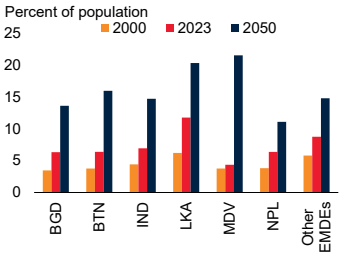
C. Years to transition from aging to aged status



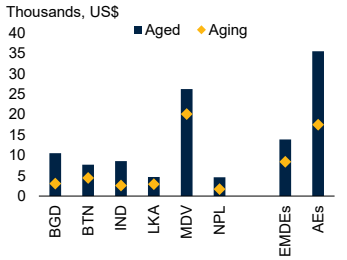
D. Timing of the transition from aging to aged status



E. Share of population aged 65 years and older



F. Per capita GDP at the start of aging and aged status



Sources: United Nations; World Development Indicators (database); World Population Prospects 2024 (database); World Bank Group.
A. Figure shows annualized working-age population (ages 15–64) growth rates for South Asia and the world. The working-age share peaks in 2028 for the world and in 2034 for South Asia. Data from 2024 onward are medium-variant projections. Aggregates are population-weighted averages.
B. Figure shows the working-age population (ages 15–64) as a share of total population. South Asia's working-age share peaks at about 69 percent in 2034, roughly six years after the global peak of about 65 percent in 2028. South Asia enters aged population status in 2049. The shaded areas show the period from the current year (2026) to 2050. Data from 2024 onward are medium-variant projections. Aggregates are population-weighted averages.
C. Bars show the number of years between reaching aging population status (share of population aged 65+ ≥ 7%) and aged population status (≥ 14%) for South Asian countries and the non-SAR EMDE average. Averages are population-weighted. The SAR population-weighted average is 25 years. Using simple (unweighted) averages, the SAR estimate declines to 22 years, compared with 30 years for other EMDEs. The AE average is 46 years. The AE figure reported in the chapter is based on simple averages to account for several AEs that began aging before UN data were available (Canada, France, Sweden, United Kingdom, and United States, data permitting). Estimates for these countries are drawn from ADB (2024).
D. The line shows the span between a country crossing aging threshold year (blue, 65+ ≥ 7 percent) and aged threshold year (red, ≥ 14 percent). Methodology and sample are the same as in panel C.
E. EMDE is the population-weighted average of non-SAR EMDEs.
F. Per capita real GDP is measured at 2024 prices and exchange rates. EMDE and AE values are unweighted averages for 62 non-SAR EMDEs and 6 advanced economies that have begun their transition from aging to aged status during the period for which both demographic and GDP data (including projections) are available. The transition periods are 2027–51 for Bangladesh, 2028–48 for Bhutan, 2024–49 for India, 2031–44 for the Maldives, 2029–59 for Nepal, and 2008–30 for Sri Lanka. Per capita incomes are assumed to grow at the same rate as each country's average per capita income growth rate during 2013–23.

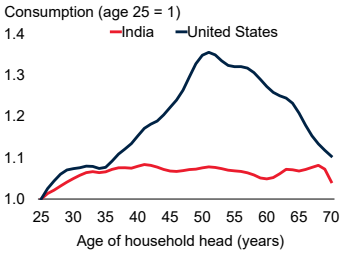
was only 61. The gap was driven by noncommunicable diseases, which now account for nearly two-thirds of the region's disease burden, up from 36 percent in 2000—the second-highest share across EMDE regions (figure B1.1.3). Older South Asians remain in the labor force well past age 65, but increasingly in informal, low-productivity, and largely agricultural work: 91 percent of workers aged 65 and above are informally employed, roughly double the emerging-economy average. With low levels of education, they are also less well equipped for more productive roles: the projected average years of schooling for the population aged 65 and above in 2054 fall below the other-EMDE average across most of the region.

BOX 1.1 South Asia's compressed demographic transition

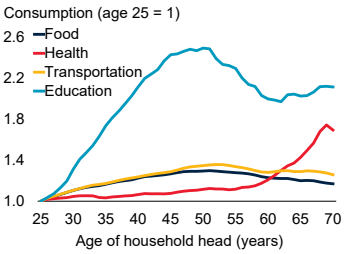
FIGURE B1.1.2 The impact of aging on consumption

Aging is associated with declining total consumption in the United States but not in India. Consumption shifts toward services such as health, communications, and hospitality and away from nondurable goods such as food and clothing as countries age.

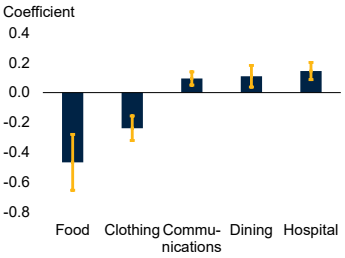
A. Consumption



B. India: Consumption of food, health, and transportation



C. Correlation of consumption basket shares and the population share aged 65 years and older



Sources: Bairoliya et al. (forthcoming); Haver Analytics; IMF Consumer Price Index (database); World Bank Group.
A.B. Results from Bairoliya et al. (forthcoming). Household consumption is normalized to that of a household whose head is aged 25. Overall household consumption is shown for both India and the United States (A), and consumption of food, health, and transportation is shown for India (B). Data for the United States come from the Panel Study of Income Dynamics. Data for India come from the Consumer Pyramids Household Survey. Total household consumption is adjusted for household size using a modified OECD scale that assigns a weight of 1 to the household head, 0.3 to each child aged 16 or younger, and 0.5 to each adult over the age of 16.
C. Bars show the coefficients from a panel regression of CPI weights for food, clothing, communications, dining and hotels, and health care on the share of population aged 65 years and older, controlling for PPP-adjusted GDP per capita and with country fixed effects. Standard errors are clustered at the economy level. Whiskers show 90 percent confidence intervals. The sample includes 155 countries (33 advanced economies and 122 EMDEs), including five South Asian countries (all except Maldives) over 1990–2025.

- Financially secure aging. Old age is often financially insecure. Only 33 percent of the labor force contributes to a pension scheme, and just 10 percent of older South Asians receive any pension benefits, the lowest coverage globally. The best-covered group—public sector pension beneficiaries—accounts for no more than 3 percent of the total population in any South Asian country (figure B1.1.3).

Policy priorities

South Asia's transition to an "aged" population is unusually compressed. Most South Asian countries will complete this transition at income levels below those at which other emerging economies even began it.

Because South Asia's transition is so compressed and likely to complete at below-average incomes, the best policy response is to address labor markets and aging simultaneously rather than sequentially. Earlier-aging economies built pension systems, long-term care, and age-friendly health systems while still growing richer. Such sequencing is less likely to succeed in South Asia. A below-average share of South Asia's working-age population is in nonagricultural employment (figure B1.1.4). Firms also create jobs more slowly than firms in other EMDEs across small, medium, and large firm sizes. This shortfall traces back to specific constraints: a lack of reliable transport and power, perceived corruption and customs delays, and a workforce with limited education all hold back firm-level employment growth. And employment and income gains while the working-age population share is still expanding increase the fiscal and institutional capacity to manage aging.

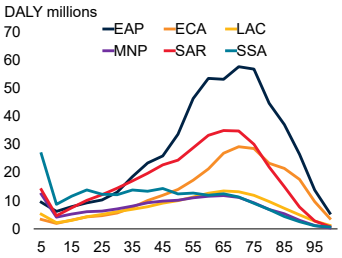
The policy mix depends on country circumstances. Countries whose working-age share has not yet peaked can prioritize job creation, female labor

BOX 1.1 South Asia's compressed demographic transition

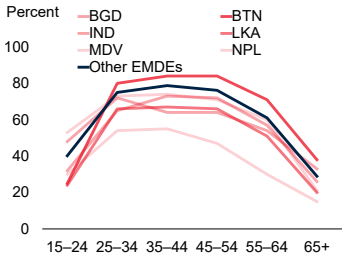
FIGURE B1.1.3 Productive and financially secure aging

Aging is often neither productive nor secure. Longer lives come with more years in poor health, older workers remain in informal, less productive jobs, and pension coverage is the lowest in the world.

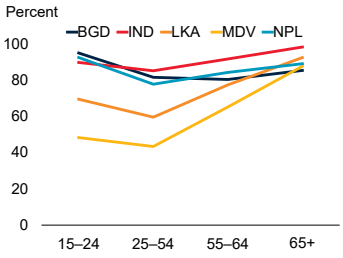
A. Age distribution of noncommunicable disease burden by region, 2023



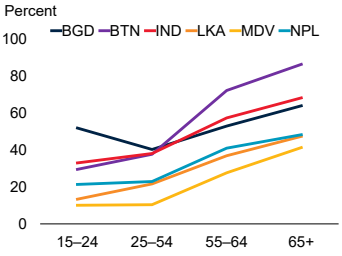
B. Labor force participation in South Asia by age group



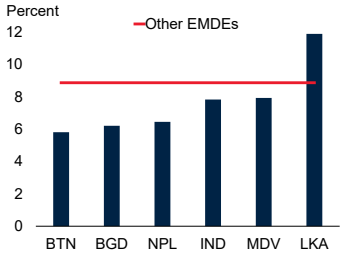
C. Informal employment share in South Asia by age group



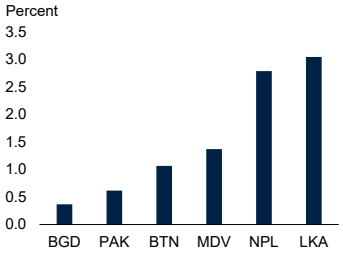
D. Employment in Agriculture share in South Asia by age group



E. Projected average years of education of population aged 65 and older, 2054



F. Public sector pension beneficiaries



Sources: Global Burden of Disease Collaborative Network; Global Burden of Disease Study 2023; Institute for Health Metrics and Evaluation; International Labour Organization, labor force participation rate (LFPR) by age group; Global Labor Database; World Bank ASPIRE Administrative Database; World Development Indicators (database); World Bank Group.
Note: DALYs = disability-adjusted life years.
A. A disability-adjusted life year (DALY) is a measure of overall disease burden expressed as the number of healthy years lost due to morbidity, disability, and premature death. One DALY represents the loss of the equivalent of one year in full health. Regional classifications include high-income countries. SAR includes Bangladesh, Bhutan, India, Maldives, and Nepal.
B. Lines show country-specific labor force participation rates for the latest available year, based on the 13th ICLS definitions. Age groups are 15–24, 25–34, 35–44, 45–54, 55–64, and 65+. The labor force participation rate is defined as the share of the working-age population that is employed or actively seeking work, expressed as a percentage. The latest data for each country are from different years: Bangladesh (2024), Bhutan (2025), India (2025), the Maldives (2019), Nepal (2017), and Sri Lanka (2024). Aggregate averages are simple non-weighted averages.
C. Informal employment is measured as the share of employed persons in informal jobs, as defined by ILO statistical standards, expressed as a percentage of total employment in the age group. The latest data for each country are from different years: Bangladesh (2024), India (2025), the Maldives (2019), Nepal (2017), and Sri Lanka (2024). Data for Bhutan are not available.
D. Share of employed persons working in agriculture expressed as a percentage of total employment in the age group. The latest data for each country are from different years: Bangladesh (2024), Bhutan (2025), India (2025), the Maldives (2019), Nepal (2017), and Sri Lanka (2024).
E. Bars show projected average years of education for the population aged 65 and above in 2054. "Other EMDEs" is the average of 143 EMDEs excluding South Asian countries.
F. Bars show public sector pension beneficiaries as a percentage of the total population.

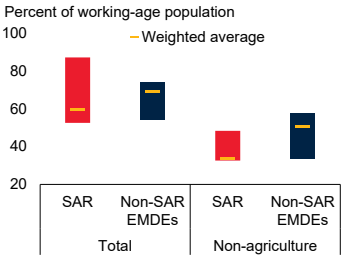
force participation, and work-linked reskilling. Raising female labor force participation would promote a shift into high-quality, formal-sector jobs, supported by girls' access to secondary and tertiary education and by antidiscrimination regulation. Those with 10–25 years before crossing the aged threshold can use that window to build health, care, and pension systems before aging pressures peak. As older workers shift out of low-productivity agriculture into urban employment, easing retirement rules, improving access to finance, and providing health interventions that extend working lives can sustain productive, healthy aging in cities.

BOX 1.1 South Asia's compressed demographic transition

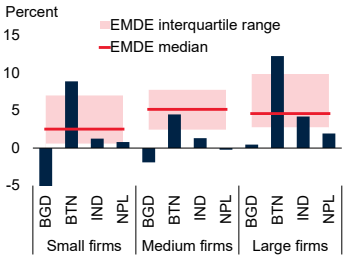
FIGURE B1.1.4 Policy options

Because South Asia's transition to an aged society is unusually compressed, the policy priority is to remove obstacles to job creation while building old-age income and health systems.

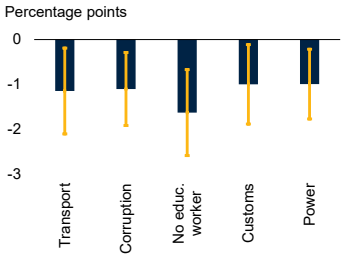
A. Employment and non-agricultural employment, latest



B. Average annual employment growth by firm size



C. Constraints associated with slower firm employment growth



Sources: International Labour Organization; Labor Force Surveys (Bangladesh 2022, India 2022, and Sri Lanka 2021); World Development Indicators (database); World Bank Enterprise Surveys; World Bank Group.
A. The latest data are for 2024 for total employment and 2023 for nonagricultural employment. Non-SAR consists of 120 EMDEs for total employment and 121 EMDEs for nonagricultural employment. Bars show the range (maximum–minimum) for SAR and the interquartile range for non-SAR EMDEs. Markers show the weighted average of country group.
B. Sample consists of the latest Enterprise Surveys for 82 EMDEs conducted between 2022 and 2025, including Bangladesh (2022), Bhutan (2024), India (2022), and Nepal (2023) in South Asia. A firm's annual employment growth is the annualized employment growth between the fiscal year preceding the survey year and the end of the third fiscal year before the survey year. For each country, the annual employment growth of formal firms is the employment-weighted average of firms' annualized employment growth. Small firms have fewer than 20 workers. Medium-sized firms have 20 to 99 workers. Large firms have at least 100 workers. Young firms are 5 years old or younger. Bars show the range for South Asian countries and interquartile range for all EMDEs in the sample. Markers show the simple average for each group. High productivity firms are those with labor productivity in the top decile within a country-year, following the methodology of Galal et al. (2025).
C. Bars show coefficients from firm-level regressions of annualized firm employment growth on an indicator of whether a factor was a major obstacle to doing business. Regressions are conducted using the full sample of 82 EMDEs. Employment growth is between one and three fiscal years before the survey year. Independent variables include a single policy correlate, sector dummies, the average GDP growth rate over the previous two years (to control for country-level macroeconomic conditions), and year dummies (to control for common time patterns). The chart shows only the coefficients significant at the 10 percent level. Whiskers show 90 percent confidence intervals around the coefficient estimates.

The region's formal pension schemes would benefit from redesign, even where expansion is impractical: default enrollment with opt-out rights, contribution levels calibrated to irregular incomes, and provident funds that curb early cash-outs while preserving some liquidity. Countries or regions already at or near aged status—such as Sri Lanka and some Indian states—can run these systems at scale while still building foundations. Across all stages, early childhood investment, labor mobility, and fiscal capacity are cross-cutting enablers.

These barriers prevent these sectors from creating jobs that are numerous enough and suited to the many people currently working low-quality jobs.

In other developing countries, manufacturing played a critical role in moving people up the job quality ladder. The movement of surplus labor from agriculture to manufacturing was a critical part of the manufacturing-led development model (Lewis 1954). Providing large numbers of relatively unskilled workers with capital allowed them to rapidly increase productivity toward the global frontier. Over time, the path of manufacturing-led development has narrowed. Labor productivity in manufacturing has risen faster than in the broader economy, meaning higher manufacturing output is now compatible with fewer manufacturing jobs. Automation and robotics are reducing the labor intensity of production even at lower ends of the

value chain. The scale and technological depth of Chinese manufacturing make it difficult for later entrants to compete for low-end manufacturing exports (Chatterjee and Subramanian 2026; Rodrik 2016).

For most countries, the share of manufacturing in total employment peaks at a lower level and at a lower share of GDP than was previously the case, meaning that countries once reached high-income status before their industrial employment peaked, but no longer. For example, the countries that reached their peak industrial employment share between 1995–99 did so at an interquartile range of income per capita between $4000 and $28,000 (constant 2015 U.S. dollars). Those countries that reached a peak industrial employment share between 2015–19 did so an interquartile range of per capita income between $900 and $5,900, well below high-income levels.

To create a large number of better jobs for people working in low-value informal activities and agriculture in the same way as manufacturing once did, these jobs must be accessible. The priority is to identify sectors where entry barriers are low enough to absorb workers at scale in the near term, while providing pathways to progressively better-paid, more productive work over time. Two sectors have particular potential to kickstart this process by creating large numbers of jobs with low entry barriers: tourism and agribusiness. These sectors tend to have low entry barriers, low minimum scales of operation, geographic proximity to agricultural workers, modular and routine task structures, and labor-intensive production processes (Baum et al. 2016; Christiaensen, Rutledge, and Taylor 2020; Muñoz, Robinson, and Marston 2025; OECD 2024). These properties reduce the friction costs associated with sectoral transitions, enabling agricultural workers to climb the jobs ladder without requiring substantial retraining, capital accumulation, or geographic relocation.

Tourism includes those employed in hospitality services such as accommodation, food and beverage, and travel agencies. This sector has already absorbed large numbers of workers at a range of skill levels, from entry-level service roles to mid-skill positions in management, logistics, and specialized services. On average, the tourism sector employs 7 percent of workers in South Asia—broadly in line with the EMDE average—and substantially more in the region's smaller countries. International tourism receipts (which undercount the sector's total contribution) accounted for 3 percent of GDP in South Asia.

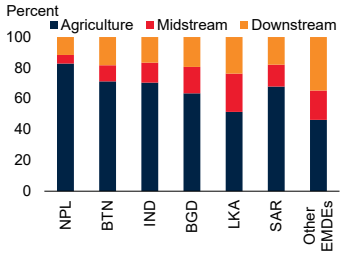
The barriers to entry into tourism are low. Workers in the sector are less likely to need a tertiary education, and more likely to under 25 years old. The experience of East Asia suggests that the sector can draw workers out of agriculture and toward higher-skill services, and act as a ladder toward better jobs. Workers entering the sector are more likely to be from the informal sector, and those exiting the sector are more likely to exit into the salaried formal sector. Policymakers can maximize tourism's potential for driving upward mobility by enabling programs for training, credential recognition and clear career pathways (Stacey 2015; Stangl et al. 2024).

Agribusiness provides another pathway that allows workers to move up the value chain from low-wage farming jobs without leaving the sector altogether. Expanding the share of agricultural activity that takes place away from farms—including midstream activities like manufacturing processing, wholesale, storage, and transportation and downstream activities like retail, food and beverage services—is associated with higher productivity for the sector and better paid jobs for individuals

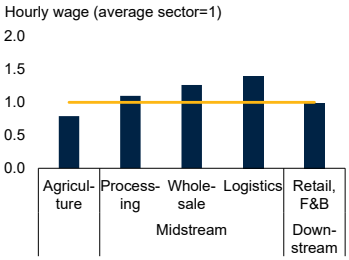
FIGURE 1.15 Creating jobs at scale in agribusiness

Moving from simple farming to downstream agribusiness activities is associated with higher wages. Agribusiness job growth is generally faster than the rest of the economy, but this growth is often stunted by an unsupportive policy environment.

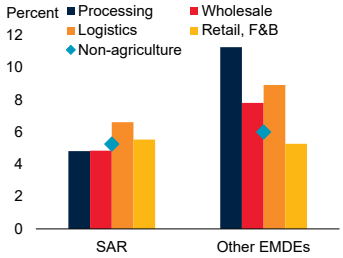
A. Employment share within the agricultural value chain



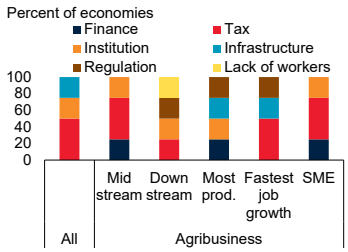
B. Hourly wages within agricultural value chain



C. Annual employment growth of firms, by position in agricultural value chain



D. Biggest obstacles to firms in South Asia's non-small states



Sources: GLD; World Bank Enterprise Surveys; World Bank Group.
A. Country groups are simple averages of Bangladesh, Bhutan, India, Sri Lanka, Nepal and 19 non-SAR EMDEs.
B. Country group is the simple average of country-level average hourly wage for the production stage (normalized by the country's average hourly wage). Sample includes Bangladesh, Bhutan, India, Sri Lanka, Nepal.
C. Country group aggregates are weighted using economy-level aggregate employment from Penn World Table. Bars show average annual firm-level employment growth for each mid- and downstream stage of the agricultural value chain. Horizontal lines show the weighted average of all EMDEs. Sample includes 6 South Asian countries, and 91 Other EMDEs.
D. Bars show the share of economies where each obstacle is ranked as the most important by the most firms, for all non-agricultural firms, and for agribusiness in the midstream (processing, wholesale, and logistics), downstream (retail and food and beverage services), the most productive (top 10 percent by labor productivity) agribusiness, the fastest growing (10 percent fastest employment growth) agribusiness, and SME agribusiness. Sample includes 4 South Asian countries. "Tax" includes constraints due to tax administration and tax rate. "Institution" includes constraints due to corruption, court, crime, and political instability. "Infrastructure" includes constraints due to electricity outage and transport. "Regulation" includes constraints due to competition from informal sector, customs regulations, labor, land, license.

(Christiaensen, Rutledge, and Taylor 2021; World Bank Group and IFC 2025; Yi et al. 2025).

In South Asia, this process is less advanced than in other EMDEs and advanced economies, and the majority of agriculture-related employment is still in farming (figure 1.15). Midstream jobs in the agribusiness value chain are both better-paid and have the potential to generate large numbers of jobs. In South Asia, the midstream sector pays a wage premium of 19–29 percent over agriculture, even controlling for worker characteristics. Many positions in the sector do not require advanced degrees and can make use of farmers' foundational knowledge.

Across EMDEs, most agribusinesses experience faster employment growth than the average non-agriculture firms. In South Asia, however, this potential is yet to be fully realized, and agribusinesses grow more slowly than both the rest of the domestic economy and agribusinesses abroad.

