NEW TECHNOLOGIES, DIGITALIZATION, AND AI

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perspectives

NOTE FROM THE GUEST EDITOR

In the past decades we have experienced several technological advances in the form of robotization and software innovation. Most recently, digitalization and Artificial Intelligence (AI) have emerged as well. These technologies have the power to reshape industries and economies, and they are bound to play a crucial role in decision making.

Some effects of digitalization are already evident, following the COVID-19 crisis. Working from home became easier, and online sales and contactless payments increased. The rapid spread of generative-AI technologies (as ChatGPT) has also raised interest in their impact compared with older waves. These technologies can be valuable tools, increasing productivity and innovation, but potential problems must be investigated.

This issue of *IMF Research Perspectives* offers a concise overview of these topics, trends, and open questions to stimulate discussion and further exploration. The articles look at the effects of these new technologies on productivity, labor market, and capital flows. We also highlight potential challenges of their broader use. We take a global perspective, looking at advanced, emerging-market, and developing economies for a more comprehensive view of these—potentially structural—changes.

We are also honored to present an in-depth interview with Prachi Mishra, Division Chief in the IMF's Research Department, covering her career, views on economics, and the future.

~Mariarosaria Comunale

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AN INTERVIEW WITH
PRACHI MISHRA

Chief of the Systemic Issues Division, Research Department, IMF

Prachi Mishra came back to the IMF in 2020 as the Division Chief in the Systemic Issues Division in the Research Department, after working in both the private and public sectors. In this in-depth interview, we talked about her career and the role of research for policymaking and discussed her views on current economic challenges and female representation in economics.

Here is a brief excerpt from the interview:

Mariarosaria Comunale: What is something that a researcher can bring which can benefit policymaking and can, in general, help in more operational work?

Prachi Mishra: Researchers can benefit operational work hugely by bringing their analytical skills to address important questions.

In an institution like the IMF, it is important to direct our resources and energy to questions of first order importance to policymakers globally. Being on the other side of the table, I can say that high quality and rigorous analytical work is deeply valued by the authorities. You will be surprised that the authorities actually check our CVs and they know our papers. When I was the mission chief of El Salvador, I was pleasantly surprised that the central bank head knew my work on international labor flows and brain drain.

Watch the interview here

DID THE COVID–19 RECESSION INCREASE THE DEMAND FOR DIGITAL OCCUPATIONS?

WE ARE HIRING

Illustration: Jillian Perdos

Myrto Oikonomou
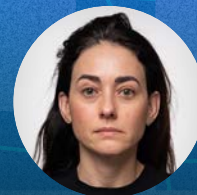✉ moikonomou@IMF.org

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The COVID-19 pandemic changed the way we live and work. The containment measures and voluntary social distancing have shifted many activities from in-person to online settings. More than three years later, even though many aspects of daily life have returned to pre-pandemic normality, the way we interact with technology in our professional and daily lives has undergone a notable transformation.

Consider the rise of virtual and hybrid meetings; what was once an alternative mode of communication is now a mainstream tool for businesses, educational institutions, and even social gatherings. This shift toward digital communication ensures that teams can collaborate, and decisions can be made regardless of geographic constraints. Similarly, in the hospitality sector, many restaurants have adapted by incorporating tablets and digital platforms for placing orders. Instead of traditional menus and waitstaff taking orders, customers can now scroll through digital menus, order, and make payments online. The changes brought about by the pandemic have not only affected our lives but may have led to a sustained rise in the demand for skills that complement digital technologies.

Understanding the nature of employment shifts, especially concerning occupations related to digital technologies, is crucial for policymakers to brace for future crises. On one hand, if the increased demand for workers in digital occupations is permanent, governments should facilitate the needed structural shift in the labor market by improving educational and training programs to meet the increased demand for digital skills caused by the pandemic. On the other hand, if the increased demand was just transitory and reflected the greater resilience of digital occupations to macroeconomic shocks compared with other types of jobs, then this finding

provides policymakers with insights into which occupations require targeted interventions to support workers most vulnerable to disruptions. Furthermore, recognizing the distribution of digital workers across different regions allows for a strategic approach, mitigating the potential adverse impacts of crises in specific regions. As a result, unpacking the pandemic's impact on employment in digital occupations is vital for shaping government policies and preparing for future crises.

In light of these shifts, our recent IMF working paper delves into the nuanced dynamics of labor demand for digital-intensive occupations during the COVID-19 recession and the ensuing recovery. Specifically, we explore (1) the extent to which COVID-19 increased the demand for digital jobs, as reflected in both employment and vacancies; (2) the persistence of this increase—whether it was a temporary swing or a lasting structural shift; and (3) the distribution of changes within digital occupations, assessing if they were widespread or localized to particular roles and regions.

Decoding digital jobs: How we measure them and understand their rise during the pandemic

At the heart of our research is the intricate task of defining "digital" occupations. Too narrow a definition could risk selecting only jobs in the Information and Communications Technology (ICT) sector, such as software engineers or network administrators. Guided by Muro and others (2017), we employ Occupational Information Network (O*NET) measures, centering on computer-related knowledge and work activities, to derive digital intensity scores for US occupations (Figure 1).[1] This approach considers actual use of technologies and required skills, rather than the feasibility of working remotely—conventionally referred to as "teleworkability." This distinction is crucial as our interest lies in the critical skills a job demands and the need for jobs possibly related to firms' investment in digital technologies. It's worth noting that while digital skills and a job's teleworkability overlap substantially (with

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[1] The O*NET database contains variables that describe occupation and worker characteristics, including skill and knowledge requirements, work description, and settings.

Figure 1. Distribution of Digital Scores for Selected Occupations

Examples of Occupations by Digital Score
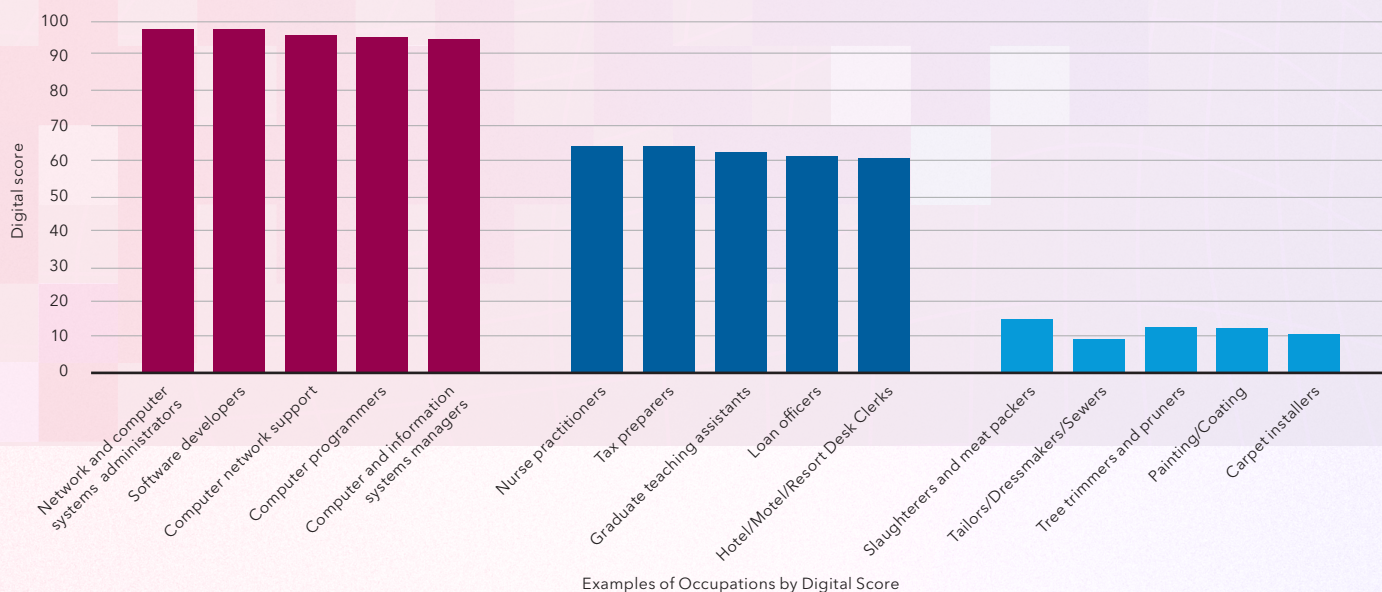
Source: US Bureau of Labor Statistics, 2010 Standard Occupational Classification System.