There are many factors constraining agribusiness growth. In South Asia, these constraints mostly relate to infrastructure and interactions with the state, rather than lack of finance. As in other sectors, tax system and institutions—notably political instability—are cited in World Bank Enterprise surveys as the biggest constraints for firms in South Asia's midstream and downstream sectors. In addition, firms in South Asia's midstream sectors also face constraints from the lack of infrastructure such as cold chain networks and warehouses, while those in downstream sectors face additional constraints from lack of educated workers and regulation. Policymakers can help agribusiness grow by streamlining tax regimes, improving infrastructure (including road access and power), and strengthening institutions.

Realizing the promise of AI

Thus far, the macroeconomic impacts of AI on South Asia have been limited. The region is not a major participant in the fast-growing global value chain for AI-related goods. Its labor market is less exposed to AI than those of other EMDEs, with only 7 percent of jobs combining high AI exposure with low complementarity, compared with 15 percent in other EMDEs (World Bank Group 2025a). Domestic adoption of AI remains low.

In India, the only South Asian economy surveyed, 23.4 percent of formal firms use some form of AI, compared with 42.7 percent in the United States (figure 1.16). This gap becomes more pronounced when the level of sophistication in AI use is considered. An AI adoption index, which reflects the type of AI technology being used in the firm and how well it is embedded in business operations, has an average value of only 0.27 in India as compared to 0.85 in the United States: a nearly three-fold gap.[1] U.S. firms are considerably ahead of Indian firms in every dimension of AI use considered in this index. For example, only 3.5 percent of Indian firms have incurred a fee or purchase cost for AI use, as compared to 23.1 percent of U.S. firms. Similarly, Indian firms lag heavily behind U.S. firms when considering the level of advancement of the AI technologies, the number of tasks and business functions for which AI is being used, and whether AI is being sourced through software platforms, not just online platforms.

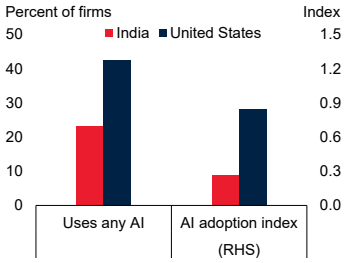
AI adoption among Indian firms is limited, but it is also broad-based in the sense that it is not systematically correlated with most observable firm-level attributes (for example, firm size, age, management experience and practices, workforce skill intensity, ownership, innovation-related activities and exporting behavior) and external factors (for example, access to electricity, ICT, and finance). Only two attributes are significantly correlated with AI use sophistication in Indian firms: foreign ownership and skill intensity. Firms with some foreign ownership have a 0.7 standard deviation higher AI index value than purely domestically owned firms, consistent with recent evidence that multinational affiliates are leading other firms in hiring workers with AI skills in South Asia (World Bank Group 2026d).

[1] The index is a z-score; that is, it has been normalized so that a 1-unit increase in it represents a movement of one standard deviation across its distribution among all the countries covered in the World Bank Enterprise Surveys.

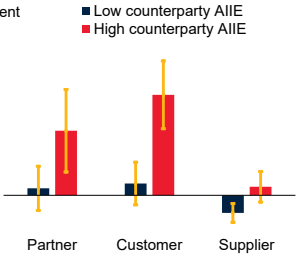
FIGURE 1.16 Realizing the promise of AI

AI adoption among Indian firms lags that of the United States. AI adoption abroad is generating new value chain demand for South Asian suppliers, most strongly for those highly exposed to AI themselves. Firms point to digital infrastructure and education as what would most raise it. Building these complements, above all workforce skills and reliable power and connectivity, can help turn exposure to AI into productivity gains.

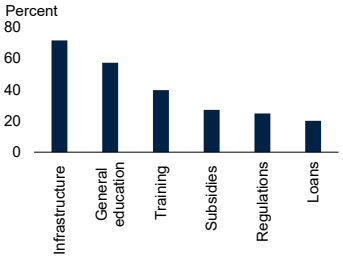
A. AI adoption in India and the United States



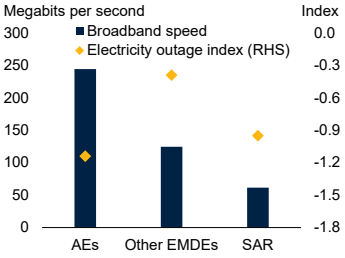
B. Impact of AI exposure on GVC connections by counterparty AI exposure: U.S. firms



C. Policy priorities: Indian firms



D. Infrastructure: Broadband speed and grid reliability



Sources: Chiplunkar et al. (2026); FactSet; Felten, Raj, and Seamans (2021); LinkUp; Speedtest; World Bank B-Ready; World Bank Enterprise Surveys AI Module 2025–26; World Bank Group.

A. Bars in panel A show the weighted average across firms of a binary indicator for any AI use and the AI adoption index.

B. Bars show the relationship between US firms' own AI exposure and the post-GPT increase in their relationship counts with South Asian firms, by their South Asian counterparties' AI exposure. Low and high counterparty exposure groups are defined by whether the average pre-GPT counterparty AI exposure is below or above the median. Refer to table A.2.2.5, panel A, for full results.

C. Bars show the percentage of establishments agreeing that each policy could increase their use of AI technologies, for each policy option listed in the WBES. The exact phrasing of the policy options in the survey is as follows: "Infrastructure" stands for "better digital infrastructure"; "General education" for "skills among university graduates"; "Training" for "training of the current workforce"; "Subsidies" for "financial subsidies"; "Regulations" for "changes in regulations around AI"; and "Loans" for "improved access to financial loans."

D. Bars show broadband speed, measured in 2026 as average country-level download speeds in megabits per second, covering 38 AEs, 5 SAR countries (all except Bhutan), and 109 other EMDEs. Yellow diamonds show the electricity outage index for 32 AEs, all 6 SAR countries, and 121 other EMDEs. The index is measured as the weighted average of the following country-level standardized variables: i) average number of electrical outages per month, ii) average duration of electrical outages, iii) revenue losses due to electrical outages, iv) percent of firms identifying electricity as a severe constraint, and v) percent of firms experiencing electrical outages. Weights are loadings from the first principal component of the variables. Variables are averaged within economies over 2009–25. Regional averages of both indicators are weighted by country population.

Foreign-owned firms may also have greater capabilities to deploy new technologies quickly, consistent with the broader literature on foreign direct investment and technology diffusion in EMDEs (Harrison and Rodríguez-Clare 2010). A 1-standard-deviation increase in a

workforce skill intensity index is associated with a 0.15-standard deviation-increase in the AI index, consistent with research suggesting that the scope for AI use is higher in knowledge-intensive tasks (Felten, Raj, and Seamans 2021, 2023), with managerial and supervisory jobs being particularly complementary to AI use (Pizzinelli et al. 2023).

A WBES survey of firms finds that many firms—especially small and medium-sized firms—see limited potential for labor productivity gains from AI. About 70 percent of firms expect a zero or near-zero gain from faster AI development, and about 15 percent of Indian firms expect that AI development will reduce their revenue per worker by 0–10 percent, perhaps because they expect to lose market share to firms that have an advantage in deploying AI rapidly. Only about 8 percent of firms expect gains of 20 percent or higher.

When asked about their main reason for currently not using AI in executing business functions, cost is the most frequently named reason by Indian firms. This is followed by regulations that restrict AI use, lack of knowledge, concerns about privacy or security, and a shortage of skills, in that order.

Because AI adoption and sophistication in U.S. firms run well ahead of those in Indian firms, some of the most immediate effects of AI on South Asian firms may be transmitted through global value chains. For South Asian firms, this could have two countervailing effects. As U.S. firms in AI-exposed sectors grow more productive, they may expand their international supplier base, drawing in new inputs from South Asia (a scale effect). At the same time, they may sever relationships involving tasks that AI can now automate (a *substitution,* or reshoring, effect). Chapter 2 provides evidence that the substitution effect is not dominating, and that AI is creating new opportunities for South Asian firms to supply and partner with U.S. firms. GVC relationships in which U.S. firms are customers or partners and South Asian firms are suppliers or partners have grown fastest when *both* parties are in high-AI-exposure sectors.

These findings lead to several possible policy priorities. The first is to spur AI adoption so that its productivity benefits are realized more widely and quickly across the region's firms. Firms themselves point to skills and infrastructure as key policy priorities for expanding AI use. Seventy-two percent of Indian firms say better digital infrastructure would raise AI use and nearly 60 percent point to better tertiary education, whereas U.S. firms rank workforce-specific training more highly. Infrastructure policy can focus on reliability and speed rather than access alone. Grid reliability in South Asia has improved, led by India, and now exceeds EMDE levels, although it remains below advanced-economy levels, while broadband speed is below the EMDE average. Governments can encourage private connectivity investment by reducing entry and foreign-ownership barriers, allocating spectrum on technology-neutral terms, and promoting tower and duct sharing (World Bank Group 2024e). In power, better utility governance and pricing are as important as new capacity: distortions from inefficient state-owned utilities, subsidies, and mispricing are estimated to cost 4 to 7 percent of GDP in Bangladesh and India (Zhang 2019). Access to computing power is also essential, and local datacenters can be one form of such access.

The second priority is to help South Asian firms move up global value chains—away from routine, automatable tasks for which global demand is falling, and toward the new, higher-value work that AI is opening. Demand is shifting toward higher-value activities adjacent to automatable tasks, such as expert review of AI-generated software and

text used to fine-tune models. Lower-value business process outsourcing is therefore more exposed to substitution, strengthening the case for helping firms move toward knowledge-intensive services, analogous to the region's earlier move toward knowledge process outsourcing (World Bank Group 2026d). South Asia has already succeeded at this type of challenge once: services accounted for 44 percent of South Asian exports in 2024, compared with a global average of 27 percent, and ICT alone exceeds 22 percent of total exports in India, 5.3 percent in Sri Lanka, and 3 percent in Nepal (World Bank Group 2026d).

The third is to make AI tools effective in local conditions, adapting them to local languages, infrastructure, and the realities of service delivery. Foundational skill gaps obstruct this goal, with adult literacy estimated at 75 percent against 85 percent across EMDEs. Priorities therefore include basic education, technical and vocational training, and the managerial and soft skills needed for higher-value manufacturing and services. Skills also matter for adapting AI tools to local languages and conditions. Training can be linked to employer demand and job matching, since evidence on stand-alone government training is mixed (Card, Kluve, and Weber 2018; McKenzie 2017), while sectoral programs combining training and matching have shown stronger results elsewhere (Katz et al. 2022).

Beyond these foundational conditions, there are further areas where public policy can help firms and AI developers make the most of AI's potential. The first is knowledge: firms often cannot tell which AI tools suit them or judge the quality of advice on offer, an information gap that public advisory and matchmaking services can help close. The second is the local innovation ecosystem: because AI capabilities cluster and build on one another, the connections, shared facilities, and demand that underpin a startup ecosystem are often undersupplied without public coordination. The third is governance: clear, predictable rules on data and AI use would reduce the regulatory uncertainty now deterring adoption. National AI strategies are in place in India (MeitY 2025) and in draft in Bangladesh (Government of Bangladesh 2026). With no established gold-standard model for EMDEs, a flexible, risk-based approach, adapted to the maturity of the local AI ecosystem and developed with industry, civil society, and academia, can address privacy, security, and accountability concerns while keeping compliance costs proportionate (World Bank Group 2024f). Together, these actions would help enable the private sector to seize AI's opportunities while safeguarding against its risks.

Annex 1.1 Policy and macroeconomic response to the energy price shock

South Asian economies are highly exposed to the current rise in energy prices, as most are net oil importers with significant Middle Eastern energy dependence. This annex provides an early assessment of how fuel subsidy policy choices have shaped the transmission of the shock to domestic retail prices and macroeconomic outcomes.

Data and country classification

The sample covers 99 countries with sufficient retail fuel price data. The Islamic Republic of Iran, Lebanon, and the United Arab Emirates are excluded due to their direct exposure to recent conflict. The shock reference date is 23 February 2026; retail price changes are measured through end-July 2026. Macroeconomic outcomes compare a December 2025–February 2026 baseline against a March–June 2026 post-shock window.

Countries were divided into three groups based on their reaction to the energy price shock.[2] "Pre-shock subsidizers" had expenditures on explicit gasoline and diesel subsidies worth more than 0.21 percent of GDP in 2024—the global median among active subsidizers—and were already holding prices below market levels. "Post-shock subsidizers" fell below that threshold in 2024, but responded to the shock by implementing fiscal measures aimed at lowering gasoline and diesel prices, as recorded in the World Bank Policy Tracker. "Free marketers" are those countries that did neither.

None of the groups are a regional or income bloc—all span multiple regions and income categories—though energy subsidizers are more likely to be energy exporters: eight of twelve are oil exporters, versus four of the thirty-four post-shock subsidizers.

Pass-through analysis

A cross-sectional OLS regression of the retail gasoline price change on country characteristics ($n = 40$, $R^2 = 0.40$) finds that the policy stance is the dominant predictor of pass-through. Once policy stance is included, a country's status as a net importer or exporter of oil does not play a statistically significant role.

Pre-shock subsidizers saw retail gasoline prices rise 37 percentage points less than free marketers (–36.94, $p < 0.001$), reflecting straightforward administrative price suppression (figure A.1.1). Post-shock subsidizers saw prices rise 10 percentage points less (–10.20, $p = 0.043$), consistent with partial buffering through new fiscal measures. The VAT rate is also significant (–10.63 per 10 percentage points, $p = 0.003$) because a VAT mechanically dampens the passthrough of global oil prices to domestic prices in percentage terms, and possibly because some countries temporarily reduced fuel taxes to absorb the shock.

Three regressors are indistinguishable from zero. The oil price change in local currency

[2] Pre-shock subsidizers include the Arab Republic of Egypt, Bahrain, Bolivia, Brunei Darussalam, Ecuador, Indonesia, Kazakhstan, Kuwait, Malaysia, Mongolia, Turkmenistan, and Zimbabwe. Post-shock subsidizers include Argentina, Australia, Bangladesh, Barbados, Brazil, Cambodia, Chile, the Dominican Republic, Ethiopia, Greece, Guatemala, Honduras, India, Ireland, Jamaica, Japan, Kenya, the Lao People's Democratic Republic, Mexico, Mozambique, Namibia, Pakistan, Palau, Portugal, Romania, St. Kitts and Nevis, Serbia, South Africa, Spain, Sri Lanka, Thailand, Uruguay, Viet Nam, and Zambia. Free marketers include Afghanistan, Albania, Austria, The Bahamas, Belgium, Bhutan, Cabo Verde, Canada, China, Colombia, Croatia, Cyprus, Denmark, Djibouti, Fiji, France, Germany, Haiti, Hungary, Italy, Jordan, Lithuania, Madagascar, Malawi, Maldives, Mauritius, Morocco, Myanmar, Naoero, Nepal, the Netherlands, New Zealand, Nigeria, Norway, Panama, Papua New Guinea, Peru, the Philippines, the Republic of Korea, Samoa, Senegal, Singapore, Slovenia, Solomon Islands, Sweden, the Syrian Arab Republic, Timor-Leste, Tonga, Türkiye, Uganda, the United States, Vanuatu, and the Republic of Yemen.

(p = 0.816), net import dependence (p = 0.882), and GDP per capita (p = 0.568) all fail to predict pass-through once subsidy posture is controlled for.

Price, inflation, and macroeconomic outcomes

Retail fuel prices confirm the regression pattern. Pre-shock subsidizers contained pump price increases to around 8 percent, though with wide variation across countries; free marketers and post-shock subsidizers witnessed increases of roughly 19 percent, with no statistical difference. Diesel results closely mirror gasoline across all groups.

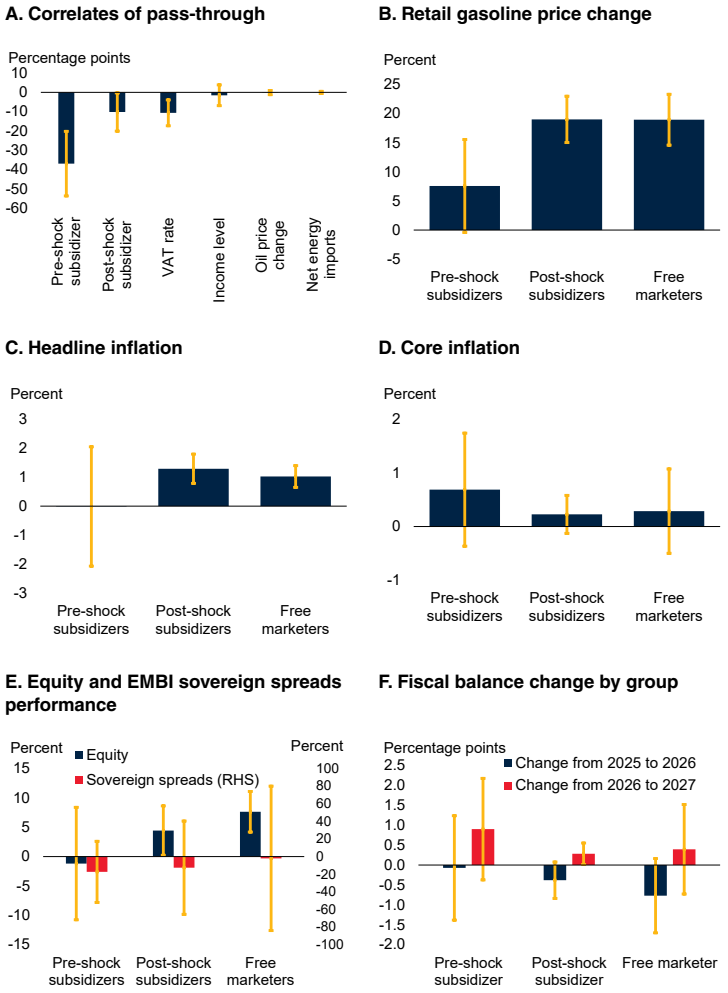
Headline CPI inflation follows a similar pattern, with pre-shock subsidizers suppressing price increases relative to the other groups, but the differences are not significant. The pattern does not extend to core inflation, however, where outcomes were broadly similar across all three groups, suggesting that fuel subsidies suppressed headline prices without restraining the broader price level.

Financial market outcomes—equity returns and sovereign spreads—showed no statistically significant differences across the three groups, suggesting that markets did not systematically differentiate between subsidy and non-subsidy policy stances in the aftermath of the shock.

Changes in the **forecast fiscal balance** as a share of GDP from 2025 to 2026, and from 2026 to 2027 were not statistically differentiable between the three groups. All three groups had deteriorations in their fiscal balance in 2026 and improvements in 2027, on average, but the differences were not statistically significant.

FIGURE A.1.1 Policy and macroeconomic response to the energy price shock

Pass-through of global oil to domestic retail gasoline prices was lower for countries that had subsidies in place. Subsidies were not effective at containing overall inflation, however. Subsidies did not play a significant role in determining equity or bond market dynamics, nor did they have a significant impact on fiscal balance forecasts.



Sources: Global Petrol Prices; Haver Analytics; IMF Fossil Fuel Subsidies Data; J.P. Morgan EMBI Global; Malaysia Ministry of Finance; Pertamina Patra Niaga; World Bank Policy Tracker; World Bank Group.
A. VAT is scaled per 10 pp of the gasoline tax rate. Oil price changes are in local currency terms. Net energy imports are 2024 net oil and gas imports (% of GDP). Income is World Bank income level coded 1–4.
B. Changes of 23 February relative to end-July 2026.
C.D. December 2025-February 2026 average to March-June 2026 average.
E. Changes are measured from the February 2026 average to end-July 2026. Sovereign spreads refer to EMBI strip spreads. Sample composition varies across indicators. Group differences are assessed using 95% confidence intervals.
F. The sample comprises countries with MPO fiscal balance forecasts available. It includes 67 EMDEs and 1 advanced economy (Croatia). Pre-shock subsidizers account for 11 countries, post-shock subsidizers for 28, and free-marketers for 29. Fiscal balance is expressed as a percent of GDP. Group differences are assessed using 95% confidence intervals.

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CHAPTER 2

Delivering the Promise of AI in South Asia

Chapter 2. Delivering the Promise of AI in South Asia

Artificial intelligence (AI) can transform South Asia's development prospects through several channels, including by boosting the growth of labor productivity, by increasing export opportunities, and by improving the delivery of public services. AI adoption among the region's firms is rising fast but still trails the frontier: about 23 percent of Indian firms report using AI, against 43 percent in the United States, and the gap is wider for more sophisticated uses. Global value-chain links between South Asian suppliers and U.S. customers have grown faster when suppliers and customers are in sectors that are more exposed to AI, suggesting that AI is generating new global market opportunities for the region's firms. Prospects for AI-enhanced public service delivery are mixed: evidence suggests that AI's success in this area depends on tailoring to local conditions. Access to computing power underpins AI, and local data center investment is one means to secure it. For most of the region, the greatest gains lie in adopting AI and adapting it to local conditions—including through small AI applications suited to low-resource settings. Realizing AI's promise will therefore depend on policy action to secure the analog foundations for success, by strengthening workforce skills, establishing a more business-enabling environment, and improving the physical and digital infrastructure. It will also depend on complementary measures to reduce barriers to AI adoption by small firms, foster local AI innovation, and establish a clear regulatory framework that reduces uncertainty and safeguards data security and privacy.

Introduction

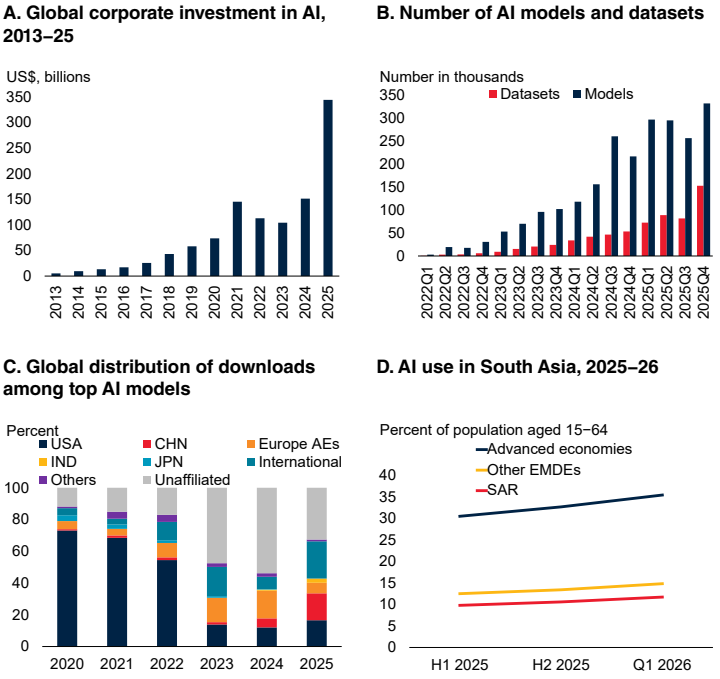
The promise of AI. The rapid advancement of artificial intelligence (AI), a general-purpose technology, offers great promise for economic development. In only a few years, AI has progressed from predictive machine-learning algorithms to Generative AI (GenAI) models that generate content from text, audio, and video, and most recently to autonomous agents. Global corporate investment in AI more than trebled, in nominal U.S. dollar terms, between 2022—when the first major GenAI model was launched—and 2025, with a concomitant increase in the number of AI models released (figure 2.1). AI's applications already span manufacturing, services, and agriculture. For emerging market and developing economies (EMDEs), including those in the South Asia region (SAR), this breadth matters because AI can supply capabilities that are locally scarce: firms, farmers, teachers, and health workers can all draw on AI-enabled expertise to become more productive (World Bank Group 2026a). Usage data for leading AI models reveal rising engagement in South Asia and other EMDEs, although per capita usage rates remain well below advanced-economy levels.

Exposure to AI in South Asia's labor market. AI can raise labor productivity by augmenting non-routine, higher-value tasks or by automating—substituting for—more routine ones. Its effects on employment and productivity depend on an occupation's exposure to AI—how far its required skills overlap with AI's capabilities—and its complementarity with AI, or the degree to which humans remain non-substitutable. South Asia faces lower AI automation risk than other EMDEs, with only 7 percent of jobs combining high exposure and low complementarity, well below the 15 percent average in other EMDEs (World Bank Group 2025). In part, this reflects the region's large agricultural workforce. At the same time, 15 percent of South Asian workers are in jobs where both exposure and complementarity are high, a segment that stands to gain the most from AI-augmented productivity growth.

This chapter was prepared by Jonah Rexer and Siddharth Sharma (DECPA).

FIGURE 2.1 AI investment and cross-country diffusion

Corporate investment and product launches in AI have risen sharply worldwide. Emerging market and developing economies (EMDEs) trail advanced economies in the share of the population using AI, and South Asia falls below even the EMDE average.



Sources: Maslej et al. (2025); Microsoft (2026); Sajadieh et al. (2026); World Bank Group.
Note: For country code abbreviations, refer to the International Organization for Standardization, https://www.iso.org/obp/ui/#search.
A. Bars show total AI investments in corporations that develop AI models globally during 2013–25.
B. Bars show the number of models and datasets on Hugging Face during 2022–25.
C. Bars show the global distribution of downloads among top Hugging Face models during 2020Q2–2025Q3. Data for 2021–24 are annual.
D. Lines show the simple average of AI use in 4 South Asian economies (Bangladesh, India, Nepal, and Sri Lanka), 31 advanced economies, and 110 other EMDEs.

These account for about 70 percent of all AI-exposed jobs in the region, the highest share among EMDE regions (figure 2.2).

Emerging effects of AI in South Asia. There are early signs that South Asian firms have been reorganizing their workforces to benefit from AI (World Bank Group 2026b). As revealed in online job postings, hiring has slowed among firms whose workforces are highly exposed to AI; this may reflect automation, or caution in the face of technological uncertainty. Demand for AI-related competencies has risen sharply, however, with positions requiring these skills commanding a wage premium of nearly 30 percent. Firms have also shifted the composition of their hiring, posting jobs that are on average less exposed and more complementary to AI (figure 2.2).

The adoption challenge. These early developments notwithstanding, historical experience suggests that the productive deployment of AI by South Asian firms will take time to materialize. Firms are often slow to adopt new technologies and use them well; even when a general-purpose technology such as AI is readily available, capturing its benefits typically requires costly reorganization and complementary investment (Chatterji, Rock, and Talamàs 2025). It took four decades for U.S. manufacturing to fully implement electrification because it required factory redesign and task reallocation (David 1990; Hall 2004). The spread of networked computing followed a similar path (Brynjolfsson and Hitt 2000; Greenan and Guellec 1998).

Opportunity and risk from AI adoption in global value chains. For export-oriented firms, the impetus to adopt AI may come from abroad. AI is likely to give rise to risks and opportunities for EMDEs through international trade. An opportunity is that rising productivity from AI adoption abroad could generate increased demand for inputs from EMDEs, as seen in earlier waves of automation (Artuc, Bastos, and Rijkers 2023; Cilekoglu, Moreno, and Ramos 2024). A risk is that AI enables foreign buyers in global value chains (GVCs) to reshore automatable functions previously sourced through imports. Firms in business process outsourcing that specialize in lower-value tasks, such as customer support and routine software development, are particularly exposed to this risk. Reshoring of this kind followed the spread of industrial robots in advanced economies (Faber 2020; Krenz, Prettner, and Strulik 2021; Kugler et al. 2020). However, GenAI may be different

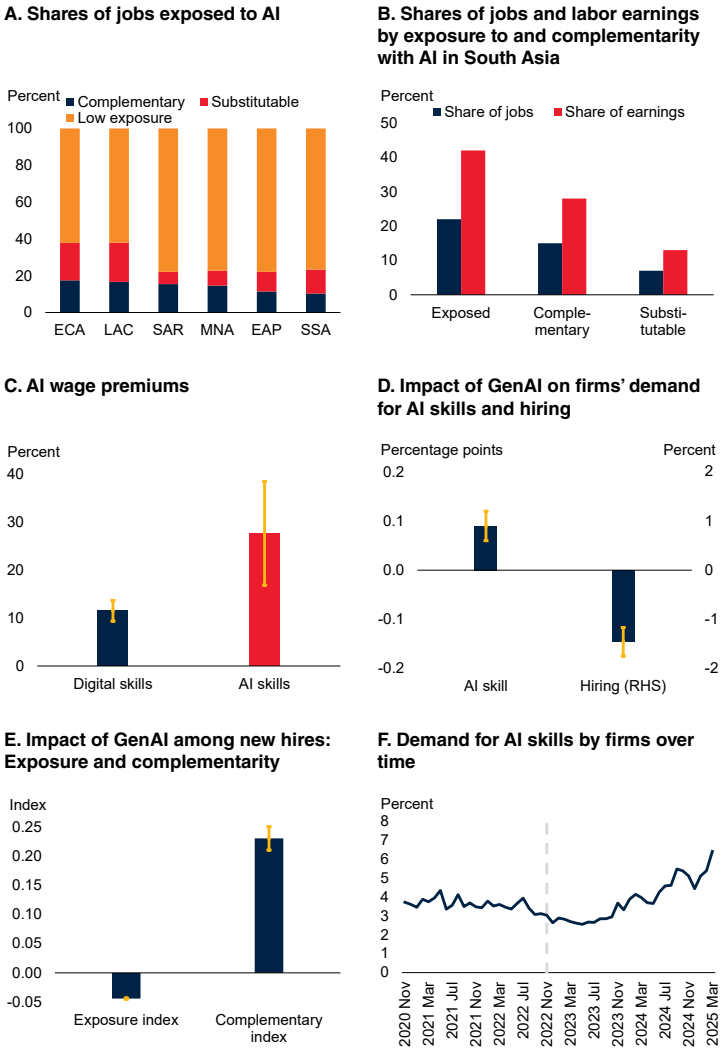
because it reaches a wide range of cognitive work in which exporters from higher-income countries tend to specialize (Kruse and Yu 2026).

Adapting AI for development. AI's promise is not confined to firms. It can address South Asia's development challenges in areas where skilled personnel are scarce, such as health, education, and agricultural extension. Early evidence on some of these applications is promising, ranging from weather forecasts that help farmers time planting and harvesting (Burlig et al. 2024) to clinical screening and image-grading tools that improve efficiency in frontline healthcare (Abramoff et al. 2023; Mathenge et al. 2022). Capturing these gains, however, requires adaptation to local conditions. Foundation AI models are trained overwhelmingly on content from a few major languages and regions, and may miss local contexts. Adaptations may also be required for applications to be workable with locally varying regulations and users' digital skills, intermittent electricity, and low-bandwidth connectivity.

Focus on adopting and adapting. For most South Asian economies, these considerations point to a strategy focused on adopting existing AI tools and adapting them to local needs rather than on advancing the frontier by building new models from the ground up, an activity concentrated among a few firms in advanced economies (World Bank Group 2026a). One promising form of adaptation is small AI: compact or narrowly scoped models that run on basic devices and limited connectivity, suited to the low-resource settings that characterize much of the region. India is the exception: given its sophisticated digital infrastructure, it can also consider targeted investment in advancement in areas where its scale and diversity give it a natural advantage, such as the development of large language models trained on local languages.

FIGURE 2.2 Labor market exposure and impacts of GenAI in South Asia

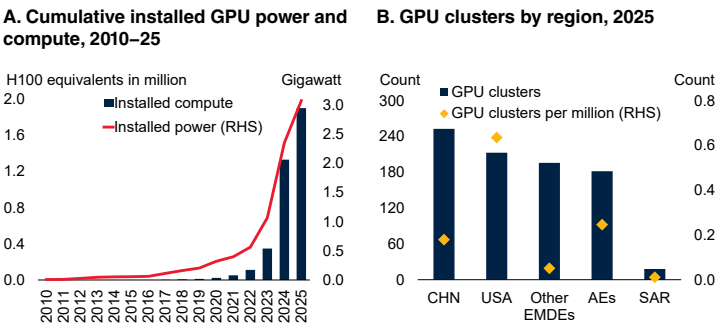
South Asia's labor market exposure to AI is below the average for emerging market and developing economies, with an above-average share of its AI-exposed jobs complementary to AI rather than substitutable by AI. The region's AI-exposed firms are showing early signs of adjustment: reducing net hiring while shifting it toward AI-complementary occupations.



Sources: World Bank Group (2025, 2026b).
Note: Yellow whiskers show a 95 percent confidence interval.
A. Bars show the percentage of jobs in three categories: high exposure to and high complementarity with AI; high exposure to and high substitutability with AI; and low exposure to AI.
B. Bars show the shares of jobs and total wage earnings exposed to AI, complementary to AI, or substitutable with AI.
C. Bars show the estimated wage premiums associated with digital and AI skills. Estimates are based on 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. See World Bank Group (2026b) for details.
D.E. Bars show coefficients from firm-level regressions of indicated outcomes on average AI exposure of pre-ChatGPT job postings interacted with a post-ChatGPT indicator. Regressions include firm and month fixed effects. In panel D, the outcome variables are the share of job postings requiring AI skills and the log of total job postings. In panel E, the outcome variables are the average AI exposure and complementarity of posted jobs. Standard errors are clustered at the firm level. See World Bank Group (2025) for details.
F. Line shows the share of total job postings that require AI skills. Vertical line indicates the release of ChatGPT in November 2022.

FIGURE 2.3 The global rise of AI data centers

Installed compute and power in AI data centers have risen dramatically since 2022. China and the U.S. lead in terms of the total number of data centers, with South Asia being a minor participant in this part of the AI value chain.



Sources: Epoch AI; Ramp; World Bank Group.
Note: GPU = graphics processing unit.
A. H100 equivalents refer to computing power of NVIDIA H100-series chips.
B. Bars show the number of GPU computing clusters in 2025 for China, the United States, 42 AEs, 6 South Asian economies, and 148 other EMDEs.

Data centers and access to AI. Applications of AI depend on access to computing infrastructure. Rising digitalization and AI take-up among firms and consumers have driven sharp growth in demand for cloud computing, and installed AI compute capacity has expanded rapidly. This expansion has a large energy footprint: data centers are among the fastest-growing sources of electricity demand, and AI workloads are intensifying it. Data center capacity remains heavily concentrated in the United States and China, and South Asia is a minor participant in this part of the AI value chain (figure 2.3). Local data centers are one means of accessing compute but they can create trade-offs for host communities.[1]

Questions. This chapter examines the following questions:

- Which firms in South Asia have adopted AI and what constraints to adoption do firms face?
- How is AI changing GVC opportunities for South Asian firms?
- Can AI tools improve foundational learning outcomes in low-resource areas?
- What is the role of local data center investment for securing access to AI's benefits?
- How can policies facilitate AI adoption in South Asia?

Contributions to the literature

Several studies have documented hiring cutbacks in South Asia's AI-exposed occupations, firms, and activities (Copeland et al. 2023; World Bank Group 2025, 2026b). This chapter explores firms' behaviour beyond hiring cuts and examines experience with AI use more broadly.

This chapter presents the first published analysis of the adoption of AI by firms in a South Asian country, India, using comprehensive firm-level survey data; and on this basis it compares the Indian experience with that of the United States. The data source used in this analysis, the 2025–26 World Bank Enterprise Survey AI Module, is the result of the first harmonized survey to measure AI use in representative samples of formal firms in a group of EMDEs, along with the United States. Previously published research on AI adoption has been based on three types of data, none of which comprehensively measures the characteristics of AI adoption in EMDE firms: firm surveys conducted in advanced economies and China, aggregated chat log-based user-level data released by AI companies, and job posting data (where firms' job postings requiring AI skills serve as a proxy for adoption). These data all have major shortcomings: in particular, as recent research from the United States finds, survey-based measures of AI use differ systematically from estimates based on chat-log

[1] "Compute" is a generic term used to reference processing power, memory, networking, storage, and other resources required for computational operations. It is often used, as here, to refer particularly to the capacity of data centers.

data of GenAI platforms (Betai and Chen 2025). Job postings data only reflect adoption through hiring and may be particularly biased against firms which do not have sufficient scale to justify hiring specialized AI talent. The analysis in this chapter, on the basis of the answers to detailed survey questions, goes beyond simple binary measures of AI adoption and assesses the sophistication of AI use in firms.

This chapter also presents the first published analysis of how AI is reshaping GVC relationships between firms in an advanced economy—the United States—and a group of EMDEs—those of the South Asia region—using micro data. The analysis, which builds on work presented in World Bank Group (2026a), uses a unique monthly dataset on GVC-linked U.S. and South Asian firms. The dataset is constructed by merging three large datasets on firms' online job postings and international relationships. This analysis contributes to the literature on the effects of automation in advanced economies on firms in EMDEs. Past studies, with the exception of Betai and Chen (2025), have been on industrial robots and manufacturing; in contrast, AI can affect both services and manufacturing firms along GVCs. The empirical analysis described here complements past efforts to model the impact of AI on global trade (Goldfarb and Trefler 2018) and the location of non-routine versus routine work (Ide and Talamàs 2026).

This chapter presents, as well, the findings of a randomized controlled trial of a winter school pilot for elementary school students, which contributes to the nascent literature on the impact of AI-assisted tools in education and healthcare in EMDEs (Burneo et al. 2026; Sautmann and Weinert 2026). The experiment differs from most existing research on AI in foundational learning in EMDEs in that it studies an AI tool that assists teachers and does not interact directly with students. Furthermore, it compares the AI tools with a teacher-led instructional program, thereby helping assess the additionality from AI.

Finally, this chapter contributes to the literature on the determinants and impacts of data center investment in EMDEs by examining data center location choices and assessing the comparative advantage of South Asian countries in hosting data centers. Previously published evidence on these questions has mostly been from advanced economies, with limited research on EMDEs (Gutiérrez, Gallego, and Herrera Giraldo 2025).

Main findings

Several findings emerge from this study.

First, the comparison of Indian and U.S. firms adds to evidence that AI adoption in South Asia remains well behind that in advanced economies, although it has recently been accelerating and catching up. Some 23 percent of Indian firms report using AI, against 43 percent of U.S. firms, and the gap widens for more sophisticated and more embedded activities: on an index capturing these dimensions, adoption among Indian firms averages not even one-third that among U.S. firms. Although still lagging, AI adoption in India is broad-based, being uncorrelated with firm characteristics beyond foreign ownership and workforce-skill intensity. Expectations of productivity gains from further AI development are significantly higher in Indian firms with higher skill-intensity, more innovative activity, and better access to information and communications technologies.

Second, GVC links between U.S. and South Asian firms have grown since 2022 and, in relationships in which the U.S. firm is the customer of the South Asian firm, this growth has been concentrated in AI-exposed sectors. A one-standard-deviation increase in a U.S.

firm's industry exposure to AI is associated with a 27.5 percent larger post-ChatGPT rise in its customer links with South Asian firms, and the result is mirrored on the South Asian side. The association is stronger still when both customer and supplier are highly exposed to AI. This double complementarity suggests that AI is generating new opportunities in tasks adjacent to those South Asian suppliers already perform, and that firms in AI-exposed sectors on both sides are best placed to capture them.

Third, the results of a randomized trial of an AI-assisted teaching tool suggest that the promise of AI in public service delivery is clearer in principle than in practice when school systems lack the basics. The trial, conducted in Balochistan, Pakistan, tested a six-week winter school, comparing a teacher-led targeted instruction program with an arm in which an AI app helped teachers deliver targeted instruction (Asad et al. 2026). The teacher-led arm raised test scores sufficiently to offset the winter break learning loss observed in the control group; the AI-assisted arm produced a smaller effect that was not statistically distinguishable from zero.

Fourth, AI use depends on access to computing power and local data centers are one means of access. Local data centers can speed up response times and create local economic spillovers. But they tend to locate where energy supply is abundant and reliable, business environments are favorable, and skilled workforces are large—all factors with considerable gaps in parts of South Asia. The region's water and human capital endowments are below the EMDE average, and energy generation, in its current fuel composition, causes above-average pollution. Each kilowatt-hour of energy use carries a pollution cost three times that in advanced economies. The policy focus could therefore be on improving foundational factors that would attract data centers as well as investment more broadly.

Fifth, for most of South Asia the returns to AI lie in adopting and adapting the technology to local conditions. These returns could be raised significantly by strengthening the analog foundations on which AI depends, primarily workforce skills, reliable digital and energy infrastructure, and a business-enabling environment. Other policy priorities are lowering unnecessary regulatory barriers to AI adoption by small firms, supporting the local innovation systems and small AI applications needed to adapt AI tools to local contexts, and developing a clear regulatory framework that reduces uncertainty while safeguarding data security and privacy.

Data and methods

Firm-level AI Adoption. The chapter uses data from the World Bank Enterprise Surveys (WBES) AI Survey to analyze firm-level AI adoption. The surveys were conducted in 2025–26 in eight EMDEs, including only India among South Asian countries, and one advanced economy, the United States (Davies et al. 2026). The surveys covered formal firms with at least five employees, with a sample size of 1,355 in India and 401 in the United States. The survey results include information on the adoption of AI, its timing, and how it is being used; expectations of productivity gains from AI development; and obstacles to, and policy priorities for AI adoption. The analysis of the correlates of adoption and expected gains from AI also uses data on the firm's internal attributes and external environment from the main WBES dataset and employs ordinary least square (OLS) regressions with sector fixed effects to control for differences in sectoral composition across countries. Given the small and non-representative set of other EMDEs covered by the surveys—only five countries—the analysis in this chapter focuses on comparing India with the United States (details in annex 2.1 and annex 2.2). India has larger domestic markets and more

advanced institutional underpinnings for AI than other South Asian countries, so its adoption rates are likely to be higher than in the rest of the region.

GVC analysis: data. The GVC analysis uses unique data on firms' job postings and international GVC relationships to examine how exposure to AI shapes firms' demand for AI skills and GVC participation in South Asia and the United States (Chiplunkar et al. 2026). Sectoral AI exposure is measured using a sector-level index which builds on occupation-level task-based indices from Felten, Raj, and Seamans 2021, 2023. Firm-level demand for AI skills is captured from online job postings datasets. For South Asia, the analysis uses data on roughly 25 million online job postings from Lightcast, covering 435,249 firms between 2020 and 2025. For the United States, the analysis uses data on roughly 111 million job postings from Linkup, covering 44,690 firms between 2020 and 2025. These data are merged at the firm level with GVC data from FactSet, which identify buyer, supplier, and partnership relationships between South Asian and foreign firms. These mergers result in two unique monthly firm-level panel datasets: a dataset of U.S. firms containing information on their job postings, GVC connections with South Asian (and other international) firms, and the job postings of the South Asian GVC counterparties; and a mirroring dataset of South Asian firms.

GVC analysis: methods. The empirical GVC analysis estimates, in a difference-in-differences approach, how firms' pre-existing sectoral exposure to AI shapes AI skills demand and participation in GVCs using the monthly panel data. To identify the effect of GenAI, all regressions relate changes in firm outcomes after the introduction of ChatGPT, the first major GenAI product, to pre-ChatGPT AI exposure and include firm and month fixed effects (details in annex 2.1 and annex 2.2). Because of data limitations, the analysis considers effects on the number of GVC relationships but not the value of each relationship. The analysis also applies sectoral AI exposure measures based on U.S. occupational structures to both U.S. and South Asian firms. While such a measure may be less accurate for the latter because of potential differences in occupational structures between the U.S. and South Asia, this approach is adopted for consistency. It also reflects the focus on the demand-side effects of AI adoption in advanced economies on South Asia—for which a measure based on the advanced economy's occupational structure is the more relevant exposure measure. Another caveat is that the GVC dataset might be oversampling large South Asian exporters—as suggested by the disproportionate share of the sampled firms in job postings (annex 2.1)—and as such, the findings may not apply to small- and mid-sized exporters.

AI-assisted teaching tools. The case study of AI-assisted teaching is based on the preliminary results of a randomized controlled trial (RCT) conducted in public elementary schools in the city of Questta, Pakistan, during the 2025–26 winter season (Asad et al. 2026). The RCT consisted of three experiment arms to which students that had applied to a winter school were randomly assigned: a control arm, a non-AI teacher-led winter school, and an AI-assisted winter school. The winter school, which was housed in 30 schools across the city of Quetta, served children in grades 2–5 in a single multi-grade classroom. The study assessed students' foundational learning levels in language and math through a standardized evaluation conducted at baseline (before the winter school) and endline (after the winter school). The RCT impact estimates are based on OLS regressions which are estimated on the endline sample of 4,938 students and compare the endline learning levels of students in the treatment arms to those in the control arm.