about 70 percent of digital jobs also classified as teleworkable), the two concepts don't fully align. While teleworkability reflects the working arrangements in a given occupation, digital skills capture the skills required to perform specific tasks in an occupation. The digital scores we construct for each occupation draw from the most recent pre-pandemic O*NET data. In other words, the definition of whether an occupation is digital or not considers the jobs' characteristics on the eve of the pandemic. As such, our analysis can identify compositional shifts in employment and vacancies along an "extensive margin" of digitalization—share of digital employment or vacancy—rather than an "intensive margin" of digitalization—the degree of digitalization within occupations. It is possible that over the course of the pandemic jobs that were not historically digital began to require more frequent interactions with these technologies. However, as subsequent vintages of O*NET update only the information for a small subset of occupations at a time, this intensive margin is difficult to measure over a short period.

We focus on the impact of employment, which reflects both the impact of changes in labor demand and supply, and vacancies, which are more closely related to the labor demand of workers.

For employment, we use data at the state level from the IPUMS Current Population Survey, a standard data source for labor market analysis. For vacancies, we leverage data from Indeed—a large online job advertisement platform—to measure the quarterly number of postings related to digital and non-digital jobs at a granular city level.

To ascertain how the pandemic reshaped the demand for digital occupations, we use variation in the severity of the employment contraction during COVID-19 across regions of the US. For this purpose, we compute a so-called Bartik-style shock for each region and city. This approach consists of constructing a proxy for the employment contraction experienced by a region based on the area's industrial composition prior to COVID-19 and the national-level employment dynamics of each industry. This measure captures the ex-ante exposure to the labor market disruption caused by the pandemic based on the area's economic structure. We then examine the dynamics of digital employment and vacancies against this backdrop of regional Bartik shocks, taking into account any regional trends that might simultaneously influence the demand for digital jobs.

Figure 2. Effect of COVID-19 on the Change in the Share of Digital Employment and Vacancies
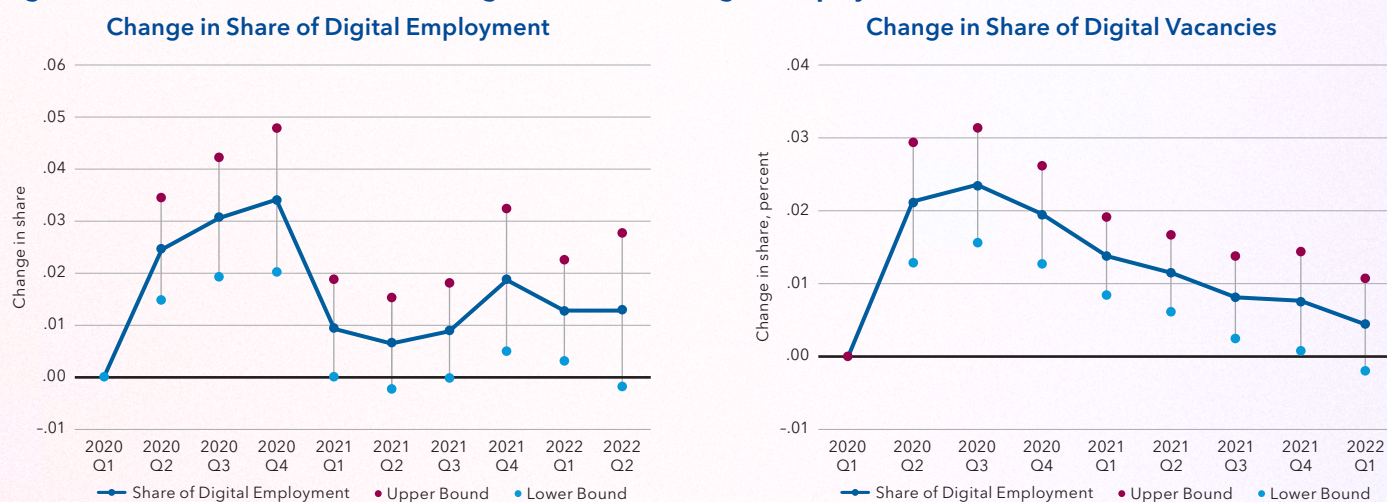
Sources: Economic Analysis; US Bureau of Labor Statistics, Job Openings and Labor Turnover Survey; US Census Bureau, American Community Survey, Quarterly Workforce Indicators; and authors' calculations.

Note: The figure shows the differential increase in the digital employment and vacancy shares between harder-hit regions and less-hard-hit regions. A positive increase means that harder-hit regions saw a larger increase in the share of digital employment and vacancy than those that were hit less hard.

Unraveling the digital job trend: Insights from the COVID-19 aftermath

Our research shows that regions hit harder by the COVID-19 recession experienced a more pronounced shift toward digital employment and job vacancies (Figure 2). Even when we control for regional characteristics and trends in digital employment prior to the pandemic, this result holds firm.

This increase in the share of digital employment could hint at a major transformation in the demand for digital skills, especially in the regions most affected by the pandemic. However, the estimates in Figure 2 clearly suggest that this digital shift didn't last more than a few quarters. By mid-2022, regardless of how severe the initial total employment contraction in a region, the differential across regions in the share of digital employment and vacancies had returned to what it was before the pandemic. Moreover, when focusing on the *level* of employment and vacancies rather than their composition (Figure 3), it becomes apparent that the shifts reflect non-digital occupations' deeper contraction in employment and vacancies in hard-hit regions; the response of digital occupations was more homogeneous across the country. The increasing share is hence driven by a relative shielding of digital occupations, rather than an increase in demand.

While COVID-19 brought about a change in the way we live and work, it didn't permanently change labor markets. Our results indicate that digital jobs were simply more resilient during the beginning of the pandemic.

A closer look at other occupational characteristics and geographic features reveals that in urban areas digital jobs held up better than in rural areas. In addition, more cognitive-based digital jobs (roles that call for deep thinking and analysis) were more strongly shielded from the pandemic's impacts than routine or manual digital tasks. As for the ability to work from home, initially, the surge in digital vacancies was all about work that could be done remotely; that is, teleworkable jobs. However, as 2020 came to an end, even digital jobs that required a physical presence were in demand, suggesting that the sheer value of digital skills played a huge role in how jobs coped with the pandemic's impact separately from teleworkability.