Data center costs and location determinants. The analysis of the correlates of data center location uses data on the location of data centers from the Data Center Map and employs cross-country regressions of the number of data centers on measures of resource endowments, human capital and infrastructure quality assembled from datasets including the World Bank Worldwide Governance Indicators and B-Ready Indicators.

Firm-level AI adoption: Evidence from a representative sample of formal firms in India

Firm survey data show AI adoption among Indian firms lagging well behind U.S. firms in both level and sophistication, but catching up. Adoption is broadly spread, being uncorrelated with firm characteristics except for positive correlations with foreign ownership and workforce skill-intensity. Larger, more innovative firms with better-skilled workforces and better access to information and communication technologies expect greater productivity gains from AI.

Limited direct evidence on how firms are using AI. The adoption of AI by firms is the first step toward realization of its productivity benefits, but direct, firm-level measures of AI adoption and obstacles to adoption have hitherto been unavailable. Indirect evidence from online job postings data show that firms in South Asia have increasingly been hiring workers with AI-specific and AI-complementary skills, a pattern suggestive of AI adoption (World Bank Group 2026b). Also, a cross-country benchmarking index ranks India among the world's leading economies in terms of AI penetration, but it is built from aggregate indicators—including user-level data released by AI companies, research publications, and AI startup activity—rather than direct firm-level evidence (Misra et al. 2026). But this indirect evidence is hard to reconcile with recent firm-level research findings that advanced digital technologies are diffused more slowly, and used less intensively, in EMDEs than advanced economies (Cirera et al. 2026).

New firm-level evidence on adoption. To help fill this gap, this section draws on the WBES AI Module, which measures AI use in a representative sample of formal firms in India alongside a benchmark sample of U.S. firms at more advanced stages of adoption. The survey covers a broad cross-section of formal Indian firms across states and sectors.

Adoption rates. AI adoption among Indian firms lags that in U.S. firms, and the gap is more pronounced for more sophisticated AI uses. The basic AI adoption rate in India is about half that in the United States: 23.4 percent of Indian firms report using some form of AI, compared to 42.7 percent of U.S. firms (figure 2.4). However, this comparison does not reflect differences in the type of AI technology used or how well it is embedded in business operations. A comprehensive AI Adoption Index is constructed to address these shortcomings by taking into account several dimensions of sophistication in AI adoption, including whether the firm has purchased AI software; the number of uses of advanced AI technologies (such as AI agents); the number of uses of AI for cognitively demanding functions (such as data analysis and control of production processes); the number of core business functions for which AI is used; and the use of dedicated AI sourcing arrangements, as opposed to the simple use of online AI platforms. The AI Adoption Index for India has an average value of 0.27, less than one-third the 0.85 average for the United States.[2] U.S. firms are well ahead of Indian

[2] The index has been normalized so that a one percentage point increase in it represents a movement of one standard deviation across its distribution among all the countries covered in the World Bank Enterprise Surveys.

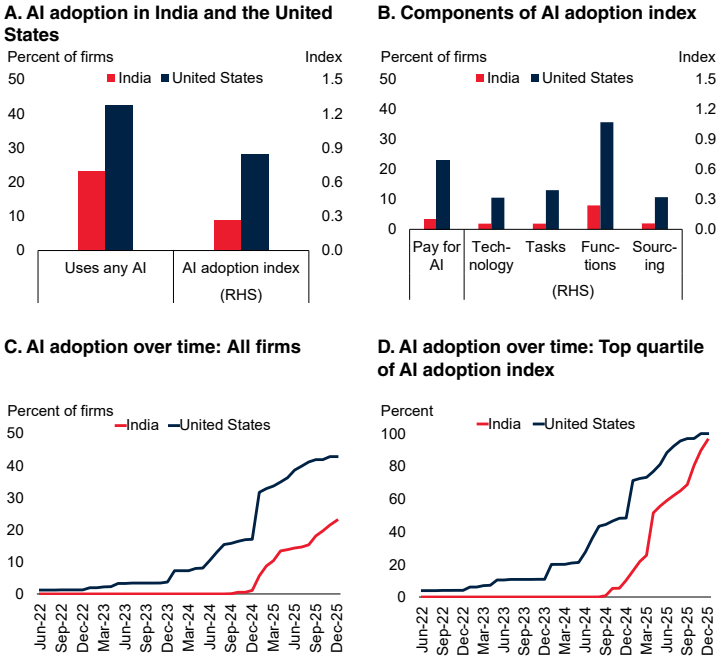
firms in every component of this index. For example, only 3.5 percent of Indian firms have incurred a fee or purchase cost for AI use, as compared to 23.1 percent of U.S. firms. Similarly, Indian firms lag behind U.S. firms in the level of advancement of their AI technologies, the number of tasks and business functions for which AI is being used, and whether the sources of AI include custom-built software, not just online platforms.

AI adoption trajectories. Indian firms started late but have been catching up with U.S. firms in terms of basic AI adoption in the past two years (figure 2.4). In mid-2024, the share of Indian firms using AI was near-zero, while the corresponding share of U.S. firms was already about 20 percent. AI use grew rapidly in both countries between late-2024 and early 2025, stimulated partly by the sharp drop in the cost of using Generative AI (and the embedding of Generative AI in legacy software platforms) (Cottier et al. 2025). Since early 2025, adoption in India has continued to accelerate, while its growth in the United States has slowed down. Similar adoption trajectories are observed among firms in the top quartile of the AI adoption index. The pace of increase in basic AI uptake is unusual: AI is diffusing far faster than earlier general-purpose technologies such as electricity or the internet (World Bank Group 2026a). However, since the other components of the AI Adoption Index are observed only at a single point in time, it is not possible to tell if the sophistication of AI use is catching up at the same pace. It could be that the binding constraint in South Asia is not the basic uptake of AI but its productive deployment by firms.

Adoption by sector and size. In both India and the United States, the AI Adoption Index does not differ significantly between manufacturing and services (figure 2.5). Adoption is cross-cutting even at the industry level: India's top adopters include

FIGURE 2.4 AI adoption in Indian and U.S. firms

Indian firms lag their U.S. counterparts in AI adoption, and the gap widens further for more sophisticated AI uses. They are, however, catching up after a late start.

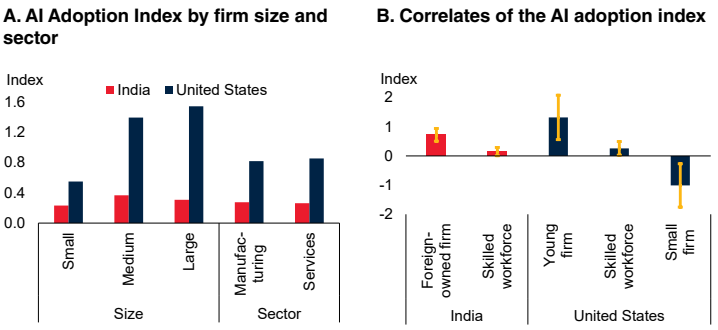


Sources: World Bank Enterprise Surveys AI Module 2025–26; World Bank Group.
A.B. Bars in panel A show the weighted average across firms of a binary indicator for any AI use and the AI adoption index. The index is a weighted average of six components—the "any use" indicator and the five components shown in panel B: (1) "Pay for AI": whether a firm purchases AI software or pays a subscription fee; (2) "Technology": the number of advanced AI technologies used; (3) "Tasks": AI use for tasks such as coding, data analysis, and controlling business processes; (4) "Functions": the tasks and business functions for which AI is used; and (5) "Sourcing": whether a firm uses AI beyond online platforms, such as off-the-shelf or custom-built software. See annex 2.1 for details.
C.D. Lines show the monthly cumulative share of firms using any AI among all firms (C) and those in the top quartile of the AI Adoption Index (D), from June 2022 to December 2025.

firms in information and communication technology services, pharmaceuticals, and manufacturing of motor vehicles and machinery (table A.2.1.1). Firm size matters more than sector. In the United States, the AI Adoption Index in large firms (100-plus employees) is about three times that in small ones (fewer than 20), suggesting that the scope for sophisticated use is greater in larger firms, perhaps because they have more internal specialization and complementary inputs, such as information technology systems and more capable management. The size gradient is far weaker among Indian firms, so that the India–U.S. gap is widest among large firms. This could be because large Indian firms trail their U.S. counterparts in the

FIGURE 2.5 Which firms are adopting AI?

AI adoption is broad-based among Indian firms, not differing significantly by size or sector; foreign ownership and a skilled workforce are the only characteristics systematically correlated with AI adoption. In contrast, adoption among U.S. firms is significantly higher in younger firms and lower in smaller ones.



Sources: World Bank Enterprise Surveys AI Module 2025–26; World Bank Group.
A. Bars show the average of the AI Adoption Index by firm size and by broad economic sector. Small firms have 5 to 19 employees, medium firms 20 to 99 employees, and large firms 100 or more employees.
B. Bars show statistically significant estimates from firm-level regressions of the AI Adoption Index on firm attributes. Effect sizes are expressed in standard-deviation units of the outcome variable. "Foreign owned," "Young firm," and "Small firm" are indicators for firms with foreign ownership, firms less than 5 years old, and firms with fewer than 20 employees, respectively. "Skilled workforce" is an index of firm workforce skill intensity, normalized to standard-deviation units. Its components include whether the firm offers formal training to workers and the ratio of highly skilled production workers in the last fiscal year. Yellow whiskers show 95 percent confidence intervals. See annex 2.2 for regression description and table A.2.2.1 for full results.

organizational capabilities needed to use new digital technologies well (Bloom et al. 2012; Bloom, Sadun, and Van Reenen 2012).

Correlates of AI adoption: India. Regression analysis indicates that AI adoption among Indian firms is broad-based, since it is not systematically correlated with most observable firm-level attributes. The attributes included in the analysis comprise both factors internal to the firm—such as size, age, management experience and practices, workforce skill-intensity, ownership, innovation-related activities, and exports—and factors external to it, such as access to electricity, information and communication technologies and finance. Only two of these factors are found to be statistically significantly correlated with the AI Adoption Index in Indian firms: foreign ownership and skill-intensity (figure 2.5).

- **Foreign ownership.** Firms have an AI index value 0.7 standard deviation higher than purely domestically owned firms, consistent with recent evidence that in South Asia multinational affiliates lead other firms in hiring workers with AI skills (World Bank Group 2026b). Foreign-owned firms may have greater capabilities to deploy new technologies quickly, consistent with the broader literature on foreign direct investment and technology diffusion in EMDEs (Harrison and Rodríguez-Clare 2010).

- **Skill-intensity.** A one-standard-deviation increase in a workforce skill-intensity index is associated with a 0.15 standard deviation increase in the AI index, consistent with research suggesting that the scope for AI use is higher in knowledge-intensive tasks (Felten, Raj, and Seamans 2021, 2023), with managerial and supervisory jobs being particularly complementary to AI use (Pizzinelli et al. 2023).

Correlates of AI adoption: United States. As in India, and despite the two countries' different stages of AI adoption, the correlations between most key firm attributes and the AI Adoption Index are generally weak in the United States (figure 2.5). Again, workforce skill-intensity is among the few statistically significant correlates of adoption. Unlike in India, however, AI adoption in the United States is significantly higher among younger firms and lower among smaller firms; foreign ownership, not surprisingly, is not a significant factor.

Expected productivity gains from rapid AI development. The WBES survey asks firms about their expected growth in sales per worker over the next three years in scenarios with rapid and slow AI development (relative to the current rate of development).

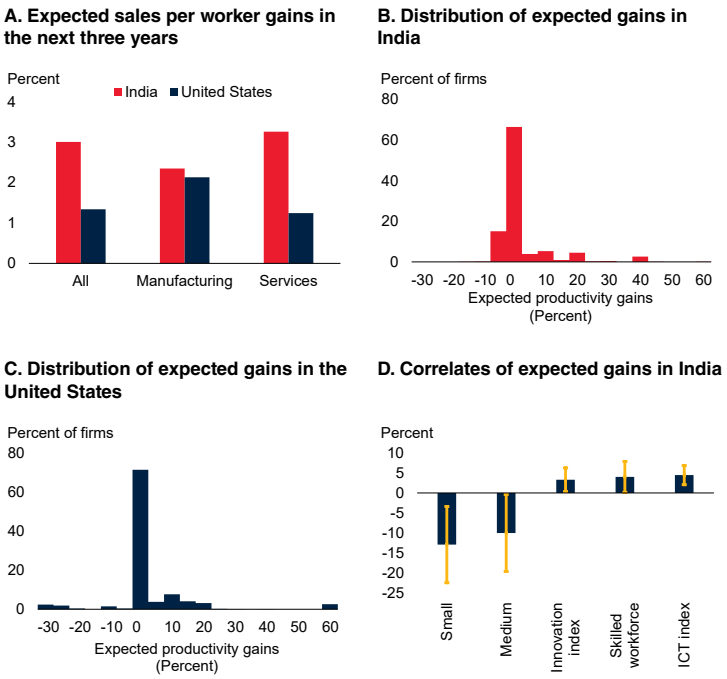
The difference between the fast and slow AI scenario expectations provides a measure of expected labor productivity gains from more rapid AI development, since the only difference in assumptions between the scenarios is in the speeds of AI development. The average expected three-year gains from faster AI development are 3 percent among Indian firms and 1.3 percent among U.S. firms. In India, the expected gains are concentrated in a few firms: almost three-quarters of Indian firms expect near-zero gains, 8 percent of firms expect gains of 20 percent or higher, and 15 percent expect that faster AI development would reduce their revenue per worker by up to 10 percent, perhaps because they expect to lose market share to firms that have an advantage in deploying AI rapidly. The United States displays a less dispersed distribution of expected gains from AI, with 84 percent of firms expecting gains of up to 10 percent (figure 2.6).

Correlates of expected gains from AI development in India. Expected gains in labor productivity in India from faster AI development are larger among larger firms: expected gains are about 13 and 9 percentage points lower, respectively, in small and medium-sized firms than in large firms (figure 2.6). This suggests that smaller firms perceive fewer productive uses or complementary inputs for AI. Productivity gains from faster AI development are also found to be higher in firms rated highly on indexes of innovativeness, skill-intensity, and access to information and communication technologies—all factors plausibly complementary with AI. The fact that some of these complementary factors do not significantly predict AI adoption suggests that, in this early stage of diffusion, even firms that expect low gains are experimenting with AI.

Reasons for not using AI in business functions. When asked about their main reason for not using AI in executing business functions, costs of adoption are most frequently named by Indian firms, followed by regulations that restrict AI use, knowledge, concerns about privacy or security, and a shortage of skills (figure 2.7). In contrast, costs are not cited as the main reason for non-adoption among U.S. firms. Moreover, unlike Indian firms, a non-trivial share of U.S. firms report that unmet expectations from previous or current AI use are their main reason for not using AI. Given the more mature AI diffusion in the United States, this suggests that there are frictions in the use of AI that only become apparent to firms with experience.

FIGURE 2.6 Which firms expect to gain most from AI?

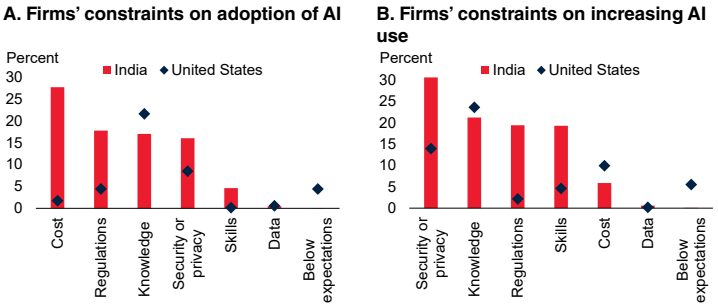
Most firms in India and the United States expect minor gains in sales per worker from faster AI development, with a small share expecting sizable gains. Expected gains are smaller in small and medium-sized firms than large ones, and higher in firms with greater innovation activity, workforce skills, and access to information and communication technologies.



Sources: World Bank Enterprise Surveys AI Module 2025–26; World Bank Group.
A. Bars show the mean expected three-year gain in sales per worker, defined as the difference between expected growth in sales per worker under fast and slow AI development.
B.C. Bars show the distribution of expected three-year gains in sales per worker among firms in India (B) and in the United States (C).
D. Bars show the coefficients from firm-level regressions of expected sales per worker gains from faster AI development on firm-level attributes, with 95 percent confidence intervals. Small and medium firms have fewer than 20 and 20–99 employees, respectively. Innovation index, skilled workforce index, and ICT index are normalized to standard-deviation units. The skilled workforce index indicates whether the firm offers formal training to workers and the share of highly skilled production workers in the last fiscal year. The ICT index indicates whether the firm has an internet connection, its own website, the ease with which internet providers can be switched, and the reverse-coded number of internet disruptions in the last fiscal year. See annex 2.2 for regression description and table A.2.2.2 for the full results.

FIGURE 2.7 Constraints and policies

Among firms not using AI, cost is the barrier most often cited by Indian firms, while unmet expectations from past applications are most often cited by U.S. firms. Indian firms are likelier than U.S. firms to cite regulations and skills. Among firms already using AI, security and privacy concerns and lack of knowledge are the most-cited constraints on increasing use in both countries.



Sources: World Bank Enterprise Surveys AI Module 2025–26; World Bank Group.
A.B. Bars show the percentage of firms citing each constraint as their main reason for not adopting AI (A) or increasing their AI use (B). "Cost" indicates that AI is too expensive. "Regulations" refers to laws and regulations that prevent or restrict AI use. "Knowledge" indicates a lack of relevant knowledge. "Security/privacy" indicates concern about the security or privacy of data when using AI. "Skills" indicates a lack of skilled workforce. "Data" indicates insufficient data. "Below expectations" indicates that previous or current AI use did not meet expectations.

Constraints to increasing AI use. Among both Indian and U.S. firms currently using AI, the two factors most frequently cited as the main constraint on increasing AI use are concerns over security or privacy and lack of knowledge (figure 2.7). This suggests that regardless of the country context, as firms start to use AI, they become more aware of security- or trust-related issues, and of the learning required for increasing use. In India, other constraints frequently cited are regulations and lack of skills.

How AI is shaping South Asia's GVC relationships

Analysis of data on firm-to-firm relationships shows that since the public release of ChatGPT in late 2022, GVC links between U.S. customers and South Asian suppliers have grown fastest in sectors where AI exposure is high, on both sides of the relationship. This "double complementarity"—growth being strongest when the U.S. customer and the South Asian supplier are both highly AI-exposed—suggests that AI is opening new GVC opportunities for South Asian suppliers.

Scale and substitution effects of global AI adoption. Apart from raising labor productivity, a second channel through which AI may reshape opportunities for South Asian firms is foreign trade. Participation in GVCs has been an important route to growth for EMDEs, allowing firms to access foreign demand, technology, and know-how. South Asian firms that have GVC relationships with advanced-economy firms, especially in the industries most exposed to GenAI, may experience some of the most immediate effects of AI, because such advanced-economy firms are likely to be leaders in adopting AI and experiencing its productivity impacts. Thus in the United States, a major GVC partner for South Asia, after the launch of ChatGPT, hiring for AI skills by firms rose significantly faster in more AI-exposed sectors (figure 2.8). For South Asian firms, this could have two countervailing effects.

- ***Scale effect.*** As U.S. firms in AI-exposed sectors grow in terms of output as well as productivity, they may expand their demand for inputs from South Asian suppliers.

- ***Substitution (or reshoring) effect.*** They may sever relationships involving tasks that AI can automate.

Reshoring concerns in ICT and BPO services. The substitution channel is highly salient in the EMDE public discourse, for two reasons. First, reshoring occurred in the last major automation wave, when industrial robots eroded the labor-cost advantage of EMDE manufacturers and redirected production back to advanced economies (Faber 2020; Kugler et al. 2020; Krenz, Prettner, and Strulik 2021). Second, the concern is especially acute for South Asia's information and communications technology (ICT) and business process outsourcing (BPO) services, which account for an above-average share of the region's exports and which specialize in

precisely the functions—customer support, back-office processing, routine software development—that AI can most readily automate.

Prior evidence on reshoring pressures. Early evidence is suggestive of these reshoring pressures. Among Indian firms supplying global value chains, those selling highly AI-exposed services cut hiring sharply after the release of ChatGPT, and the decline was concentrated among suppliers whose foreign buyers were themselves highly exposed to AI, and among those whose workforces had low complementarity with AI, the profile typical of routine BPO and ICT providers (World Bank Group 2026b). Because these suppliers did not adopt AI at higher rates than other firms, the hiring declines appear to reflect external demand pressure from foreign buyers automating previously outsourced tasks in-house—that is, reshoring—rather than the suppliers' own automation decisions.

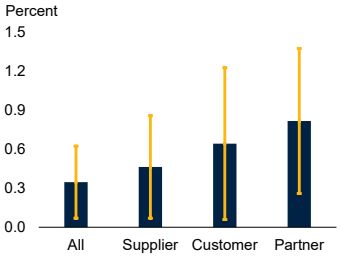
From hiring to value chain flows. Evidence from hiring alone, however, is not enough to assess whether substitution or scale dominates. A slowdown in hiring could coexist with growing value chain flows if productivity is rising. In other words, employment effects cannot distinguish productivity-driven scale gains from displacement through reshoring, since both can reduce hiring. To weigh the two channels against each other directly, this chapter discusses new evidence from firm-level data on GVC relationships themselves, rather than on hiring (Chiplunkar et al. 2026).

AI exposure and GVC relationships between U.S. and South Asian firms. The number of U.S. firms' international GVC relationships—including those with South Asian firms—has risen steadily in recent years, across all three relationship types: with U.S. firms as customers, suppliers, or partners (figure 2.8). If AI is driving this trend through the two channels above, the scale effect would tend to concentrate the increase among U.S. firms in more AI-exposed sectors, while the substitution effect would tend to result in a muted increase, or even a decrease, where the South Asian counterparty is highly exposed to substitutability and its tasks are

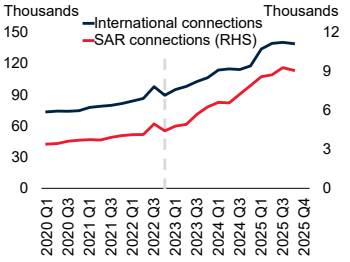
FIGURE 2.8 AI and the GVC relationships of U.S. firms with South Asia

After the release of ChatGPT, U.S. firms in more AI-exposed sectors increased their hiring of AI skills. A larger AI exposure by a U.S. firm is associated with a larger post-ChatGPT increase in its customer and partner links with South Asian firms; and the association is stronger where the South Asian counterparty is itself more AI-exposed.

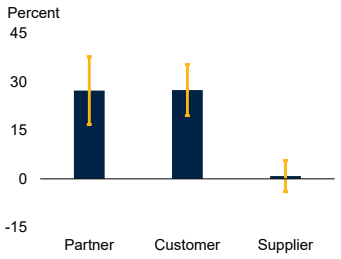
A. Impact of AI exposure on hiring for AI skills: U.S. firms



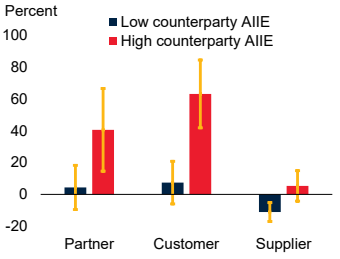
B. GVC connections over time: U.S. firms



C. Impact of AI exposure on GVC connections: U.S. firms



D. Impact of AI exposure on GVC connections by counterparty AI exposure: U.S. firms



Sources: Chiplunkar et al. (2026); FactSet; Felten, Raj, and Seamans (2021); LightCast; World Bank Group.
Note: AIIE = AI industry exposure; GVC = global value chain. Yellow whiskers show 95 percent confidence intervals. Regression sample consists of all U.S. firms observed in at least one GVC relationship with a South Asian firm during 2020–25. The terms "Supplier," "Customer," and "Partner" denote the status of U.S. firms in their GVC relationships. AI exposure is measured at the industry level. See annex 2.2 for regression details.
A. Bars report the estimated relationship between U.S. firms' AI exposure and the post-ChatGPT increase in their AI hiring. The baseline estimates are for all U.S. firms, while "Customer," "Supplier," and "Partner" refer to firms with at least one customer, supplier, and partner relationship with South Asian firms pre-ChatGPT. See table A.2.2.3 for full results.
B. Lines show the average quarterly number of U.S. firms' international and South Asian connections. The vertical dashed line marks the release of ChatGPT in November 2022.
C. Bars report the relationship between U.S. firms' own AI exposure and the post-ChatGPT increase in their relationship counts with South Asian firms. See table A.2.2.4, panel A, for full results.
D. Bars report the relationship between U.S. firms' own AI exposure and the post-ChatGPT increase in their relationship counts with South Asian firms, by their South Asian counterparties' AI exposure. Low and high counterparty exposure groups are defined by whether the average pre-ChatGPT counterparty AI exposure is below or above the median. See table A.2.2.5, panel A, for full results.

therefore more automatable. The regression analysis suggests that the scale effect is dominant: a U.S. firm's industry AI exposure strongly predicts the post-GPT rise in its customer and partner links with South Asian firms, with a one-standard-deviation increase in exposure associated with a 27.5 percent larger increase in each. Exposure does not predict any rise in the number of U.S. firms' relationships as suppliers, which is consistent with a demand-side (originating in the United States), rather than supply-side (originating in South Asia), mechanism.

Counterparty AI exposure and the GVC relationships of U.S. firms with South Asia. The substitution effect can also be tested using data on the AI exposure of the South Asian counterparty, which proxies how automatable its tasks are. If U.S. firms were reshoring, the positive association between a U.S. firm's own exposure and its customer and partner links should weaken where the counterparty is highly exposed. But this is not the case in the data: the association between U.S. firms' own AI exposure and the increase in customer/partner links with South Asian firms is found to be significantly stronger when the South Asian party's AI exposure is higher (figure 2.8). For example, in the case of U.S. customer links, a one-standard-deviation increase in a U.S. firm's own AI exposure index is associated with a 63.1 percent higher post-GPT increase in the number of links when the mean AI exposure of the firm's pre-GPT South Asian counterparties is the above median. In comparison, when the pre-GPT AI exposure of South Asian counterparties is below the median, the effect is just 7.4 percent. The difference between high and low counterparty exposure is statistically significant. In sum, counterparty AI exposure amplifies the effect of own AI exposure on connections between U.S. customers and partners.

AI exposure and the GVC relationships of South Asian firms with the United States. A scale-up in the number of GVC relationships from the U.S. side may still be insignificant from the perspective of the average South Asian GVC supplier if U.S. demand concentrates in a few South Asian firms. So, the analysis re-examines the same relationships from the South Asian perspective. Note that from the South Asian side, a firm's own AI exposure carries two opposing meanings: its tasks are more automatable, exposing it to substitution, but greater scope for AI adoption may also raise its competitiveness as a supplier. Indeed, just like U.S. firms, the post-GPT increase in AI skills hiring in South Asian firms is significantly faster in more AI-exposed industries (figure 2.9).

South Asian firms mirroring U.S. patterns. The GVC results from the South Asian side also suggest that the forces of substitution are weaker than those of scaling up. South Asian firms' GVC connections have risen since 2020, accelerating after 2022, and a firm's own AI exposure strongly predicts its post-ChatGPT increase in supplier and partner links with U.S. firms: a one-standard-deviation increase in exposure is associated with a 30 percent larger rise in supplier relationships, with a significant but smaller effect for partnerships (figure 2.9). This mirrors the pattern on the U.S. side: on both sides, greater own exposure predicts more relationships in which the U.S. firm is the customer and the South Asian firm the supplier. The counterparty results, too, mirror the U.S. side. The effect of the South Asian firm's own exposure is amplified when its U.S. counterparties are themselves highly AI-exposed: a nearly 60 percent larger post-ChatGPT increase where counterparty exposure is above the median but a near-zero effect size when counterparty exposure is below the median.

Interpreting faster GVC growth in AI-exposed sectors. Taken together, the results from Chiplunkar et al. (2026) point to a "double complementarity": GVC relationships in which U.S. firms are customers or partners and South Asian firms are suppliers or partners have grown fastest when *both* parties are in high-AI-exposure sectors. This does not rule out some reshoring of the most automatable tasks, but the results are inconsistent with the notion that reshoring is GenAI's dominant effect on work outsourced to South Asian suppliers. It suggests instead that GenAI is creating new opportunities for South Asian firms to supply and partner with U.S. firms.

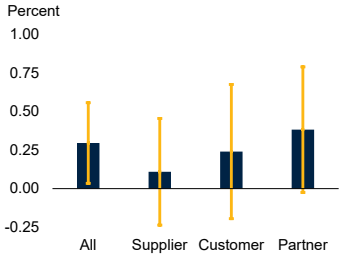
Potential mechanisms. Several factors could explain this but cannot be empirically distinguished using this dataset:

- ***Scale effect.*** As AI raises labor productivity in U.S. firms, it raises their demand for South Asian inputs, while AI-driven gains in the competitiveness of South Asian suppliers help explain why their own exposure amplifies that increase in demand.
- ***Task adjacency.*** AI may be creating new, specialized tasks in which South Asian suppliers hold a comparative advantage, because their prior specialization in lower-value, routine work is adjacent to the new tasks. A growing market for expert human review of AI-generated software and text, used to fine-tune AI models, is one example; the adjacency of such work to previously outsourced tasks would explain why the new links are concentrated among AI-exposed South Asian suppliers (Panasenko 2026; Sharma 2026; Technavio 2025).
- ***Diversification.*** Facing technological uncertainty, U.S. firms in AI-exposed sectors may be broadening their supplier base, particularly toward AI-exposed suppliers.
- ***Reduced costs.*** AI tools may be reducing the cost of sourcing foreign suppliers and identifying foreign buyers in AI-exposed sectors.

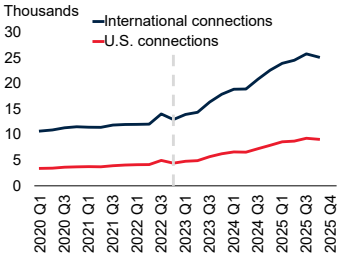
FIGURE 2.9 AI and the GVC relationships of South Asian firms with the United States

After the release of ChatGPT, South Asian firms in more AI-exposed sectors increased their hiring of AI skills. Mirroring the pattern for U.S. firms, a larger AI exposure by a South Asian firm is associated with a larger post-ChatGPT increase in its supplier and partner links with U.S. firms; and the association is stronger where the U.S. counterparty is itself more AI-exposed.

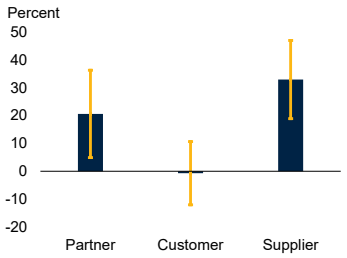
A. Impact of AI exposure on AI skills hiring: South Asian firms



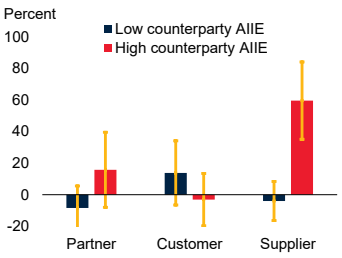
B. GVC connections over time: South Asian firms



C. Impact of AI exposure on GVC connections: South Asian firms



D. Impact of AI exposure on GVC connections by counterparty AI exposure: South Asian firms



Sources: Chiplunkar et al. (2026); FactSet; Felten, Raj, and Seamans (2021); LightCast; World Bank Group.
Note: AIIE = AI industry exposure; GVC = global value chain. Yellow whiskers show 95 percent confidence intervals. Regression sample consists of all South Asian firms observed in at least one GVC relationship with a U.S. firm during 2020–25. "Supplier," "Customer," and "Partner" denote South Asian firms' status in their GVC relationship. AI exposure is measured at the industry level. See annex 2.2 for regression details.
A. Bars report the estimated relationship between South Asian firms' AI exposure and the post-ChatGPT increase in their AI hiring. The baseline estimates are for all South Asian firms, while "customer," "supplier," and "partner" refer to firms with at least one corresponding relationship with a U.S. firm pre-ChatGPT. See table A.2.2.6 for full results.
B. Lines plot the average quarterly number of South Asian firms' international and U.S. connections. The vertical dashed line marks the release of ChatGPT in November 2022.
C. Bars report the relationship between South Asian firms' AI exposure and the post-ChatGPT increase in their relationship counts with U.S. firms. See table A.2.2.4, panel B, for full results.
D. Bars report the relationship between South Asian firms' own AI exposure and the post-ChatGPT increase in their relationship counts with U.S. firms, by U.S. counterparty AI exposure. Low and high groups are defined by whether average pre-ChatGPT counterparty AI exposure is below or above the median. See table A.2.2.5, panel B, for full results.

The impact of AI-assisted teachers: Evidence from a winter school

AI is increasingly supporting government back-office functions such as forecasting, case allocation, and audit targeting, as well as frontline public service delivery in agriculture, health, and education. These applications show promise but rest on a small evidence base. A randomized controlled trial (RCT) of a pilot learning camp for elementary school students on school break found that a teacher-led targeted-instruction program raised foundational learning, while a version of the program in which an AI tool supported teachers had no statistically significant effect. The results point to the difficulty of making AI-assisted frontline tools work in educational settings marked by weak conditions, such as low attendance and poor school infrastructure.

AI use in government: back-office functions. There are two distinct ways in which AI can improve public services. The first is in government back-office functions: using predictive AI to forecast, allocate scarce resources, and monitor programs. For example, Kenya's judiciary has used a predictive algorithm to assign more than 10,000 court cases a year to over 1,500 mediators, making assignments fairer, raising the odds of successful mediation, and helping clear a large backlog; and Brazil uses municipal audit data to predict which local governments are at elevated risk of corruption, so that federal oversight can be targeted where problems are most likely (World Bank Group 2026a). Government use of AI in such predictive, back-end applications is growing in EMDEs.

AI use in frontline public service: agriculture. The second main use of AI in delivering public services is at the frontline, where AI tools assist the teachers, extension agents, and health workers who serve citizens directly. Agricultural extension is one major area of application in South Asia, since the ratio of advisory extension agents to farmers is extremely low across the region. In Telangana, India, AI-based weather forecasts delivered to smallholder farmers changed planting decisions and generated savings of up to $560 per farmer (Burlig et al. 2024). Conversational advisory tools are now being deployed at scale: in Maharashtra, India, MahaVISTAAR, a voice-and-text platform that answers farmers' questions in local languages by drawing on verified institutional sources, reports more than 2 million downloads and over 1.5 million questions answered; and FarmerChat, a generative-AI advisory service embedded in public extension systems, has onboarded more than 400,000 users across multiple Indian states (IndiaAI Mission 2026). It is important to note, however, that many of these examples are based on descriptive case studies rather than impact evaluations, and rigorous evidence such as that provided in Burlig et al. (2024) remains rare.

AI use in frontline public service: health. Health is another area where AI tools can help address frontline shortages: it is where AI's screening and diagnostic capabilities are most developed. The most common AI application in health is in interpreting medical images and signals, such as retinal photographs, chest radiographs, and electrocardiograms, allowing frontline health workers to perform screening that would otherwise require scarce specialists. In Bangladesh, AI-assisted retinal screening raised the number of patients checked for a diabetic complication by nearly 40 percent a day, and a cough-based tuberculosis screener developed with India's Central Tuberculosis Division correctly flags nine in ten cases (World Bank Group 2026a). A systematic review of frontline health AI in low-resource settings notes that the evidence is promising, albeit limited, with only 17 identified studies

reporting causal evidence—concentrated in image-based screening, and almost none using generative AI (Sautmann and Weinert 2026). Most of these found gains early in the care pathway (detection, referral, and triage), but few followed patients long enough to measure health outcomes, and ten of the seventeen did not validate the model on the population it was deployed in. There are two routes to deployment: buying an externally developed product, which is faster but rarely validated in local conditions, or adapting a model to the local setting, which fits local conditions better but demands a higher level of institutional capacity (Sautmann and Weinert 2026).

Constraints to frontline AI tools. Whereas predictive, back-office AI is constrained mainly by the state of government data, frontline AI is limited by a host of local factors, including connectivity and the scarcity of tools developed in local languages. The educational AI tool trial examined in the remainder of this section tests whether a frontline generative tool can overcome these constraints: it is a teacher-facing tool, deployed in a low-resource setting marked by exactly the factors above.

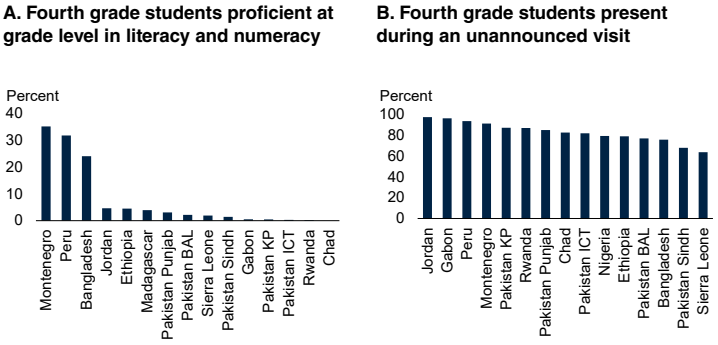
The challenge: Improving foundational learning. Foundational education in literacy and numeracy is a critical challenge in EMDEs. According to recent assessments conducted by the World Bank's Global Educational Policy Dashboard, in 14 out of 17 EMDE school systems, fewer than 10 percent of Grade 4 students have achieved the literacy and numeracy skills expected at this grade level (figure 2.10). Explanations include high student absence rates and long breaks between school semesters. For instance, in 10 out of 17 EMDEs, at least 15 percent of Grade 4 students were absent during an unannounced visit. And recent studies show that children in low- and middle-income countries often lose the equivalent of several months of learning during school closures or long breaks, with the youngest and most disadvantaged students falling furthest behind (World Bank Group 2022).

Potential role for AI in targeted learning programs. Efforts to find solutions to shortfalls in foundational education outside regular classes have grown over the past two decades. One approach that has shown promise is to provide targeted instruction, or "Teaching at the Right Level," often outside regular class time. Examples include assigning a teaching assistant to pull lagging students out of class and teach them foundational competencies (Banerjee et al. 2007), and running learning camps outside school hours where teaching can target the right level without the pressure of completing the prescribed curriculum (Banerjee et al. 2016). A small but growing evidence base suggests that computer-assisted learning programs can help scale up such approaches by delivering individually customized content and reducing the need for intensive, one-on-one human tutoring. In India, a randomized study of a personalized, computer-assisted after-school instruction program for middle-school students found that it had significant positive impacts on mathematics and language learning (Muralidharan, Singh, and Ganimian 2019). Computer-assisted tutoring programs have also shown positive impacts in settings as varied as China (Lai et al. 2015a; Lai et al. 2015b), Cambodia (Ito et al. 2021), and wartime Ukraine (Dinarte-Diaz et al. 2025). These findings, which are based on pre-AI digital technologies, point to a potential role for AI in helping deliver targeted instruction.

Prior evidence on AI teaching tools. The evidence on the success of educational AI tools is promising but thin, particularly for low-resource settings. A recent meta-analysis of research results for both adaptive, computer-assisted learning and generative AI tools identifies only 14 randomized trials

FIGURE 2.10 Foundational learning gaps in EMDEs

In 14 of 17 EMDE countries whose education systems were assessed, fewer than 10 percent of Grade 4 students have mastered grade-level literacy and numeracy. In 10 of the 17 systems, at least 15 percent were absent during an unannounced visit.



Sources: Marin et al. (2026); World Bank GEPD Database; World Bank Group.
Note: BAL = Balochistan; GEPD = Global Education Policy Dashboard; ICT = Islamabad Capital Territory; KP = Khyber Pakhtunkhwa. Data are from the February 2026 update and cover 2019–25.
A.B. Bars show the de facto percentage of children proficient in literacy and numeracy at the country or subnational level, according to the GEPD School Survey (A), and the percentage of Grade 4 students present during an unannounced visit (B). The latest available year for each country or subnational area is used.

meeting its inclusion criteria, of which only six were conducted in EMDEs and none in a low-income setting (Burneo et al. 2026). Only one of the six EMDE trials examines a teacher-facing AI tool, and that tool is pre-GenAI (Ferman, Lima, and Riva 2021). Pooling across tools and the six EMDE settings, these interventions are found to have raised learning by 0.125 standard deviations relative to traditional instruction—above the median for the 14 education interventions evaluated by randomized trial. However, the newer, AI-assisted technology does not outperform the older, computer-assisted technology; and the effects of the teacher-facing tool on teaching practices are not statistically significant. The evidence also does not address the question of how such tools would perform at scale in low-resource conditions, and carries only limited information on the cost of the technology and how it was adapted to local conditions.

RCT in Quetta, Pakistan. A recent RCT in the city of Quetta in Balochistan, Pakistan explores whether a structured learning camp can mitigate learning losses during long school breaks, and whether incorporating AI-based tools into teaching practices can enhance its effectiveness (Asad et al. 2026). In Pakistan, according to the 2023 Annual Status of Education Report, only 50 percent of Grade 5 students can read a simple story in Urdu, Sindhi, or Pashto, and just 46 percent can do two-digit division (ITA 2024). Learning levels are especially low in Balochistan—a low-income, conflict-affected province—and a long winter school break in the province's colder parts (from mid-November till early March) further exacerbates the learning challenge. Working in collaboration with the provincial department of education, the RCT piloted a 6-week winter school for public school students in grades 2–5 during January-February 2026 in Quetta, the province's capital city.

RCT design. The RCT consisted of three arms: a control arm, a non-AI winter school delivering a teacher-led, targeted instruction program, and an AI-assisted winter school. The teacher-led arm aimed to help elementary-level students catch up to their grade level by mastering foundational skills in Urdu, math and English. It was delivered by trained schoolteachers using specially designed assessments and teaching/learning materials. In the AI arm, an AI-assisted mobile app supported the teachers by generating differentiated lesson plans, creating assessments, grading student work, and providing coaching feedback based on classroom audio recordings. Unlike most previous RCTs of AI-assisted learning in EMDEs, only the teacher, not the student, interacted directly with the AI app. Notably, both winter school arms consisted of multi-grade classrooms, with the teacher tailoring their instruction to students across several grades and learning levels. The main potential benefit of the AI app was that it made it easier for the teacher to rapidly tailor instruction while reducing preparatory time.

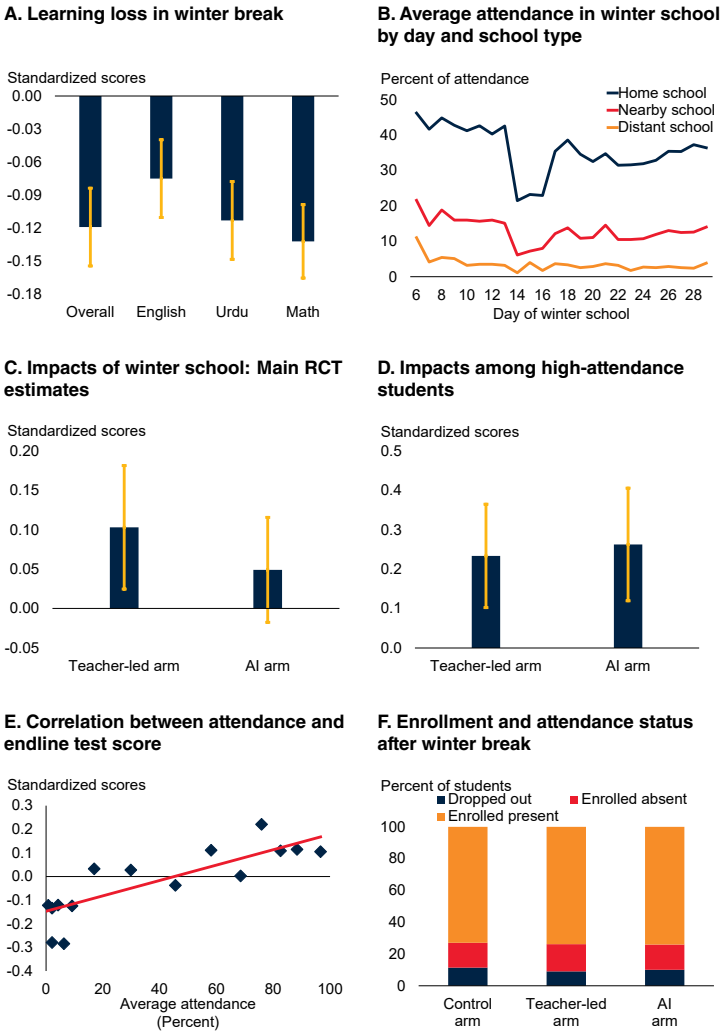
Learning loss and absence rates. The learning and attendance trajectories observed in the RCT are consistent with the learning losses and high absenteeism reported in previous research on schools in EMDEs. The primary outcome of interest in the RCT is a composite student test score combining performance in Urdu, math, and English. On average, the test score of the control group students fell by 0.11 standard deviations (standard deviation) between November 2025 and April 2026, a sizable learning loss potentially caused by the long winter break (figure 2.11). Despite the sizable losses seen over this time, the average attendance rate in the winter school arms was low: 26.3 percent. The attendance rates varied across schools and were lower the greater the distance between the assigned winter school location and the student's home school.