An important constraint on our work is the inability to fully observe labor demand and labor supply separately since employment results both from firms hiring new workers and from workers looking for jobs. Vacancies are a somewhat better proxy for worker demand, because they reflect firms' forward-looking hiring intentions. However, worker availability and preferences concerning

Figure 3: Effect of COVID-19 on the Cumulative Growth of Digital Employment and Vacancies

Cumulative Growth of Digital Employment — Cumulative Growth of Digital Vacancies

Legend: Digital Employment — Total Employment — Non-Digital Employment
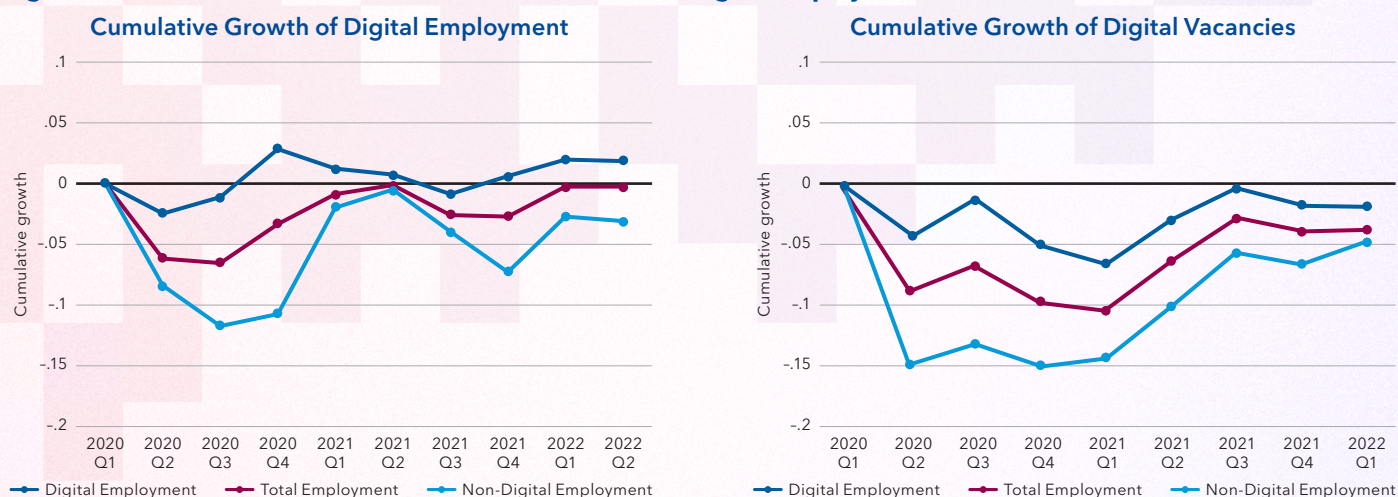
Sources: Indeed; IPUMS, Current Population Survey; US Bureau of Economic Analysis; US Bureau of Labor Statistics, Job Openings and Labor Turnover Survey; US Census Bureau, American Community Survey, Quarterly Workforce Indicators; and authors' calculations.

Note: The figure shows the differential cumulative increase in digital employment and vacancies between harder-hit and less-hard-hit regions.

work may also affect job postings. For instance, a rise in vacancies could reflect firms' need to replace workers who quit. To address some of these concerns, we also inspect quit rates across types of occupations; we don't find that workers in digital roles quit their jobs more than non-digital workers during the pandemic. This provides some supporting evidence that the resilience of digital occupations was driven by steadier labor demand during the downturn rather than by labor supply shifts.

Beyond the pandemic: Preparing for the digital future

At first glance, the increased demand for digital occupations during the pandemic hinted at a potential structural shift in the labor market. However, the transient nature of this surge underscores the importance of cautious interpretation. Although crises can induce rapid short-term changes, long-term structural shifts might require more sustained forces. Nevertheless, the relative stability of digital jobs, even in harder-hit regions, underscores their resilience and highlights the value of digital skills, not just in the context of remote work, but as foundational capabilities in the modern economy. This result

may drive educational institutions and training centers to further emphasize digital literacy and skill development. Our research also suggests that not all digital roles are created equal. Cognitive digital occupations displayed more robust demand compared with their routine or manual counterparts. This distinction is crucial for policymakers and educators as they strategize on workforce development, ensuring emphasis is placed on skills with the highest demand and resilience.

Finally, over the past year, the interest of policymakers and academics alike has turned to the potential impact of fast-developing Artificial Intelligence (AI) technologies. This crucial topic has been explored in our recent IMF working paper, which analyzes the various ways AI is poised to transform the labor market. A key question will be how AI will interact with the tasks workers currently perform in each occupation and what types of skills will be needed. While not all jobs will require advanced AI-specific knowledge, many will require a type of AI literacy—that is, a basic understanding of its functioning and its limits—which is very likely strongly related to basic digital skills.

AI
& SERVICES-LED GROWTH

Evidence from Indian Job Adverts

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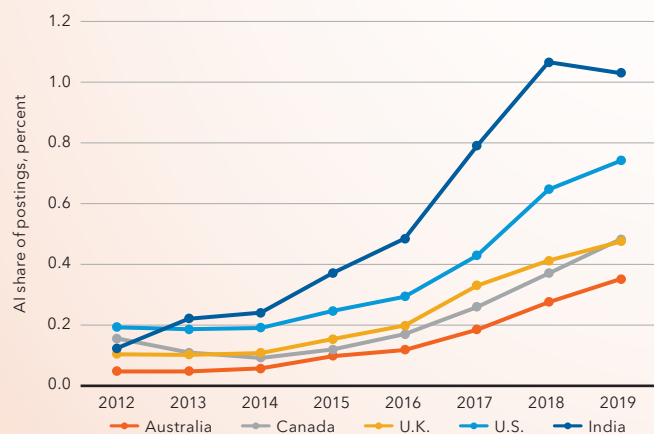
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Official statistical surveys have only recently begun collecting data on Artificial Intelligence (AI) usage, but we can spot the emergence of the phenomenon in historical job postings. These reveal that demand for AI-related skills took off around the world in the mid-2010s (Figure 1). Among myriad implications, this is particularly important for countries pursuing a services-led development model. Many of the services industries that have driven growth and job creation could be susceptible to machine-learning-based automation. In India—the archetype of services-led development—Information Technology (IT) and business process outsourcing have grown rapidly to employ more than 4 million people and contribute about 8 percent to GDP. Any threats to employment in such sectors are a significant concern given the 200 million young people expected to age into the labor market by 2030.

Economic theory is not clear-cut, however, regarding reduced employment in services as a result of AI. On one hand, advances in machine learning have improved firms' ability to automate the task of "prediction"—prevalent in many services occupations—which may suggest displacement of labor in favor of AI. On the other hand, AI could expand labor demand by reducing overall costs of production or boosting quality, hence raising productivity. Indeed, AI could complement human labor, create entirely new tasks, or incentivize changes in organizational structure. There is growing evidence that AI is a General-Purpose Technology (GPT), an "invention of a method of invention." Emerging market economies such as India could even benefit from new global AI value chains, capitalizing on their abundance of engineering talent, existing expertise in IT outsourcing, and further declines in communication costs.