Impacts of winter school. Preliminary results of the RCT show that the teacher-led arm of the winter school significantly improved learning. In sharp contrast, the AI-assisted arm did not have a statistically significant impact. The study estimates that being assigned to the teacher-led arm of the winter school improved test scores by 0.10 standard deviations on average, a statistically significant effect size (figure 2.11). This estimated effect is large: large enough to offset the winter learning loss observed in the control group and large enough to persist after a 10-week gap between the end of the winter school and the test date. In contrast, the estimated impact of being assigned to the AI arm of the winter school is 0.05 standard deviations, and it is not statistically significant.

Attendance and impact. Students with greater attendance had larger effects. Students with at least 40 percent attendance scored 0.26 standard deviations above the control group regardless of whether they were assigned to the teacher-led arm or the AI arm. This suggests that stronger efforts to raise attendance could

FIGURE 2.11 Impact of AI-assisted teaching: Randomized trial of a winter school

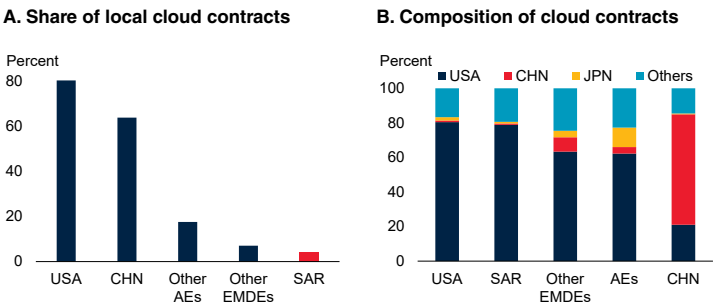
A teacher-led targeted-instruction program delivered in a learning camp for primary school students during their four-month winter break significantly improved learning outcomes, offsetting the learning loss experienced over that break. An AI-assisted arm did not have a significant impact. Higher attendance was strongly associated with improved learning outcomes in both arms.



Sources: Asad et al. (2026); World Bank Group.
Note: Yellow whiskers show 95 percent confidence intervals. See Asad et al. (2026) for regression details.
A. Bars show the change in standardized test scores before and after the winter break in the control arm of a randomized trial of a winter school for primary school students.
B. Lines show the average attendance rate by school type on each winter school day, from day 6 to day 29. Students are classified into three school types: (1) home school; (2) nearby school, where the student's residence is 2 km or less from the school; or (3) distant school, where the student's residence is more than 2 km from the school.
C. Bars show the impact of assignment to the winter school on endline test scores. The impact is estimated using a difference-in-differences intention-to-treat estimator for the two treatment arms: a teacher-led targeted instruction program and an instruction program in which teachers are assisted by an AI application.
D. Bars show the impact of the winter school on endline test scores among those whose attendance exceeded 40 percent. The impact is estimated using a difference-in-differences estimator, comparing the control group with the subsamples of high-attendees in the two treatment arms.
E. The binned scatter plot shows the association between average student attendance and learning scores after the winter school, pooled across both treatment arms.
F. Bars show enrollment and attendance status after the winter break for the control arm and the two treatment arms.

FIGURE 2.12 Cloud demand and imports

Cloud computing services are partly tradable. Firms from the United States and China serve most of the global cloud market, with most firms elsewhere using foreign cloud providers.



Sources: FactSet; World Bank Group.
Note: For country code abbreviations, refer to the International Organization for Standardization, https://www.iso.org/obp/ui/#search.
A.B. The sample comprises all firms reporting contracts with cloud computing service providers in the FactSet Supply Chain Relationships database in 2024. It covers 34 AEs, 35 EMDEs including three SAR economies (Bangladesh, India, and Sri Lanka), and 32 other EMDEs. Simple averages are used for economy groups.

enable such programs to realize far larger gains. Student retention is a major issue in such settings: between November and May, nearly 10 percent of students in the trial, across all three programs, dropped out of school altogether (figure 2.11).

Implications for the use of AI in learning tools. Although these results are preliminary and do not constitute a comprehensive assessment of AI teaching tools, they reinforce previous findings that targeted learning camps can improve foundational learning outcomes. They also indicate that while AI-assisted tools could, in principle, support learning programs by making it easier to customize instruction, it may be challenging in practice to obtain successful results in places lacking in basic infrastructure, teaching resources, and other essentials of a good school system. Furthermore, it could be that AI-assisted teaching leads to gains in the short term that are not sustained, while more intensive, teacher-led models succeed in providing children with gains that are more durable. It is also possible that introducing AI assistance crowds out teacher effort. More research may improve understanding of how more effective AI tools for education can be designed.

Data centers: Benefits and costs in South Asia

AI use depends on access to computing power and local data centers are one means of access. Local data centers can speed up response times and create local economic spillovers. But they tend to locate where energy supply is abundant and reliable, business environments are favorable, and skilled workforces are large—all factors with considerable gaps in parts of South Asia. Improvements in these foundational factors would attract data centers as well as investment more broadly.

Data center location and access to cloud computing. The three channels examined so far depend on a common input: access to computing power. Local data centers are one means of accessing computing power. AI data center capacity is heavily concentrated in a few economies. However, "cloud compute" is an internationally traded digital service, and South Asia imports it at scale. Most EMDE firms purchase their cloud services from technology providers based in the United States, China, and Japan where data center capacity is concentrated. South Asia's cloud contracts are dominated by U.S. providers (figure 2.12), but the region also hosts more than 350 data centers.

Data center proximity and latency in AI compute. Although proximity to data centers does not dictate access to AI compute, it does provide a benefit to AI users: a reduction in latency, or the delay between a user's compute request and the system's response. In other words, it means faster response times. For example, a packet of data sent from Chennai to Mumbai on Microsoft Azure's network has 90 percent lower latency than one sent to the U.S. state of Virginia. Latency matters more for firms that are using AI for inference than for those training AI models. The fact that response time—and therefore, proximity to data centers—matters less for training AI

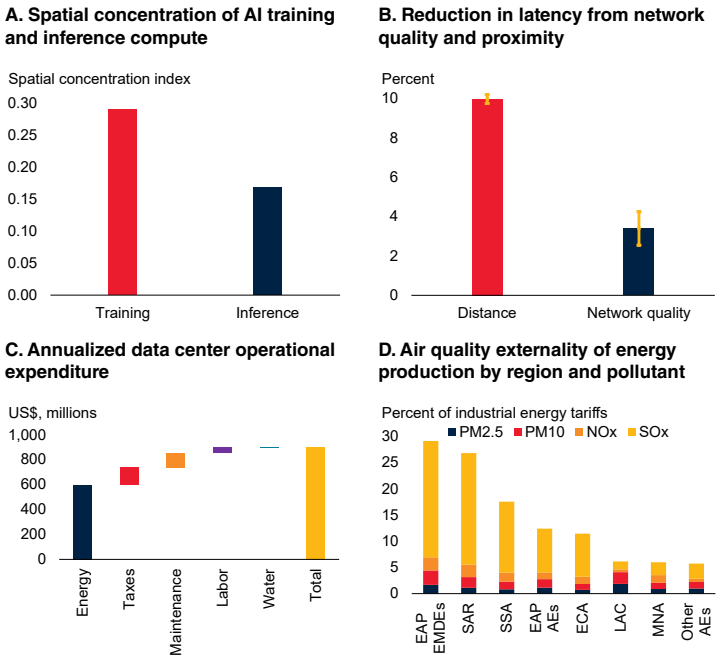
models may explain why it tends to be more spatially concentrated than AI use (figure 2.13). In addition, whether or not the data center is located locally, latency depends on the quality of the local broadband network.

Energy costs of data centers. Energy is a major input to cloud computing, accounting for 65 percent of data center operating expenditures (figure 2.13), so large local AI data centers could push up energy prices in South Asia. Evidence on whether data center entry has pushed up energy prices—largely from advanced economies—is, however, mixed (Alvarez et al. 2026; Feher, Garcia-Appendini, and Mihet 2025; Yue and Zeng 2026). Notably, because AI services are traded while data centers connect to local power grids, the productivity benefits of data centers in the U.S. are shared more widely than their infrastructure costs (Hong 2026). Moreover, energy prices exclude the negative externalities involved in the local environmental costs of production, which are particularly high in South Asia where coal accounted for 70% electricity generation on average in 2020-24. Indeed, the pollution cost of a kilowatt-hour of grid electricity is three times greater in South Asia than in advanced economies.

Fundamental drivers of data center investment. Because compute is internationally tradable, and assuming a competitive market, data center location choices across countries will reflect the sources of comparative advantage in data center investment. These sources fall into three groups: resource endowments, the quantity and quality of infrastructure, and the quality of institutions of governance. Energy and water endowments are critical, as is human capital (figure 2.14). Infrastructure is the second group, with broadband speed and electricity grid reliability both significantly correlated with data center investment. Crucially, it is reliable supply of power, not its cheapness, that draws data centers: while a one-standard-deviation gain in reliability raises investment by 20 percent, energy prices are broadly uncorrelated with data center locations across countries. The third group is governance: countries with lower regulatory burdens and stronger governance host more data centers. These patterns are consistent with prior research on the determinants of data center location (Charlita De Freitas et al. 2026).

FIGURE 2.13 Costs and benefits of data center proximity

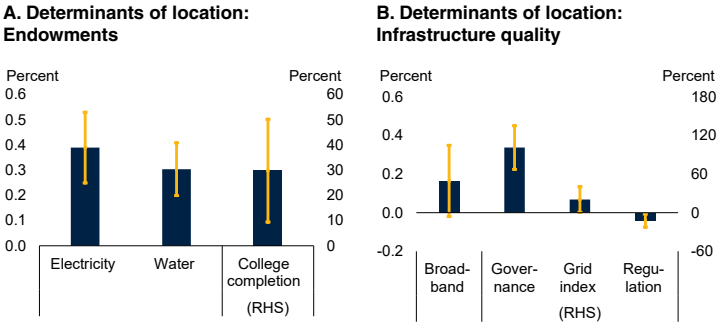
Running trained AI models (AI inference) is more latency-sensitive than AI training and therefore less spatially concentrated. Latency responds strongly to distance and the quality of the local broadband network. Energy costs account for the majority of data center operational expenditures. South Asia has an above-average environmental cost per unit of energy use in data centers.



Sources: AI Data Center Index; Ember; EPIC India; Epoch AI; European Environment Agency; International Energy Agency; McKinsey and Company; Microsoft Azure; Speedtest; Tsai et al. (2021); World Bank Group.
Note: NOx = nitric oxide and nitrogen dioxide; SOx = sulfur oxides; PM = particulate matter.
A. Spatial concentration index is calculated as sum of squared country-level shares of total installed power in AI data centers focusing on inference or training. Sample is 344 AI data centers collected in the AI Data Center Index.
B. Latency is the time delay it takes for a data packet to travel from the user to the cloud server and back again. Network quality is measured as a principal components analysis-weighted index of download speeds in Mbps and fixed broadband subscriptions per capita. The blue bar indicates how a one-standard-deviation increase in network quality reduces latency. The red bar indicates how a 1,000-kilometer reduction in distance reduces latency. Regressions control for origin and destination latitude and longitude. The sample comprises 2,348 city-pairs in the Microsoft Azure cloud network. All effect sizes are expressed as percentages relative to the mean latency.
C. Estimates are from Epoch AI for a representative 1-gigawatt data center in the United States.
D. Externality cost per kWh of energy production is calculated by converting energy production into emissions of PM2.5, PM10, SOx, and NOx by energy source using conversion factors from the European Environment Agency, and then converting emissions to social costs using estimates from Tsai et al. (2021). Regional averages are weighted by total energy production.

FIGURE 2.14 Drivers of data center location

Data center operators prefer locations with abundant energy and water, a skilled workforce, reliable power and high internet speeds, less red tape, and better institutional quality.



Sources: Data Center Map; Ember; FAO Aquastat; Speedtest; World Bank B-Ready; World Bank Enterprise Surveys; World Bank World Development Indicators; World Bank Worldwide Governance Indicators; World Bank Group.
Note: Regional averages are weighted by country population. Composite indexes are weighted averages of standardized component variables, with weights given by their first-principal-component loadings.
A.B. Bars show estimates from a regression of the number of data centers on energy production per capita, water resources per capita, the share of adults with college education, download speeds, a governance index, a regulatory burden index, and an electricity reliability index. All time-varying variables are country averages over 2005–25. The model is estimated by Poisson pseudo-maximum likelihood for 108 economies, controlling for temperature, population, and region fixed effects. Estimates correspond to the percent change in data centers for a one-standard-deviation increase in Electricity, Water, and Broadband and a one-percent increase in Governance, Regulation, and Grid index. Yellow whiskers show 95 percent confidence intervals.

Apart from these three groups of factors, research suggests that proximity to demand also shapes location, reflecting the fact that trade in compute is not frictionless: data centers locate closer to customers particularly for latency-sensitive uses such as financial transactions, big data, and video conferencing (Fang and Greenstein 2025; Leka 2026).

Endowment, infrastructure and institutional gaps in SAR. The centrality of resource endowments, infrastructure quality and governance in determining comparative advantage in data center location puts South Asia at a disadvantage relative to advanced economies and some other EMDE regions. South Asia's water endowments are the second smallest among EMDE regions. Its broadband speed and higher-education attainment rate are below the averages for other EMDEs. Grid investments and reforms, particularly in India, have raised the region's grid reliability above levels in other EMDEs, but it is still below advanced-economy levels. South Asia is also disadvantaged in terms of institutional quality, scoring 29 percentage points below the advanced economy average on a comprehensive governance index, though somewhat higher than other EMDEs, and below other EMDEs, as well as the advanced economies, on a comprehensive index of the regulatory burden on firms (figure 2.15). These endowment, infrastructure and institutional gaps suggest that it would be costly for South Asia to attract data center investment through special incentives. It may also be unnecessary: private data centers have an incentive to locate near large markets because of latency benefits, so that those parts of the region where the market is large may be able to attract sufficient private investment by improving their investment climate. In other words, the region can consider competing for data centers on investment climate rather than special incentives.

Broader ecosystem and capability benefits. Local data centers may also yield benefits beyond faster response times and productivity spillovers. Data center investment could be part of a broader strategy of building an AI ecosystem, since compute capacity may attract cloud providers, AI startups, and skilled workers that reinforce one another. It could also contribute to domestic technological capabilities, including the development of local-language models and AI applications tailored to local needs. India's Sarvam AI illustrates this: its foundation models, built for the country's 22 official languages, were trained on domestic data center capacity provided under the IndiaAI Mission (World Bank Group 2026a). These broader benefits, however, are harder to quantify, and realizing them may depend on the same conditions that determine data center location choices—reliable power, connectivity, skills, and a supportive business climate— rather than on data center investment alone.

Resilience and dependency considerations. Sovereignty and resilience concerns factor in the policy discourse on data centers. Because advanced chips, data centers, and commercial cloud services are concentrated among a few providers, reliance on them carries dependency risks. This is a particular concern for smaller economies with limited bargaining power. Building data centers domestically does not necessarily reduce dependency: the chips inside them are still supplied by the same few global suppliers. Diversification rather than sovereignty may be a more cost-effective route to resilience: sourcing models and cloud services from multiple providers and prioritizing interoperability, so that any one provider can be substituted without rebuilding the system (World Bank Group 2026b).

Policies to realize AI promise in South Asia

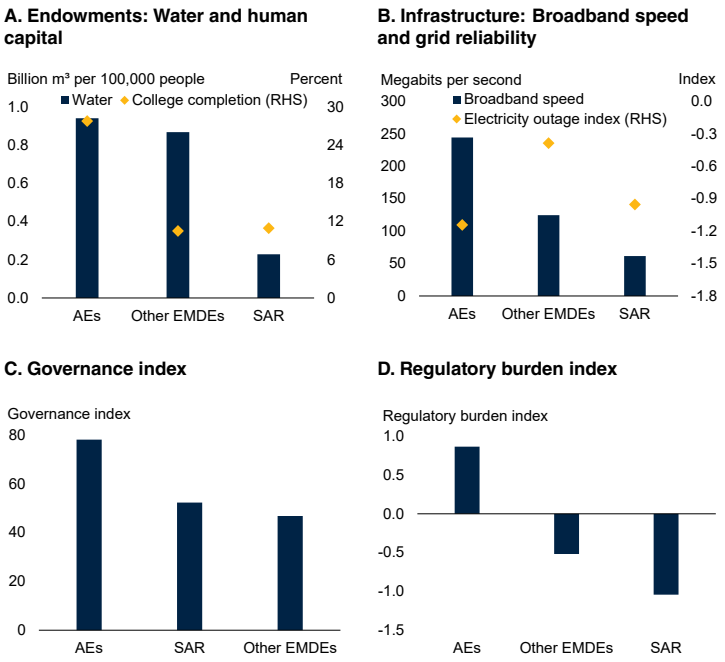
For the benefits of AI to be reaped, complementary conditions need to be met, in terms of workforce skills, infrastructure, and governance. Apart from securing these foundations, policies have roles in lowering the barriers that small firms face in adopting AI, strengthening local innovation systems to facilitate adaptation, and setting clear regulatory frameworks that minimize uncertainty.

The findings of this chapter point to four priority objectives for policy.

- The first is to spur AI adoption—not just its diffusion across the region's firms but the sophistication of use—so that its productivity benefits are realized more widely and quickly across the region's firms.
- The second is to help South Asian firms move up global value chains—away from routine, automatable tasks for which global demand is falling, toward higher-value work where AI is opening up fresh opportunities.

FIGURE 2.15 Factors for comparative advantage in compute

Most of the factors that driver data center location—energy and water, a skilled workforce, reliable power and high internet speeds, and better institutional quality—are abundant in advanced economies and scarce in EMDEs, with South Asia suffering particularly from scarcity of skilled labor, water, fiber networks, and regulatory ease.



Sources: Data Center Map; Ember; FAO Aquastat; Speedtest; World Bank B-Ready; World Bank Enterprise Surveys; World Bank World Development Indicators; World Bank Worldwide Governance Indicators; World Bank Group.
Note: Regional averages are weighted by country population. Composite indexes are weighted averages of standardized component variables, with weights given by their first-principal-component loadings.
A. Bars show total annual renewable water resources in billion cubic meters per 100,000 people for 39 AEs, all 6 South Asian countries, and 147 other EMDEs. Yellow diamonds show the share of adults aged over 25 that have completed higher education among 39 AEs, all 6 South Asian countries, and 136 other EMDEs. Water data are averaged within-country over 2010–25, and completion rates over 2006–24.
B. Bars show the average of country-level median download speeds in megabits per second, covering 38 AEs, 5 South Asian countries (all except Bhutan), and 109 other EMDEs, as of March 2026. Yellow diamonds show an index of outage frequency and duration, associated revenue losses, and firms' reported exposure to and constraints from outages, for 32 AEs, all 6 South Asian countries, and 121 other EMDEs. It uses each country's latest available data, ranging from 2009–25.
C. Bars show averages of country-level scores for regulatory quality, rule of law, and government effectiveness for 2005–2024.
D. Bars show weighted averages of firms' reported days to obtain an import license, operating license, and construction permit, and management time spent dealing with officials. Variables are averaged within each country using that country's latest available data, ranging from 2020–25.

- The third is to help make AI tools fit local conditions, adapted to local languages, infrastructure, and the realities of service delivery.
- The fourth is to secure reliable access to AI compute at reasonable cost, regardless of the location of the compute.

Fundamental factors. For these objectives to be met, certain fundamental factors are essential, and in all of them South Asia falls short: they relate, above all, to strong workforce skills, reliable basic infrastructure, and a business-enabling environment. The importance of these factors is acknowledged in firms' own assessments. When asked which policies would most help them use AI, 72 percent of Indian firms name improvements in digital infrastructure, and 55 percent better tertiary education (in contrast to U.S. firms' concerns about firm-specific skills and training; figure 2.16). The chapter's other findings echo this assessment. Skill intensity is among the few firm characteristics that predict both AI adoption and the productivity gains firms expect from it; growth in value-chain relationships is concentrated among firms already equipped to take on AI-adjacent work; and the winter school trial faltered where attendance was weakest.

AI-specific policies. Beyond these foundational conditions, the chapter's findings point to four AI-specific areas where public policy can help firms and AI developers make the most of AI's potential. The first is cost-effective access to compute: cloud services carry high fixed costs and small firms individually lack the scale to secure good terms, but a coordinated approach, supported by government, could ease such terms. The second is firms' knowledge about AI: firms are often ill-equipped to judge which AI tools suit them best and the quality of advice on offer, and public advisory services can help close this information gap. The third is the local innovation ecosystem: because AI capabilities cluster and build on one another, the connections, shared facilities, and demand that underpin a startup ecosystem are often undersupplied without public coordination. The fourth is governance, particularly the regulatory system: clear, predictable rules on data and AI use would reduce the regulatory uncertainty now often tending to deter adoption. Government action in these four areas would help enable the private sector to seize AI's opportunities while safeguarding against its risks.

Positioning South Asia on the adoption–adaptation–advancement ladder. A country's use of AI can be thought of as a progression across three stages, with each demanding more investment and complementary factors than the last: adopting existing tools, adapting them to local languages and conditions, and advancing the technology by building frontier models and the infrastructure behind them (World Bank Group 2026a). The evidence in this chapter suggests that most of South Asia is in the first two stages, and has most to gain from adoption and adaptation. Advancement currently lies beyond the reach and the priorities of most of the region, with the exception of India, which—given its scale, diversity, and sophisticated digital ecosystem—can consider targeted investments in advancement in market segments where it has an inherent advantage. India's Sarvam AI illustrates the case: its models, trained from scratch in India on compute provided under the IndiaAI Mission, are built specifically for the country's 22 official languages; this is a niche where India's linguistic diversity and scale give it an advantage that global models, trained largely on English, do not share (World Bank Group 2026a).

Small AI, big applications. A practical route to adoption and adaptation for the region is "small AI": models compact or narrow enough to run on basic devices, offline or over low-bandwidth connections, and adapted from larger models for specific tasks such as crop-disease diagnosis or medical screening (World Bank Group 2026a). Because small AI is designed to work where complementary factors such as power, connectivity, and devices are scarce, it is especially suited to the

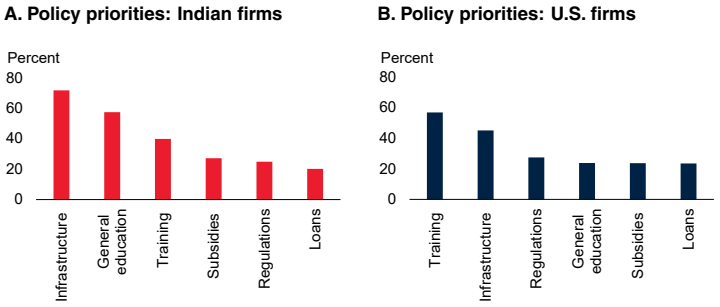
low-resource settings that characterize much of the region outside its major urban centers.

Adoption and adaptation priorities across a diverse region. The firm-level adoption evidence in this chapter draws on India, the only South Asian economy in the enterprise survey. India has larger domestic markets and more advanced institutional underpinnings for AI—such as the IndiaAI Mission—than other South Asian countries, so much of the region may be at an earlier stage of AI adoption and adaptation than India. The priorities discussed here apply across the region, but South Asian countries that are least advanced in terms of the preconditions for AI adoption may consider placing most of their policy emphasis on foundational conditions—digital infrastructure, skills, and institutions—before the more advanced measures become relevant for them.

Digital infrastructure. Use of AI applications requires the ability to access, process, and transmit large volumes of data, which in turn demands reliable and affordable access to electricity and affordable high-speed internet. But in both cases provision in South Asia remains well below advanced-economy levels. Government policy shapes both. Governments can spur private investment in connectivity by promoting competition in telecommunications and lifting restrictions on foreign ownership, which tend to deter entry and keep prices high; opening previously closed markets can attract sizable new capital, as it has in other EMDEs. Policies such as technology-neutral spectrum licensing, which lets operators repurpose existing bands for newer networks, and frameworks that encourage sharing of passive infrastructure such as towers and ducts can lower the cost of extending high-speed coverage (World Bank Group 2024a). Electricity grid reliability in the region is constrained not just by inadequate investment but also by inefficient use of existing capacity. Power-sector distortions—inefficient state-owned utilities, subsidies and mispricing that discourage supply, and unreliable delivery—are estimated to cost 4–7 percent of GDP in Bangladesh and India (Zhang 2019). This implies that not only measures to spur investment in new generating capacity, but also reforms to utility governance and pricing will be needed for the reliability and affordability of power supplies for AI users to reach needed levels.

FIGURE 2.16 Policies to spur AI adoption: What do firms prioritize?

Asked which policies would most help them use AI, Indian firms point chiefly to policies to improve infrastructure and general education, followed by workforce training. U.S. firms instead rank workforce training highest, followed by infrastructure, with general education ranked far lower than it is by Indian firms.



Sources: World Bank Enterprise Surveys AI Module 2025–26; World Bank Group.
A.B. Bars show the percentage of establishments agreeing that each policy could increase their use of AI technologies for each policy option listed in the WBES survey. The exact phrasing of the policy options in the survey is as follows: "Infrastructure" stands for "better digital infrastructure"; "General education" for "skills among university graduates"; "Training" for "training of the current workforce"; "Subsidies" for "financial subsidies"; "Regulations" for "changes in regulations around AI"; and "Loans" for "improved access to financial loans."

Business-enabling environment. South Asian firms tend to remain small and grow slowly (Hsieh and Olken 2015). The prevalence of small firms may limit the scope for productive deployment of AI in the region, as suggested by the strong association between firm size and the use and sophistication of AI among U.S. firms. The growth of firms in South Asia, and hence their technological advancement, is constrained by the business environment (Hsieh and Klenow 2014). Policies to promote competition, greater openness to trade, and regulatory reforms would help ease these constraints and increase adoption of AI.

Workforce skills. Workforce skills are an essential complement to AI in firms. The strong association between workforce skill-intensity

and both Indian firms' AI adoption and their expected productivity gains suggests that firms with more skilled labor are more able to adopt AI and can expect higher returns from its use. Workforce skills also underpin the region's other economic opportunities: moving up global value chains into higher-value manufacturing and services draws on a range of technical, managerial, and soft skills, some of them sector-specific. Firm-level evidence suggests, for instance, that better management practices raise product quality and exports (Bloom et al. 2013). Acquiring skills that support AI use can also protect workers from AI-related job displacement. The skills that make workers complementary to AI are broad, encompassing analytical skills (such as mathematics and problem-solving) and social (including communication) skills. Strengthening these competencies through education may be among the most effective ways to promote high employment as AI spreads. A large part of South Asia's workforce lacks these skills, reflecting the poor performance of general education: adult literacy is estimated at around 75 percent, against 85 percent across all EMDEs.

AI skills: near-term priorities. In the near term, the priority for AI-specific skills is to ensure that those equipped with foundational numeracy and digital skills are equipped to make use of AI at work—a task where governments may be expected to play a key role. The evidence on traditional, government-run training programs is mixed (Card, Kluve, and Weber 2018; McKenzie 2017), but comprehensive sectoral programs pairing occupational and soft-skills training with job matching, and involving strong employer and community links, have shown sizable effects on earnings and employment in the United States (Katz et al. 2022). This model could be adapted to South Asia. Beyond skilling, social protection to cushion displaced workers and labor-market flexibility to speed up new job creation will help smooth the labor market transition triggered by AI adoption (World Bank Group 2025).

Supporting AI adoption by SMEs: cost-effective access to compute and advice. Although not all high adoption costs represent market failures that might warrant government action, access to cloud platforms—the main doorway to AI compute—entails high fixed costs that may be a particular deterrent to small firms. Such firms are individually too small to negotiate viable terms of access with cloud service providers, indicating a coordination problem related to economies of scale. Governments can help address this problem through measures such as cloud-service vouchers for small firms, or arrangements that aggregate demand over many small users so that they obtain the scale advantages they could not achieve individually (World Bank Group 2026a). Small firms may also lack the resources to work out which AI tools best suit their needs, where to obtain them, or how best to use them. The market for the advice they need on such questions may be underdeveloped because firms cannot judge its quality before they pay for it and experience the results (McKenzie et al. 2025). Governments can help address this problem by setting standards for private consultants and establishing tools such as directories and registries (Cirera, Cruz, and Davies 2020; World Bank Group 2026a). Advisory support for firm-level digitization may also help, since many small firms have yet to digitize and organize their business data.

Supporting local AI innovation clusters for successful adaptation. An ecosystem for local AI innovation is needed for the development of AI tools that fit the local context. AI builds on other technologies, and its early adopters

tend to cluster, with knowledge spillovers reinforcing agglomeration (McElheran et al. 2024). Successful innovation clusters need strong connections to research centers like universities, access to skills and finance, and ease of business entry. Governments in South Asia can help support provision of these needs by reforming business-entry regulations, addressing coordination failures that hamper collaboration between research centers and startups, and improving access to inputs that the market alone may under-provide, including the infrastructure and shared facilities used by startup incubators and accelerators. For example, the IndiaAI Mission subsidizes shared compute and datasets (MeitY 2026a). Governments can also shape AI innovation from the demand side through public procurement, which amounts to 15–22 percent of GDP in many EMDEs. This indicates that even if AI-related procurement represents only a small share of the total, it can be a large source of demand for AI service providers. This enables governments to incentivize AI developers to build better tools by imposing strong standards in public contracts, including for interoperability, auditability, and data portability (World Bank Group 2026a).

Digital public goods to underpin adaptation. Developing frontier large language AI models from the ground up may be neither necessary nor cost-effective for EMDEs, given the potential for local AI adaptation. Training frontier models is costly and concentrated among a few firms in the advanced economies. More cost-effective options, based on adaptation, are available to South Asian firms and governments. For example, open-weight large language models (LLMs) (i.e., LLMs whose core components are publicly released) could be fine-tuned to suit local languages, education curricula, and regulatory and administrative data at a fraction of the cost of developing frontier models; and, particularly given the wide variation in conditions across the region, smaller models fine-tuned to locally relevant data may outperform, in many tasks, frontier models trained overwhelmingly on other regions' content (World Bank Group 2026a). Governments can support adaptation by easing access to high-quality datasets in local languages and domains—a public good that no single firm has the incentive to provide at scale but which the whole AI ecosystem can use as an input. For example, India's Bhashini platform provides open language-AI datasets and translation services across the country's many official languages (MeitY 2026b). More broadly, India's digital public infrastructure—the shared platforms for identity, payments, documents, and consent-based data sharing on which services in health, education, and commerce are built—gives firms and public institutions common digital rails on which to deploy AI applications, lowering the cost of adapting and scaling them. When AI runs on such public infrastructure, its benefits can diffuse more widely and quickly (World Bank Group 2026a).

Improving AI governance and clarifying AI regulations. AI governance is the fourth area where policy can promote AI adoption. Indian firms that have not adopted AI rank laws and regulations among the top reasons, even though the country has enacted no AI regulations except for sector-specific rules in healthcare and capital markets. This points to uncertainty about existing and prospective rules, in the near-absence of AI-specific regulation. Firms citing regulations may, for instance, have in mind general data protection law (India's Digital Personal Data Protection Act, 2023), which regulates use of consumer data, including data used to build or run AI. For a region still at an early stage of AI adoption, the priority for regulation is to address genuine risks without deterring safe adoption and innovation through unnecessary or badly designed regulations.

The risks include rising cyber threats, such as fraud and criminal activity, arising from the growing power of AI tools (Misra et al. 2026). AI governance also needs to be effective in addressing issues relating to bias and fairness, data privacy and security, and the transparency of automated decisions. There is as yet no "gold standard" for AI governance in EMDEs (World Bank Group 2026a). Several South Asian governments have set out national AI governance strategies. For example, India has articulated a "safe and trusted AI innovation" strategy, whose main goals are to encourage innovation and adoption while protecting individuals and society from the risk of harm, with AI applications being governed through the relevant sectoral regulators (MeitY 2025). Bangladesh's strategy is in draft (Government of Bangladesh 2026). In all countries in the region, however, binding AI legislation is less advanced. In each case, the governance system needs to be flexible, tailored to the maturity of the country's AI ecosystem and its existing legal landscape, and developed in consultation with industry, civil society, and academia (World Bank Group 2024b).

Annex 2.1 Data sources

This study combines multiple data sources to characterize firm-level AI adoption, labor demand, and global value chain (GVC) linkages for firms from the South Asia region (SAR). The core datasets include World Bank Enterprise Surveys (WBES) firm-level survey data, industry AI exposure indices, online job postings data, and firm-to-firm global supply chain relationships.

World Bank Enterprise Surveys

The main source of the firm-level AI adoption data in this chapter is the World Bank Enterprise Surveys (WBES) AI Module, fielded in 2025–26. The survey covers 4,546 formal firms across 8 EMDEs and one advanced economy: India, Jordan, Malaysia, Mexico, Nigeria, Kenya, Thailand, Türkiye, and the United States. However, owing to low response rates, the survey administrators recommended excluding Malaysia and Türkiye from the analysis, leading to a final sample of 4,205 firms from 6 economies. In the EMDEs, the survey was conducted as a follow-up to the most recent core WBES survey conducted between 2023 and 2025. Of these firms, 1,355 were surveyed in India and 401 in the United States. The survey includes nine sub-modules covering firms' use of AI, labor adjustments, sales growth expectations from AI, constraints to AI use, and policy priorities for increasing AI use. The AI module data are merged with the data on firms' internal characteristics and operating environment that are collected in the main WBES survey using unique firm identifiers.

Sampling strategy

The survey adopted a CATI (phone-based) approach, re-interviewing firms from the original WBES sample; no new establishments were added. Embedded quality-control checks were implemented. The baseline WBES used random sampling stratified by firm size, business sector, and geographic region within an economy. It covers formal firms with 5 or more employees. The AI follow-up adds another layer of stratification by the likely AI intensity at the two-digit ISIC Rev. 4 level.

All summary statistics presented in the chapter are weighted by inverse sampling probability weights included in the WBES dataset.

AI indices

AI adoption index. The index is a composite index of six components, capturing how sophisticated a firm's AI use is across multiple dimensions. It is computed as an inverse-covariance-weighted summary index

(Anderson, 2008). Each component is first converted into a z-score by subtracting its mean and dividing by its standard deviation in the pooled sample of all firms surveyed. The standardized components are then combined using weights derived from the inverse of their covariance matrix, which down-weights components that are highly correlated with one another and up-weights those that contribute unique information. The index is therefore expressed in standard deviation units, such that a one-unit increase represents a one-standard-deviation movement across its pooled distribution. The index scale is also shifted by subtracting its minimum value across the sample, so that all values are non-negative.

Components of the AI adoption index

- **"Any AI"** is a dummy indicating whether the firm adopts any form of AI, including a rule-based or traditional chatbot, a general purpose AI chatbot, an AI agent, AI-powered searching or recommendation tools, AI-driven automation, and AI-driven decision tools (e.g., predictive analytics).

- **AI technology index** measures the number of advanced AI technologies that a firm uses. Advanced AI technologies include AI agent, AI-driven automation, and AI-driven decision-making.

- **AI task sophistication index** counts the number of cognitively demanding tasks that a firm uses AI for. Those tasks include coding or software development, data analysis, and controlling production processes.

- **AI business function index** reflects the number of business functions that a firm uses AI for. The functions are: (1) research and development (R&D) and innovation; (2) marketing, sales and product development; (3) sourcing, procurement and supply chain management; (4) business administration, such as accounting and human resource work; (5) strategic decision-making; (6) compliance checks and governance; and (7) quality control.

- **AI sourcing sophistication index** comprises two indicators: a dummy for whether the firm pays for any AI technology, and the number of AI software or systems that the establishment is using. The software or systems include commercial ones (e.g., Microsoft Copilot) and custom-built ones developed either externally or within the business. This captures whether the firm has dedicated sourcing arrangements instead of merely using online AI platforms and open-source AI technologies.

Expected sales per worker gains from AI

The expected AI productivity gain variable is defined from two WBES questions asking firms how much they expect sales to grow over the next three years under rapid versus slow AI development, each relative to the current pace, and each holding employment constant. Taking the difference isolates the perceived gain in sales per worker attributable to faster AI, netting out factors that would affect productivity expectations regardless of AI.

Business climate indices

In addition to the AI indices, five composite indices are constructed to measure firms' capabilities and operating environment. All five are built following the Anderson (2008) inverse-covariance weighting procedure described above, with higher values denoting more favorable conditions. The indices are constructed from the baseline WBES for the economies covered by the AI follow-up module, using the latest available survey round for each economy.

ICT access index measures a firm's access to information and communication technology (ICT), with components indicating whether the firm has an internet connection, whether it has its own website, whether internet providers can be switched easily, and the reverse-coded number of internet disruptions in the last fiscal year.

Electricity index measures the availability and reliability of electricity for business operations, with components indicating whether electricity is not reported as a major or severe constraint, whether the firm experienced no power outages in the last fiscal year, and the reverse-coded number of outages in a typical month and duration of a typical outage.

Regulation index measures the regulatory burden on business operations, with components indicating whether business licensing and permits are not reported as a major or severe constraint, and the reverse-coded share of senior management time spent dealing with requirements imposed by government regulation in a typical week over the last fiscal year.

Contract enforcement index measures the quality of legal enforcement for business operations, with components indicating whether courts are not reported as a major or severe constraint, whether the firm perceives the court system as independent and impartial, and whether it regards arbitration or mediation as a reliable alternative. Missing values on the latter two components are imputed with the pooled-sample mean.

Access to finance index measures a firm's ease of access to finance in the last fiscal year, with components indicating whether access to finance is not reported as a major or severe constraint, the reverse-coded share of working capital financed from internal funds, whether the firm did not face unfavorable interest rates, collateral requirements or application procedures, whether the firm has a bank account, and whether it has a bank loan or line of credit. Missing values on the unfavorable-terms component are imputed with pooled-sample mean.

Firm-level characteristics

Firm size. Small firms have 5 to 19 employees, medium firms have 20 to 99 employees, and large firms have 100 or more employees.

Firm age. Young firms are those 5 years old and younger, and mature firms are those 5 to 14 years old. The omitted category is old firms, which are older than 15 years.

Firm ownership. Two dummies related to ownership are constructed: whether the firm's largest owner is the top manager, and whether the firm is owned by foreign entities.

Firm exporter. An indicator of whether the firm is an exporter.

Management experience. A dummy equal to one if the firm's manager has more than 15 years of experience.

Skilled workforce index measures a firm's workforce skill intensity, normalized to standard-deviation units following the Anderson (2008) inverse-covariance weighting procedure described above, with components indicating whether the firm offers formal training to workers and the share of highly skilled production workers in the last fiscal year.

Innovation index measures a firm's innovative activities, with components indicating whether the firm introduced a new product, introduced a new process, and undertook spending on research and development in the last fiscal year. It is also a z-score constructed using the inverse-covariance weighting method.

All business climate indices are averaged at the stratum level (size, sector, and location cells) because individual firm-level responses to business constraint rating questions may be endogenous to the firm's growth performance. Taking averages across firms in the same stratum helps make the indices more objective measures of the firm's external environment.

Firm-level AI hiring and global value chain relationships data

The GVC analysis presented in this chapter uses unique data on firms' job postings and international GVC relationships to examine how exposure to artificial intelligence shapes firms' demand for AI skills and GVC participation in South Asia and the United States. Exposure to AI is measured using an industry-level AI index.

Industry-level AI Exposure Index

The analysis uses an AI Industry Exposure index (AIIE) for 4-digit NAICS codes, which is built up from an occupation-level index of AI exposure (AIOE) developed by Felten, Raj, and Seamans (2021; 2023). The index quantifies the extent to which the abilities required for a given task overlap with the capabilities of existing AI systems. Exposure is initially measured at the U.S. Standard Occupational Classification (SOC-10) level using task- and ability-level data from the Occupational Information Network (O*NET), a comprehensive database maintained by the U.S. Department of Labor. Indices are first computed separately for text- and image-based generative AI systems, then averaged and standardized across occupations. Finally, the exposure index is aggregated to the industry level (4-digit NAICS codes). When aggregating to the industry level, each occupation's AIOE score is weighted by its share of total U.S. employment in the industry, using 2019 U.S. employment data (Felten, Raj, and Seamans 2021; 2023).

Online job postings and firm-level measures

Firm-level labor demand for South Asia is measured using online job postings data from Lightcast, a labor market analytics firm that aggregates vacancies from major online job platforms. The dataset covers approximately 25 million job postings in South Asia between January 2020 and March 2025, originating from 435,249 unique firms. Each posting reports required skills—including digital and AI-related skills such as machine learning, neural networks, and natural language processing—as well as occupation (four-digit ISCO), sector (2-digit NAICS), location, and, for roughly 16 percent of postings, a posted salary. More specifically, 4 percent of all job postings are classified as AI-related and roughly 10 percent of South Asia firms have posted at least one AI job.

Firm-level labor demand for the United States is measured using online job postings from LinkUp, a labor market analytics firm that aggregates vacancies from major online job platforms. The dataset contains 44,690 U.S. firms and approximately 111 million job postings from January 2021 to December 2025. Approximately 0.92 percent of postings are identified as AI jobs, while 32 percent of U.S. firms have posted at least one AI vacancy for the sample period.

To facilitate firm-level analysis, both Lightcast and LinkUp job postings are collapsed to the firm–month level, generating measures of total AI-related postings in South Asian and U.S. firms.

Global Value Chain Relationships of U.S. and South Asian firms

To measure firms' participation in global value chains, the analysis uses firm-level relationship data from FactSet, a global corporate data provider. The FactSet dataset includes time-

varying inter-firm buyer, supplier, and strategic partnership relationships among firms worldwide; the third category broadly captures strategic partnerships through equity investments, joint ventures, research collaborations, and integrated product offerings. The initial FactSet sample contains 324,862 South Asian firms, of which 5,958 are observed to have at least one international relationship between January 2020 and December 2025; of these, 46 percent have at least one relationship with a U.S. firm.

South Asian firms appearing in FactSet and Lightcast are matched using a two-stage fuzzy matching algorithm based on company names. The first stage generates candidate matches using MinHash locality-sensitive hashing to identify firms with high token-level Jaccard similarity. The second stage refines matches using normalized Levenshtein edit distance to account for spelling and formatting differences. Using this approach, 9,443 Lightcast firms are successfully matched to FactSet firms, of which 2,031 have connections with U.S. firms, representing about 74 percent of U.S.-connected FactSet firms. The 2,031 firms connected to U.S. firms—equivalent to 0.47 percent of all firms in the sample—posted 42,341 AI-related vacancies, accounting for 4.52 percent of all AI-related postings during the sample period. The resulting firm–month panel contains 2.85 million observations, with approximately 1.4 percent corresponding to U.S.-connected firms. However, these firms are disproportionately large, and account for nearly 7 percent of all jobs posted during the period. Since the largest, most productive firms export, they are likely to comprise an even larger share of total value-added.

U.S. firms in FactSet and LinkUp are matched using a similar two-stage fuzzy-matching algorithm based on company names. Using this method, 31,912 LinkUp firms are matched to FactSet firms, of which 2,003 have connections to South Asia, representing roughly 37 percent of South Asia-connected FactSet firms. South Asia-connected U.S. firms posted 23,356,540 vacancies, 2 percent of which were AI-related, compared with 87,997,664 vacancies posted by other firms, of which 0.66 percent were AI-related. The 2,003 South Asia-connected U.S. firms posted 21 percent of all vacancies, while the remaining firms posted 79 percent.

These mergers result in two unique monthly firm-level panel datasets: a dataset of U.S. firms containing information on their job postings, GVC connections with South Asian (and other international) firms, and the job postings of the South Asian GVC counterparties; and a mirroring dataset of South Asian firms.

The merged datasets are subject to selection concerns. Not all internationally connected firms post vacancies online, and not all firms appearing in Lightcast and LinkUp are covered by FactSet. The datasets disproportionately cover larger firms with stronger public reporting, and no quantitative information is available on the economic size or intensity of individual GVC relationships, limiting the ability to measure trade volumes directly.