Demand for AI skills in India's services sector
In a recent study, we investigate the labor market impact of AI on India's white-collar services sector using a novel dataset of vacancy postings from the country's largest jobs website. Following the literature, we gauge firm-level AI adoption using demand for machine learning skills observed in the text of posted job descriptions. We see a rapid takeoff in this AI demand after 2016, particularly in the IT, finance, and professional services industries (Figure 2).

Figure 1. Share of Online Job Postings Listing AI Skills

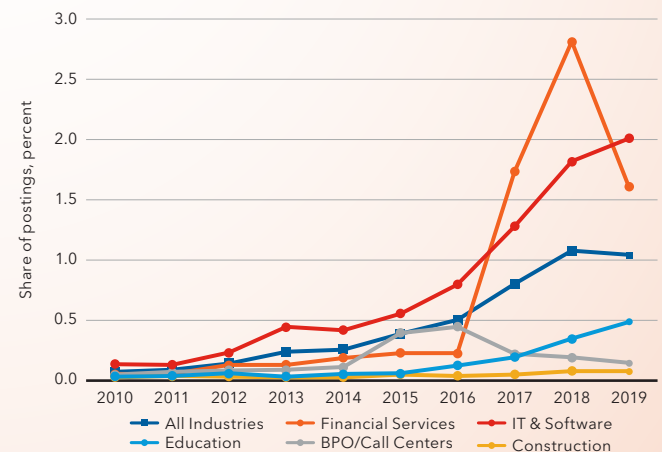Source: Copestake and others (2023).
Note: The figure shows the percentage of all online vacancies that specify particular AI skills. Data for India are from Copestake and others (2023), and data for all other countries are from Lightcast, which does not cover India.

Figure 2. Share of Online Job Postings in India Listing AI Skills, by Industry

Source: Copestake and others (2023).
Note: The figure shows the share of all postings that are AI vacancies, both for all industries and within each of the top five industries by AI share. BPO = Business Process Outsourcing.

AI roles tend to require substantially more education, particularly graduate degrees, and also pay significantly more. Even after controlling for differences across regions, industries, firms, and occupations, posts demanding AI skills still pay a 13 to 17 percent salary premium. Such roles are heavily concentrated in a few key technology clusters—particularly in Bangalore, Mumbai, Hyderabad, Pune, Chennai, and Delhi—and in the largest firms. Consistent with this spatial clustering, we find evidence of local diffusion: after the first firm in a given industry and region adopts AI, other firms in the same industry and region are, on average, more likely to start demanding AI skills, even after taking into account industry and regional trends.

Impact of AI adoption on businesses' demand for labor

With these patterns in hand, we turn to the central question of how AI adoption impacts labor demand in business establishments, defined as "firm-city pairs." We first consider the short-term impact and examine the different trends in posting of non-AI vacancies in establishments adopting AI relative to non-adopters. Since businesses seeking AI skills also look unusual in other ways, we reweight establishments in our data according to their characteristics (for example, size and age) so that the counterfactual sample of non-adopting establishments closely resembles the sample of adopters. Comparing the two, we find that AI adoption initially coincides with a small increase in vacancy postings, but it then reduces demand for non-AI workers over the subsequent few years, such that the overall effect is substantially negative. Non-AI vacancy postings are approximately 1 percent lower in AI adopters, relative to non-AI adopters, three years after adoption (Figure 3).

To assess whether these impacts lead to medium-term structural shifts, we then examine the activity on the platform of large incumbent establishments (that is, those that posted both before and after the global takeoff in AI deployment in 2015–16). To control for differences between AI adopters and non-adopters, we take advantage of the fact that some establishments—because of their ex ante

Figure 3. Posting of Non-AI Vacancies by AI Adopters vs. Non-adopters
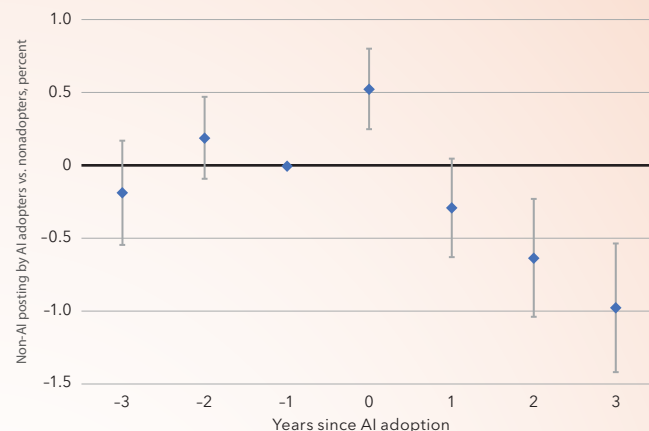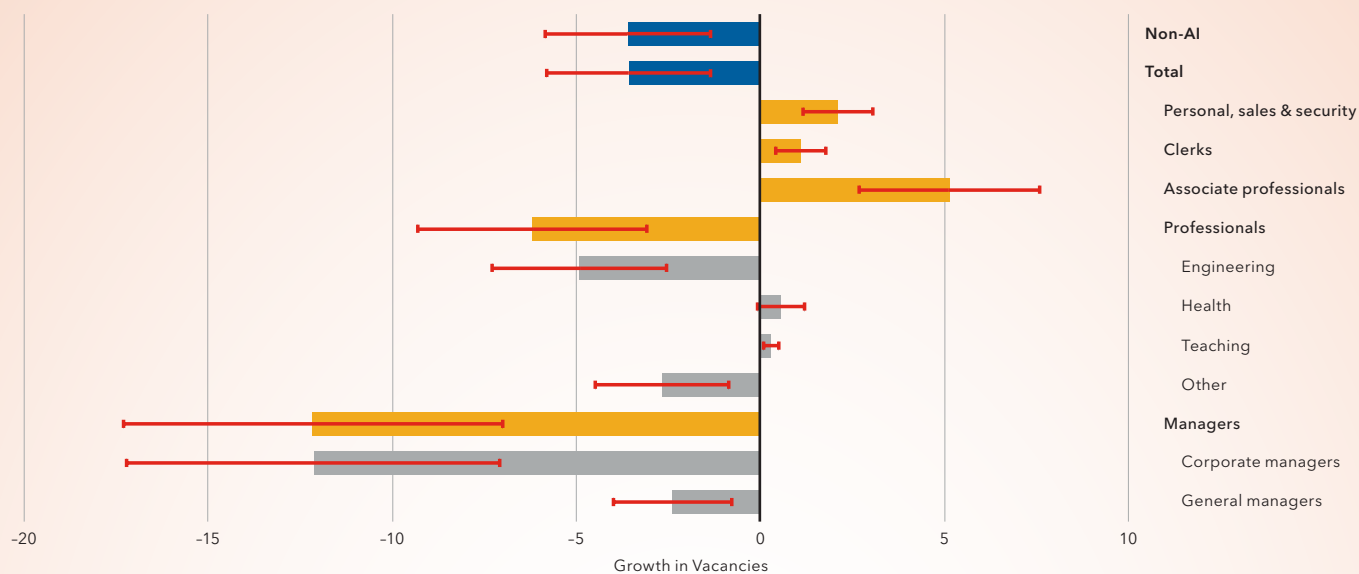

Source: Copestake and others (2023).