Winter school RCT data

The winter school RCT piloted a 6-week winter school for public school students in grades 2–5 during January-February 2026 in Quetta, the capital city of Balochistan, Pakistan, in collaboration with the provincial department of education (Asad et al. 2026). Students from 89 primary schools in Quetta applied to the winter school and were randomly assigned to three experimental arms: control arm, teacher-led arm, and AI arm. Thirty of the schools, which had the highest number of applicants, were selected as the locations of the winter school (15 for the teacher-led arm and 15 for the AI arm). The randomization was done within

home schools, so that each home school had children in a control group and in a treatment group. A baseline survey was conducted in November 2025 and an endline survey was conducted in May 2026. The surveys were conducted in the home schools of the students. The date at which schools were tested was randomized, so that any variation within baseline and within endline can be attributed to the time of testing, rather than the selection of the school. The main source of data used in the analysis presented in the chapter is the endline survey, which covered 4,938 students. The primary outcome of interest in the RCT is a composite student test score combining performance in Urdu, math, and English.

Annex 2.2 Empirical strategy and methods

Analysis of WBES data on AI adoption

The chapter estimates cross-sectional regressions on WBES firm-level data to examine the correlates of adoption and expected sales per worker gains from faster AI adoption:

$$Y_i = \alpha \mathrm{X}_i + \beta \mathrm{Z}_i + \delta_i + \epsilon_i.$$

The regressions consider two outcomes: the AI Adoption Index (Y_i) and the expected gains in sales per worker from faster AI development in firm i. The vector (X_i) is a set of internal firm-level characteristics which includes dummies for size, age group, family-managed firms, foreign ownership, and exporter status; manager years of experience; and indices of innovative activities and workforce skills. The vector Z_i is a set of external factors: indices of ICT access, electricity access, business regulation quality, contract enforcement quality, and access to finance. As explained in annex 2.1, these external environment indices are averaged across firms in the same strata (size, sector, and location cells) to enhance their objectivity in measuring the firm's external environment. The regressions also include sector fixed effects δ_i to account for broad sectoral co-variations in AI exposure and firm attributes such as size. The regressions are estimated using OLS, separately for Indian and U.S. firms. The standard errors are clustered at the stratum level.

Analysis of GVC connections

This chapter presents results from Chiplunkar et al. (2026), who study how U.S. and South Asian firms' exposure to artificial intelligence affects their demand for AI skills and global value chain (GVC) connections. The empirical strategy in Chiplunkar et al. (2026) uses firm-level panel regressions and conducts difference-in-differences-type analysis, where changes in key outcomes—labor demand and the number of GVC relationships—before and after the release of ChatGPT in November 2022 ("pre-" and "post-ChatGPT") are compared across firms with different pre-ChatGPT industry-level AI exposure and GVC relationship status. All analyses are conducted at the firm–month level using GVC relationships and job postings data from January 2021 to March 2025. The variables interacted with the Post-ChatGPT dummy on the right-hand side of the regressions—industry-level AI exposure and GVC relationship status—are fixed at pre-ChatGPT levels (January 2020–November 2022), similar to the fixed or pre-existing "share" component in a shift-share regression framework.

Impact of AI exposure on AI hiring in U.S. and South Asian firms

The following regression in Chiplunkar et al. (2026), estimated on a firm-month-level panel of U.S. firms, examines how the hiring of AI skills by U.S. firms has changed post-ChatGPT and how that change is related to their pre-ChatGPT industry-level AI exposure:

$$AIJobs_{it} = \theta PostGPT_t \times AIIE_i + \beta PostGPT_t + \alpha_i + \delta_t + \varepsilon_{it.}$$

Here, $AIJobs_{it}$ is the share of AI job posts in the total job posts of U.S. firm i in month t, and $AIIE_i$ is the firm's industry-level AI exposure index (standardized to standard deviation units). The coefficient θ measures how the post-GPT increase in AI skills hiring is associated with the firm's AI exposure. The regression controls for firm fixed effects α_i and year-month fixed effects δ_t. The regression is estimated by ordinary least squares (OLS), with standard errors clustered at the firm level.

Next, the analysis uses a triple-interaction specification to examine whether the association between AI exposure and the post-ChatGPT increase in U.S. firms' AI hiring differs by the type of their pre-ChatGPT GVC relationships with South Asian counterparties. There are three relationship types—supplier, customer, and partner—corresponding to the status of the U.S. firm in the relationship. For each relationship type, firms with that relationship are compared with firms without any GVC relationships with South Asia pre-ChatGPT, controlling for firm and month-year fixed effects:

$$\begin{aligned} AI\ Jobs_{it} = {} & \beta^r\ PostGPT_t \\ & + \theta^r\ PostGPT_t \times AIIE_i \\ & + \kappa^r\ PostGPT_t \times PreRel_i^r \\ & + \gamma^r\ PostGPT_t \times AIIE_i \times PreRel_i^r \\ & + \alpha_i + \delta_t + \varepsilon_{it,} \end{aligned}$$

where $PreRel_i^r$ is a dummy that equals one if the U.S. firm had a GVC relationship of type r (customer, supplier or partner) before the release of ChatGPT. The coefficient γ^r measures how the association between the post-ChatGPT change in AI skills hiring and the U.S. firm's AI exposure depends on the existence of a pre-ChatGPT relationship of type r with a South Asian firm.

Similar mirroring regressions are estimated on a firm-month-level panel of South Asian firms to examine the relationship between their post-GPT increase in AI skills hiring and own AI exposure, and how that relationship varies by the type of their pre-GPT GVC relationships with U.S. counterparties. Note that in this analysis, the relationship type—supplier, customer, and partner—corresponds to the status of the South Asian firm in the relationship because the unit of analysis is the South Asian firm. In the triple interaction specification, for each relationship type, South Asian firms with that relationship are compared with those without any GVC relationships with U.S. firms pre-GPT.

Impact of AI exposure on GVC relationships

Chiplunkar et al. (2026) estimate the impact of industry-level AI exposure on the increase in the number of GVC relationships of U.S. and South Asian firms after the introduction of ChatGPT using a firm-month-level panel dataset. The analysis is first conducted from the perspective of U.S. firms. The baseline specification is as follows:

$$Y_{it}^r = \beta^r\ (PostGPT_t \times AIIE_i) + \alpha_i + \delta_t + \varepsilon_{it.}$$

Here, Y_{it}^r is the number of relationships of type r that firm i has in month t. As in the AI job posts regression described earlier, $PostGPT_t$ is an indicator for a month after November 2022 (ChatGPT's month of release) and $AIIE_i$ is the industry-level AI exposure measure of the firm. The regression controls for firm fixed effects α_i and year-month fixed effects δ_t. Recall that there are three relationship types (supplier, customer, and partner), which correspond to the status of the U.S. firm in the relationship given that the unit of analysis is a U.S. firm.

The main coefficient of interest is β^r, which measures whether more AI-exposed U.S.

firms experienced larger post-ChatGPT increases in the number of relationships of type r. The regression is estimated using a Poisson pseudo-maximum-likelihood (PPML) estimator, which accommodates the large number of zeros and the skewed distribution of the relationship count outcome (Santos Silva and Tenreyro 2006; 2011; Wooldridge 1999). Because PPML specifies the conditional mean as an exponential function, β^r is interpreted as a semi-elasticity—an approximate percentage change in the expected relationship count per standard deviation of AI exposure. The standard errors are clustered at the firm level.

The next stage of the analysis examines whether the relationship between the post-GPT growth in U.S. firms' relationship counts and their sectoral AI exposure varies with the pre-GPT sectoral AI exposure of their South Asian GVC counterparties. For each relationship type r, the analysis defines a high counterparty AI exposure dummy ($HiCPA_i^r$) equal to one if the U.S. firm's counterparty AI exposure index, averaged over all its pre-GPT South Asian GVC relationships of that type, is above the sample median. Building on the baseline regression, the following triple-interaction regression is estimated for each relationship type:

$$Y_{it}^r = \delta^r \left(PostGPT_t \times AIIE_i \times HiCPA_i^r\right) + \beta^r \left(PostGPT_t \times AIIE_i\right) + \alpha_i + \delta_t + \varepsilon_{it.}$$

The main coefficient of interest is δ^r, which measures whether the relationship between the post-GPT growth in U.S. firms' relationship counts and their sectoral AI exposure varies by counterparty exposure. As an illustration of how to interpret the sign of δ^r, suppose β^r is positive. Then, a negative (resp., positive) δ^r implies that the positive relationship between U.S. firms' AI exposure and post-GPT growth in GVC relationships is weaker (resp., stronger) when the average AI exposure of their pre-GPT South Asian counterparties is higher.

Next, the analysis is mirrored from the perspective of South Asian firms, with the same type of regressions estimated on a firm-month panel of South Asian firms. In these regressions, given that the unit of analysis is a South Asian firm, $AIIE_i$ measures the industry-level AI exposure of the South Asian firm, while $HiCPA_i^r$ is equal to one if the SAR firm's counterparty AI exposure index, averaged over all its pre-GPT U.S. GVC relationships of that type r, is above the sample median. The relationship type corresponds to the status of the South Asian firm in the relationship.

Analysis of the winter school RCT

The main estimates of the impact of the winter school presented in this chapter are based on an "intent-to-treat" OLS regression estimated and presented in Asad et al. (2026). The regression specification is:

$$endline_{is} = \alpha + \beta_1 TeacherArm_i + \beta_2 AIArm_i + \sum_s \gamma_s 1\{S = s\} + \varepsilon_{it.}$$

Here, $endline_{is}$ is the endline score of the student, $TeacherArm_i$ and $AIArm_i$ are indicators for assignment to the teacher-led arm and AI arm, respectively, and the γ_s are home-school fixed effects. The school fixed effects are included because the randomization was done within-school. The coefficients β_1 and β_2 measure the causal impacts of assignment to the teacher-led arm and the AI arm, respectively.

In addition, the chapter presents estimates of the impacts of the winter school arms on the subsample of high-attendance students. This estimate is based on a similar specification, except that students from the teacher-led arm and the AI arm with less than 40 percent attendance are dropped from the estimation sample. Note that this estimate is not causal because attendance was not randomized.

Annex Table A.2.1.1 AI adoption index by sectors in India

Sector	AI adoption index
IT & IT Services	0.974
Pharmaceuticals & Medical Products	0.655
Motor Vehicles	0.456
Machinery & Equipment	0.386
Other Services	0.356
Other Manufacturing	0.348
Basic Metals	0.137
Textiles	0.120
Garments	0.115
Construction	0.101
Chemicals & Chemical Products	0.086
Wholesale	0.065
Retail	0.044
Hotels	0.041
Food	0.038
Rubber & Plastics Products	0.036
Non-Metallic Mineral Products	0.023
Transport	0.018

Sources: World Bank Enterprise Surveys AI Module 2025–26; World Bank Group.
Note: ISIC = International Standard Industrial Classification. Sectors are based on ISIC codes, and grouped according to the survey's stratification sectors.

Annex Table A.2.2.1 Correlates of the AI adoption index

	India		United States	
Dependent variables: AI adoption index	**(1)**	**(2)**	**(3)**	**(4)**
Small firm	-0.145 (0.150)	-0.072 (0.188)	-1.010*** (0.380)	-1.011*** (0.379)
Medium firm	-0.051 (0.153)	0.020 (0.185)	-0.155 (0.457)	-0.138 (0.443)
Young firm	0.223* (0.132)	0.226 (0.138)	1.317*** (0.393)	1.319*** (0.388)
Mature firm	0.033 (0.069)	0.033 (0.062)	-0.427 (0.259)	-0.432 (0.272)
Firm's largest owner is the top manager	0.023 (0.069)	0.048 (0.081)	-0.015 (0.262)	0.004 (0.273)
Manager has more than 15 years of experience	-0.056 (0.063)	-0.013 (0.065)	0.167 (0.279)	0.173 (0.290)
Foreign-owned firm	0.481*** (0.100)	0.723*** (0.111)	0.324 (0.326)	0.204 (0.385)
Exporter	-0.169 (0.128)	-0.049 (0.151)	-0.408 (0.680)	-0.439 (0.664)
Innovation index	-0.051 (0.097)	-0.068 (0.078)	0.170 (0.215)	0.170 (0.216)
Skilled workforce index	0.143** (0.072)	0.150** (0.072)	0.263** (0.126)	0.258** (0.119)
ICT access index	---	-0.076 (0.052)	---	-0.027 (0.126)
Electricity index	---	-0.196 (0.123)	---	-0.194 (0.212)
Regulation index	---	0.035 (0.060)	---	0.049 (0.134)
Contract enforcement index	---	0.065 (0.046)	---	0.000 (0.213)
Access to finance index	---	-0.027 (0.042)	---	-0.027 (0.192)
Constant	0.419** (0.168)	0.370* (0.223)	1.301** (0.528)	1.417** (0.548)
Observations	1,354	1,354	371	371
R-squared	0.061	0.093	0.239	0.244
Weighted mean of dependent variable	0.270	0.270	0.850	0.850
Sector fixed effects	Yes	Yes	Yes	Yes

Sources: World Bank Enterprise Surveys AI Module 2025–26; World Bank Group.
Note: ICT = information and communication technology. Estimates are from ordinary least squares (OLS) regressions with standard errors clustered by strata. * p < 0.10; ** p < 0.05; *** p < 0.01.

Annex Table A.2.2.2 Correlates of expected sales per worker gains from AI development

	India		United States	
Dependent variable: 3-year expected gains	**(1)**	**(2)**	**(3)**	**(4)**
Small firm	-15.249***	-12.853***	4.598	7.022
	(5.872)	(4.844)	(4.613)	(5.329)
Medium firm	-10.541*	-9.971**	-8.685	-6.380
	(5.703)	(4.886)	(7.566)	(7.296)
Young firm	3.725	4.311*	-2.041	-7.760
	(2.983)	(2.298)	(7.609)	(7.800)
Mature firm	-0.712	0.557	-1.344	0.059
	(0.957)	(0.886)	(3.742)	(4.104)
Firm's largest owner is top manager	3.153**	1.347	-4.043	-2.814
	(1.484)	(0.918)	(6.880)	(6.332)
Manager has more than 15 years of experience	0.537	-0.380	-1.485	-2.076
	(1.296)	(0.943)	(2.866)	(3.086)
Foreign-owned firm	8.905***	1.599	-3.668	-8.898
	(1.285)	(2.367)	(5.305)	(6.155)
Exporter	-2.817	-5.155	10.374	18.632*
	(3.094)	(4.617)	(8.226)	(10.687)
Innovation index	2.057	3.291**	8.413*	8.170**
	(1.301)	(1.496)	(4.600)	(4.104)
Skilled workforce index	5.066*	3.996**	1.867	2.154
	(2.983)	(1.960)	(2.672)	(2.059)
ICT access index	---	4.449***	---	5.976**
		(1.220)		(2.853)
Electricity index	---	0.252	---	-5.002
		(1.343)		(3.350)
Regulation index	---	-0.287	---	-0.712
		(0.711)		(3.437)
Contract enforcement index	---	0.044	---	-1.352
		(0.640)		(2.681)
Access to finance index	---	-2.121*	---	-3.494
		(1.117)		(3.053)
Constant	16.885***	16.890***	-6.641	-10.297
	(6.274)	(5.276)	(7.910)	(8.034)
Observations	1,219	1,219	340	340
R-squared	0.279	0.411	0.247	0.303
Weighted mean of dependent variable	3.01	3.01	1.34	1.34
Sector fixed effects	Yes	Yes	Yes	Yes

Sources: World Bank Enterprise Surveys AI Module 2025–26; World Bank Group.
Note: ICT = information and communication technology. Estimates are from ordinary least squares (OLS) regressions with standard errors clustered by strata. * p < 0.10; ** p < 0.05; *** p < 0.01.

Annex Table A.2.2.3 Impact of AI exposure on AI skills hiring: U.S. firms

Panel A: Regression				
Dependent variable	**All firms**	**US firm: supplier**	**US firm: customer**	**US firm: partner**
Post-GPT x U.S. AIIE	0.0035** (0.0014)	0.0022 (0.0018)	0.0027 (0.0017)	0.0025 (0.0019)
Post-GPT x Connection	---	0.0000 (0.0025)	-0.0038 (0.0031)	0.0042 (0.0033)
Post-GPT x U.S. AIIE x Connection	---	0.0024 (0.0022)	0.0037 (0.0031)	0.0057 (0.0035)
R-squared	0.4610	0.5087	0.4703	0.5255
Panel B: Implied total effects				
	All firms	**US firm: supplier**	**US firm: customer**	**US firm: partner**
Total effects	0.0035** (0.0014)	0.0046** (0.0020)	0.0064** (0.0030)	0.0082*** (0.0028)
Company fixed effects	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes
Standard errors clustered by	Firm	Firm	Firm	Firm
Observations	83,289	67,453	61,228	55,616

Sources: Chiplunkar et al. (2026); FactSet; Felten, Raj, and Seamans (2021); World Bank Group.
Note: Estimates are from ordinary least squares (OLS) regressions with standard errors clustered by strata. * p < 0.10; ** p < 0.05; *** p < 0.01.

Annex Table A.2.2.4 Impact of AI exposure on the number of GVC connections

Panel A: U.S. firms			
Dependent variable	**US firm: partner connections**	**US firm: customer connections**	**US firm: supplier connections**
Post-GPT x U.S. AIIE, standardized	0.2419*** (0.0421)	0.2431*** (0.0317)	0.0084 (0.0244)
Firm fixed effects	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes
Observations	107,928	121,680	165,672
Pseudo R-squared	0.5098	0.6113	0.6153
Panel B: SAR firms			
Dependent variable	**SAR firm: partner connections**	**SAR firm: customer connections**	**SAR firm: supplier connections**
Post-GPT x SAR AIIE, standardized	0.1874*** (0.0664)	-0.0070 (0.0584)	0.2849*** (0.0539)
Firm fixed effects	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes
Observations	73,296	81,936	79,560
Pseudo R-squared	0.5329	0.5838	0.7142

Sources: Chiplunkar et al. (2026); FactSet; Felten, Raj, and Seamans (2021); World Bank Group.
Note: AIIE = AI Industry Exposure index; GPT = ChatGPT; GVC = global value chain. Standard errors, clustered by firm, are reported in parentheses. * p<0.10 ** p<0.05 *** p<0.01. * p < 0.10.

Annex Table A.2.2.5 Impact of AI exposure and counterparty AI exposure on GVC connections

Panel A: U.S. firm			
Dependent variable	**US firm: partner**	**US firm: customer**	**US firm: supplier**
Post-GPT x U.S. AIIE	0.0430 (0.0679)	0.0714 (0.0636)	-0.1174*** (0.0339)
Post-GPT x U.S. AIIE x High counterparty AIIE	0.2977** (0.1185)	0.4181*** (0.1089)	0.1696*** (0.0623)
Firm fixed effects	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes
Observations	58,824	68,256	86,976
Pseudo R-squared	0.5175	0.6177	0.6289
Panel B: South Asian firm			
Dependent variable	**SAR firm: partner**	**SAR firm: customer**	**SAR firm: supplier**
Post-GPT x SAR AIIE	-0.0877 (0.0776)	0.1294 (0.0912)	-0.0409 (0.0659)
Post-GPT x SAR AIIE x High counterparty AIIE	0.2343* (0.1298)	-0.1610 (0.1365)	0.5087*** (0.1111)
Firm fixed effects	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes
Observations	40,608	35,856	45,144
Pseudo R-squared	0.5413	0.6207	0.7415

Sources: Chiplunkar et al. (2026); FactSet; Felten, Raj, and Seamans (2021); World Bank Group.
Note: AIIE = AI Industry Exposure index; GPT = ChatGPT; GVC = global value chain. Standard errors, clustered by firm, are reported in parentheses. * p<0.10 ** p<0.05 *** p<0.01. * p < 0.10; ** p < 0.05; *** p < 0.01.

Annex Table A.2.2.6 Impact of AI exposure on AI skills hiring: South Asian firms

Panel A: Regression				
	All firms	**SAR firm: supplier**	**SAR firm: customer**	**SAR firm: partner**
Post-GPT x SAR AIIE	0.0030** (0.0013)	0.0043* (0.0022)	0.0043* (0.0022)	0.0044** (0.0022)
Post-GPT x Connection	---	-0.0032 (0.0030)	0.0002 (0.0032)	-0.0007 (0.0031)
Post-GPT x SAR AIIE x Connection	---	-0.0032 (0.0028)	-0.0019 (0.0031)	-0.0006 (0.0030)
R-squared	0.2317	0.2297	0.2278	0.2386
Panel B: Total effects				
	All firms	**SAR firm: supplier**	**SAR firm: customer**	**SAR firm: partner**
Total effects	0.0030** (0.0013)	0.0011 (0.0018)	0.0024 (0.0022)	0.0038 (0.0021)
Company fixed effects	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes
Clustered standard errors	Firm	Firm	Firm	Firm
Observations	38,987	29,754	26,456	30,280

Sources: Chiplunkar et al. (2026); FactSet; Felten, Raj, and Seamans (2021); LightCast; World Bank Group.
Note: Standard errors, clustered by firm, are reported in parentheses. * p<0.10 ** p<0.05 *** p<0.01. * p < 0.10; ** p < 0.05; *** p < 0.01.

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Note: The South Asia Economic Update was called South Asia Economic Focus through Spring 2023, and the South Asia Development Update through Fall 2025.

South Asia's economy is maintaining strong momentum despite the burdens of costly energy imports and limited involvement in fast-growing global value chains for AI-related goods. The region is projected to remain the strongest-growing emerging market and developing economy region. Growth could be slowed by a severe El Niño, by energy prices remaining persistently elevated, or by global financial market strains. Looking further ahead, South Asia is aging unusually rapidly, with limited financial security for older people. The creation of more and better jobs is therefore a priority for all age groups. One promising avenue for creating more, better jobs is the widespread deployment of AI. AI adoption in South Asia remains well behind that in advanced economies, but is catching up fast. Growing global value chain connections between customers in the United States and suppliers in South Asia in AI-exposed sectors suggest that South Asian firms are using AI to find new market opportunities. AI adoption can be accelerated by strengthening the complementary conditions that foster firms' growth, above all workforce skills, a business-enabling environment, and reliable infrastructure, supported by measures to ease adoption barriers for small firms, foster local AI innovation, and provide a clear AI policy framework that reduces regulatory uncertainty while addressing risks.

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