Note: Coefficients represent the proportionate difference in posting of non-AI vacancies by AI adopters relative to non-adopters in the years before and after they first seek AI skills in their job postings, after accounting for other observable differences between the two groups. Ranges show 95 percent confidence intervals.

organizational structure—were more exposed to subsequent machine learning innovations. We measure this exposure by combining their 2010–12 occupational structure with the degree of overlap between occupations' tasks and tasks that patented AI technologies are designed to perform, as reflected in the measure of Webb (2020).

We find that firms initially more exposed to AI show a relative increase in their demand for AI skills in online vacancy postings. This AI adoption then has a significant negative impact on growth in non-AI and total postings by establishments. Specifically, a 1 percent increase in the AI vacancy growth rate results in a 3.61 percentage point decrease in establishments' non-AI vacancy growth between 2010–12 and 2017–19, controlling for differential trends across regions, industries, and firm size deciles. Growth in total establishment vacancies (both AI and non-AI) falls by a similar 3.57 percentage points: the increase within the small set of AI posts is far outweighed by the displacement effect in the larger set of non-AI vacancies.

What explains this change? It doesn't reflect a response to constrained supply; firms that adopt more AI also lower, rather than raise, their wage offer distribution. Instead, we find that the effect is driven by a change in the pattern of demand

Figure 4. Impact of Increased AI Hiring

Source: Copestake and others (2023).

Note: Coefficients represent the percentage point change in the growth rate of vacancy postings between 2010–12 and 2017–19 in response to a 1 percent higher establishment-level growth rate of AI demand over the same period. Coefficients are shown for separate regressions considering, in turn, the impact on non-AI postings, total postings, or total postings for particular occupational categories. Ranges show 95 percent confidence intervals.

for different occupations, in line with changing demand for their constituent tasks. We find that the negative effects on vacancy growth are particularly strong for higher-skill occupations, such as managers and professionals—especially corporate managers and engineering professionals (Figure 4). Increased AI adoption reduces demand particularly for occupations associated with nonroutine tasks. To go deeper, we count the frequency of all verbs in the job descriptions and classify them by meaning using Roget's Thesaurus. We find that higher AI demand at the establishment level reduces the relative frequency of verbs related to intellectual activities. In particular, the job descriptions posted by businesses seeking AI skills more intensively also show an overall net decline in the frequency of verbs associated with forecasting, analysis, and complex communication—such as "investigate," "predict," "forecast," and "describe." Our findings are thus consistent with a reduction in the number of workers required to accomplish such tasks when AI is adopted.

Conclusion

Our findings suggest that AI has had a mixed and unevenly distributed effect on jobs in India's white-collar services sector. AI roles offer a substantial wage premium but require more education and are highly concentrated in certain industries, cities, and firms. AI demand within establishments has significant negative effects on non-AI and total labor demand in both the short and the medium term. These are driven by the displacement of demand for relatively high-skill occupations and nonroutine, intellectual, and analytical tasks. This contrasts starkly with previous waves of technology, such as computerization and industrial robotics, which reduced demand primarily for routine, low-skill, and manual labor. Overall, our findings highlight the double-edged impact of AI: although AI jobs pay a substantial wage premium, these opportunities are highly concentrated, inaccessible to most workers, and can displace demand for non-AI roles.
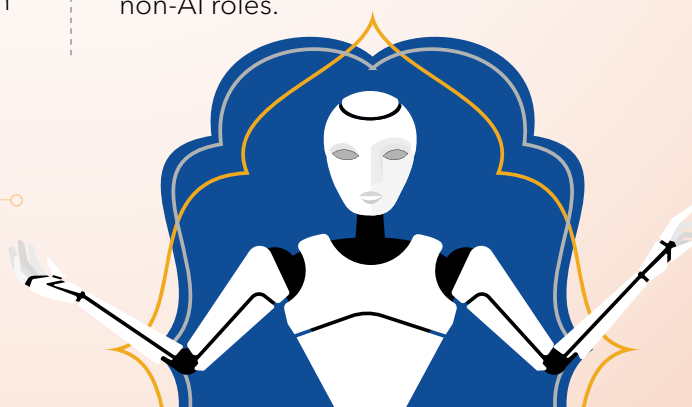
DO CAPITAL INFLOWS SPUR

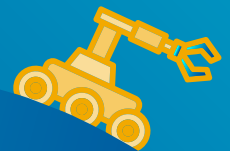# TECHNOLOGY DIFFUSION?

Evidence from a New Technology Adoption Index

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Illustration: Lindsey Kim

With geopolitical tensions on the rise, several countries have taken steps to limit the free flow of strategic goods and investments.

Even before these recent events, restrictions on international capital flows were widespread and largely unequal across countries, with emerging markets and low-income countries lagging far behind advanced economies (see Figure 1). Yet there is long-held consensus that the removal of long-standing restrictions on capital flows is beneficial. This view holds that investments flowing from advanced economies to lower-income countries not only contribute important funding, but they also spread knowledge of advanced technologies through interaction with foreign investors. This interaction, in turn, is believed to promote growth and cross-country income convergence to higher levels. Despite this consensus, there is still no conclusive evidence that openness to external financing promotes technology diffusion, especially when it comes to emerging market and developing economies, a set that includes low-income developing countries as well as richer emerging markets. One of the reasons that studies on the topic have been so inconclusive is that many emerging market and
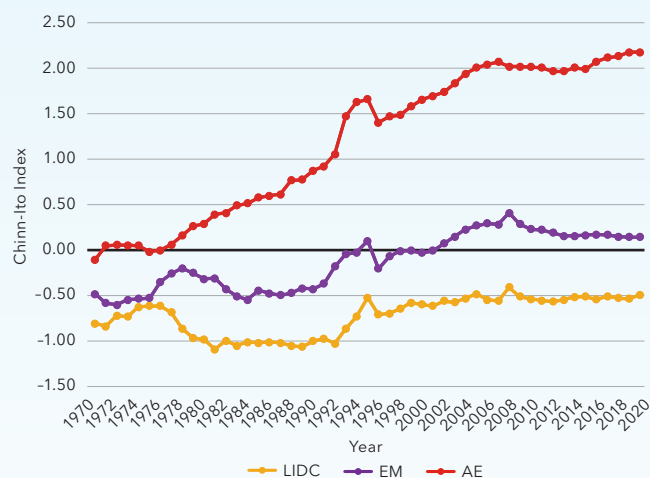
developing economies lack patent data, the most common gauge of innovation in empirical studies. In our recent working paper (Cugat and Manera, 2024), we set out to fill this gap by building a new measure of technology adoption suitable for emerging market and developing economies and then studying its response to policy reforms that increase openness to capital flows.
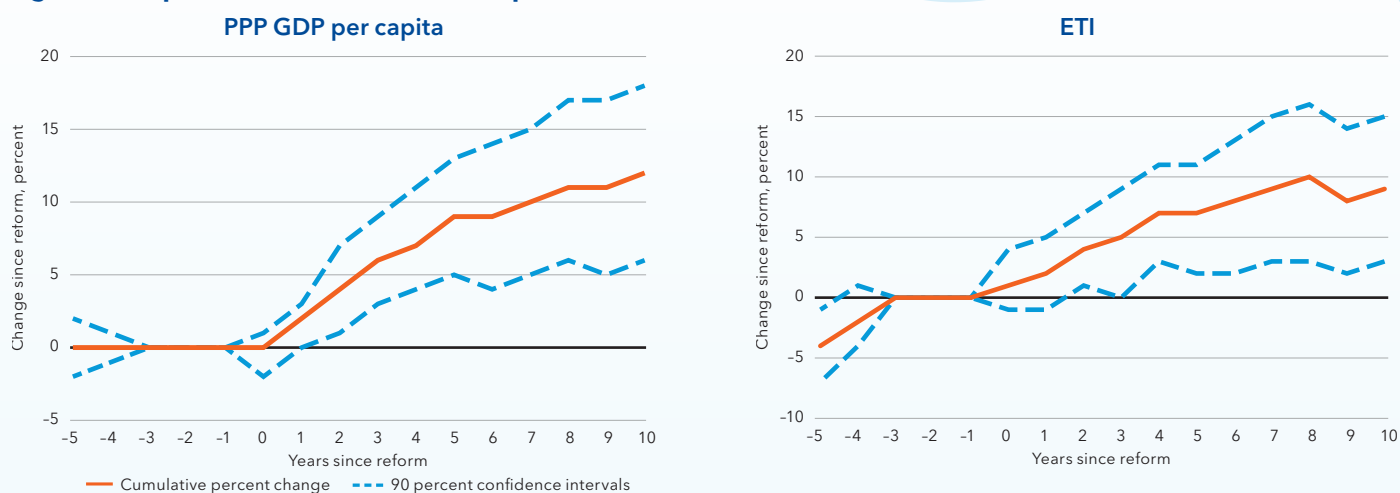
We find that improving openness to foreign capital—a broad term that includes foreign direct investment, equity and bond portfolio flows, and bank flows—boosts knowledge diffusion. These more open countries import technology that is 7 to 9 percent more advanced than in an alternative scenario featuring more restrictions on external financing. This effect manifests over time and comes with sizable increases in foreign investment, as well as a significant rise in income per capita, as measured by real purchasing-power-parity GDP (PPP GDP) per capita.

Measuring technology adoption in developing economies

When we think about innovation, our mind goes to white-coated scientists intent on developing new technologies or daring inventors running to the patent office to beat competitors to their latest discoveries. However, innovation often consists of the equally important steps of adopting and adapting existing technologies. In emerging market and developing economies, where patents are relatively scarce, innovation occurs largely through this process of technology diffusion, which is nowhere to be found in official statistics. However, we have extensive data on trade in goods across countries, which we use to quantify the adoption of foreign technologies through imports of advanced capital goods.

We combine this information with data on inventions for the countries where these imports originated to build our measure, the Embodied Technology Imports Indicator (ETI), which we construct for 181 countries, 155 of which are emerging market and developing economies, over the period 1970–2020. The ETI measures how advanced a country's imports of machinery are, based on their country of origin. We proceed

Figure 1. Evolution of Capital Openness by Income Level, 1970–2020

Source: Cugat and Manera (2024)

Note: The figure portrays the evolution of the Chinn-Ito index for countries grouped according to their income level classification by the IMF *World Economic Outlook*. Higher values denote more openness to foreign capital. AE = Advanced Economy; EM = Emerging Market; LIDC = Low-Income Developing Country.

Figure 2. Response of Main Variables to Capital Flow Liberalization

Source: Cugat and Manera (2024)

Note: The figure displays the cumulative percent change in PPP GDP per capita (panel 1) and the ETI (panel 2) for episodes of capital flow liberalization. Effects are computed relative to the year before the reform (–1 on the x-axis). PPP GDP = real purchasing-power-parity GDP; ETI = Embodied Technology Imports indicator.

in two steps for its construction. First, for each year, we assign a 0–100 score to origin countries based on how many machinery patents they have registered. The score is computed as the number of patents relative to the most advanced economy at that time. For example, a score of 100 means that the country in question has the highest number of machinery patents in the world, while a score of 50 means that the country has half the patents of that year's leader. Second, we compute the ETI as an import-share-weighted average of partners' technology scores. For example, consider a country C that imports 50 percent of its machinery from country A, with a score of 100, and 50 percent of its machinery from country B, with a score of 0. In that case, country C will have an ETI of 50 (50 percent times 100 + 50 percent times 0).

How do we know this is a good measure? Since the ETI is entirely novel, we take some steps to verify that it tracks other indicators of technology and innovation. We see that countries with higher technology scores also account for a larger share of machinery exports to the rest of the world in 1970–2020, as well as technology licensing to other countries (available only for 1995–2020). At the same time, countries with a higher ETI also appear to purchase more licenses for the use of

foreign technology. All in all, these correlations corroborate our indicator as a measure of technology adoption.

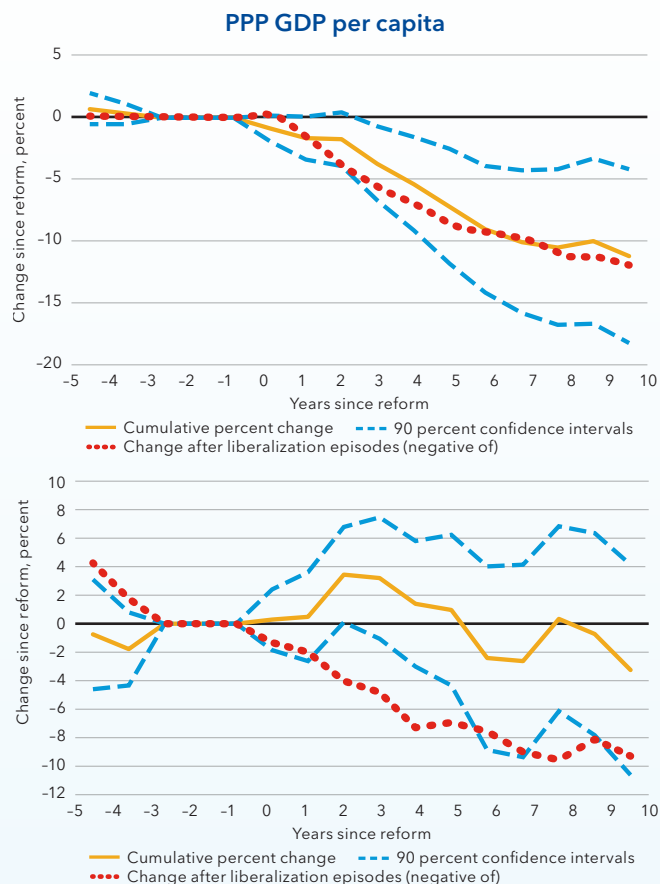**The effects of external financial liberalization**
We focus on reforms that remove obstacles to international capital flows, as measured by the Chinn-Ito Index. Chinn and Ito build variables on four major categories from the IMF Annual Report on Exchange Arrangements and Exchange Restrictions (AREAER) that relate to financial openness. Three are binary variables for the absence of (1) multiple exchange rates, (2) restrictions on current account transactions, and (3) requirements for the surrender of export proceeds. The fourth variable is the share of years in the preceding five with no restrictions on capital account transactions. The index aggregates these four variables based on results from a principal component analysis. A higher index value indicates that the country is more open to financial flows. We identify 90 reform episodes in emerging market and developing economies between 1976 and 2020, and we analyze the response of the ETI and PPP GDP per capita between 5 years before and 10 years after the reforms. In the working paper, we also establish that capital flows increase substantially by 28–33 percent, a testament to the effectiveness of increased openness.

Figure 2 shows the response of our main variables. The ETI increases 7–9 percent in the 5–10 years after the removal of capital flow restrictions (Figure 2, panel 1). Real PPP GDP per capita similarly shows a large increase of 9–12 percent over the same horizon (Figure 2, panel 2). We interpret this result as suggesting that countries can import better machinery after the reforms, thanks to better financing for firms or direct sharing of knowledge of more advanced technologies by foreign investors. This more advanced machinery is then deployed to the whole economy, leading to widespread increases in income and productivity. An interesting question for future research will be the specific transmission channels that connect capital flows to technology adoption. The aggregate nature of our data prevents us from determining whether domestic firms update their technology thanks to better funding or better ideas.

Temporary restrictions

What about capital flow restrictions? It is tempting to conclude that just as capital flow liberalization promotes knowledge transfer, restrictions stifle it. However, Figure 3 shows otherwise. While we do find that PPP GDP per capita falls by a magnitude comparable to that of the increase following liberalization, we do not see a significant effect on the ETI. This suggests that channels that reduce GDP do not act through knowledge diffusion. In fact, when we look at the path of the Chinn-Ito index, restrictions appear qualitatively different in two respects. First, they tend to have a smaller magnitude and are slowly reversed, as shown in Figure 4. Second, different components of capital flows are affected. Foreign direct investment, which increases following liberalization, does not move significantly during restriction episodes. Conversely, our findings in the working paper show that more "fickle" portfolio flows fall in this scenario. As these temporary restrictions do not affect longer-term flows, we find it reasonable that the composition of longer-term investments, like machinery, is also unaffected.

Figure 3. Response of Main Variables to Capital Flow Restrictions (solid line) **and Liberalization Episodes** (dotted line, inverted scale)

PPP GDP per capita

Cumulative percent change — 90 percent confidence intervals
Change after liberalization episodes (negative of)

Source: Cugat and Manera (2024)
Note: The figure shows the cumulative percent change in PPP GDP per capita (panel 1) and the ETI (panel 2) for episodes of capital flow restriction. Effects are computed relative to the year before the reform (–1 on the x-axis). ETI = Embodied Technology Imports indicator; PPP GDP = real GDP at purchasing-power-parity exchange rates.

Figure 4. Change in the Chinn-Ito index around Restriction (solid line) **and Liberalization Episodes** (dotted line, inverted scale)

Cumulative percent change — 90 percent confidence intervals
Change after liberalization episodes (negative of)
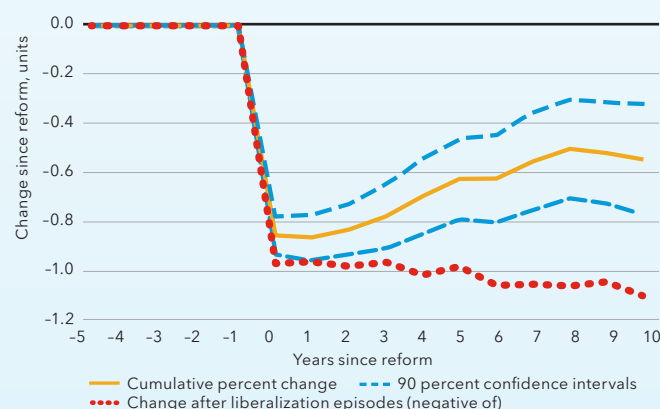
Source: Cugat and Manera (2024)
Note: The figure shows the change in the Chinn-Ito index around episodes of capital flow restriction. Effects are computed relative to the year before the reform –1 on the x-axis).

Conclusion

The IMF institutional view on the liberalization and management of capital flows rests on the principle that capital flows are desirable due to the substantial benefits they can bring, while at the same time recognizing that risks from financial volatility can be addressed through the temporary use of capital flow management measures under specific circumstances. Our work further supports this view in the context of knowledge diffusion. We have presented evidence that boosting foreign capital inflows through the removal of long-standing legal barriers can foster the adoption of better technology and improve income convergence across countries. At the same time, temporary restrictions do not have a commensurate adverse effect, which lessens the concern that short-lived capital flow management measures hinder technology diffusion.
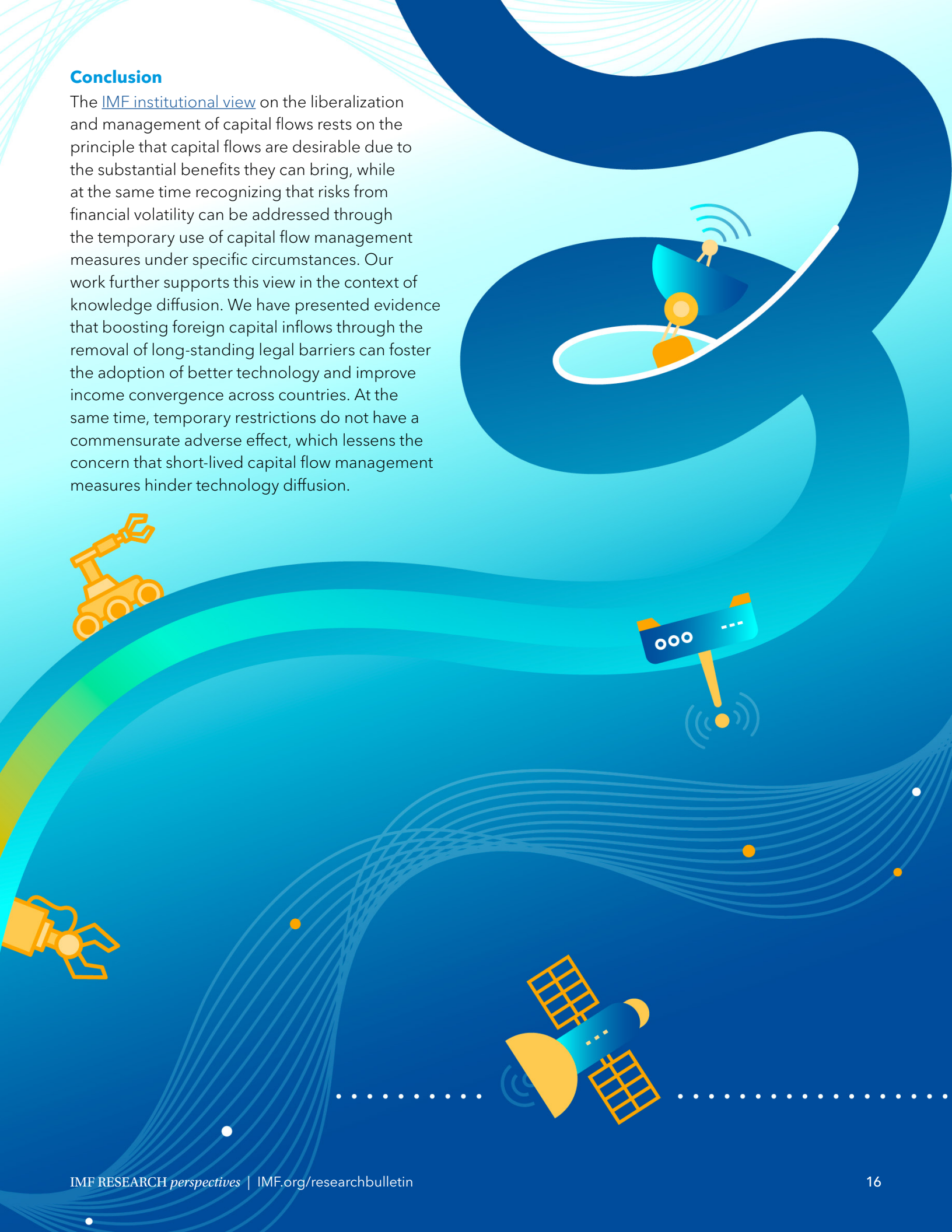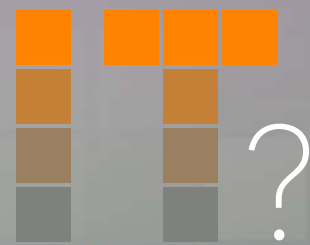
Is the impact of
AI

different from
IT?

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Technological progress creates winners and losers in the labor market. Information Technology (IT), such as software and computer equipment, is often cited as one of the primary reasons for job polarization (that is, the decline in middle-skill occupations) during 1980–2010 ([Acemoglu and Autor 2011](https://...)). Rapid and ongoing development in Artificial Intelligence (AI) during the past decade, and especially after the launch of ChatGPT in November 2022, has spurred debate on the labor market implications of this new technology. A natural question arises: Is the impact of AI different from that of IT?

Exposure of occupations to AI vs. IT

Our recent paper (Huang, forthcoming) documents a higher AI Occupation Exposure (AIOE) score for occupations with a lower share of routine tasks (that is, tasks that can be performed based on a set of explicitly defined rules). The AIOE score ([Felten and others 2021](https://...)) is constructed by mapping information on AI progress to human abilities and then computing AI exposure scores for each occupation using data on the task content of occupations. Occupations with the highest AIOE scores are concentrated among highly skilled workers, most notably professionals in accounting, finance, and law. Occupations with the lowest AIOE scores typically require significant physical exertion and control—such as dancers, fitness trainers, painters, and plasterers. IT occupations, however, can involve mainly routine-intensive, low-skill occupations—such as sorters, trimmers, and laborers.

Because routine task share captures occupational exposure to IT, whereas AIOE captures occupational exposure to AI, our empirical finding suggests that occupations less exposed to IT are more exposed to AI. To further explore what types of routine or nonroutine tasks contribute to this inverse relationship, the paper digs deeper into the relationship between AIOE and routine cognitive, routine manual, nonroutine cognitive, and nonroutine manual task scores of occupations. The inverse relationship between AI and IT exposure is found to be driven primarily by the positive correlation between nonroutine cognitive

Figure 1. Exposure of Occupations to AI vs. IT
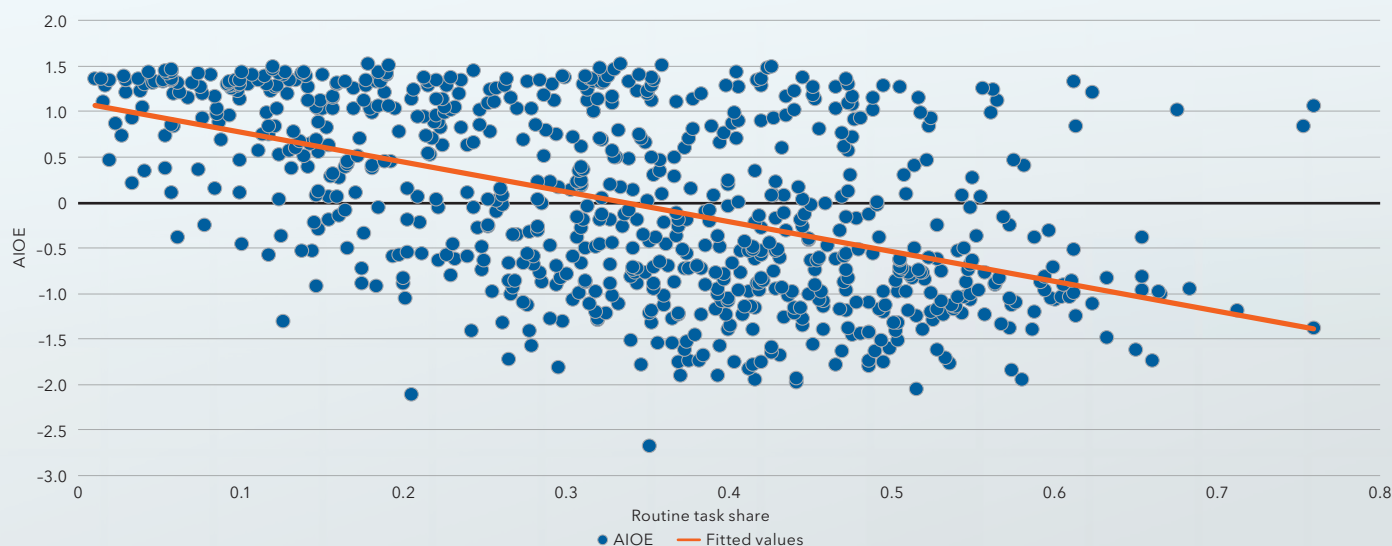
Source: Huang (2024, forthcoming).

Note: The figure shows the relationship between each occupation's AIOE (y-axis) and routine task share (x-axis). The red line is the linear fit. Each blue dot represents an occupation at the US six-digit Standard Occupational Classification system level. AIOE = AI occupation exposure.

skill-intensive occupations and AIOE, as well as the negative correlation between routine manual-intensive occupations and AIOE.

Complementarity and substitutability between humans and machines

One drawback to these measures of exposure is that they do not make a determination on the complementarity and substitutability between human beings and machines under AI and IT. The degree of complementarity or substitutability is crucial to determine the labor market impact of technological change. If humans and machines can replace each other under the new technology, higher exposure implies that labor is likely to be replaced and in decline as technology develops. If they are complements, an increase in productivity from technological improvement may increase the demand for labor.

AI and IT can either replace or complement labor, depending on the task under consideration. For example, it is widely believed that IT substitutes for labor in routine tasks but complements labor in nonroutine tasks, such as interpersonal communication and complex problem-solving ([Autor, Levy, and Murnane 2003](#)). However, the task-specific complementarity or substitutability between AI and human labor is less clear. For example, [Korinek (2023)](#) describes ways in which generative AI can take the place of economists, ranging from ideation, writing, and background research to coding, data analysis, and mathematical derivation. AI complements economics researchers in many of these tasks, such as ideation, but it can also substitute for human labor in tasks such as background research and summarizing findings. Finally, we do not really know the exact magnitude of complementarity and substitutability under AI and IT in each task.

Figure 2. Change in Employment Share by Skill Group
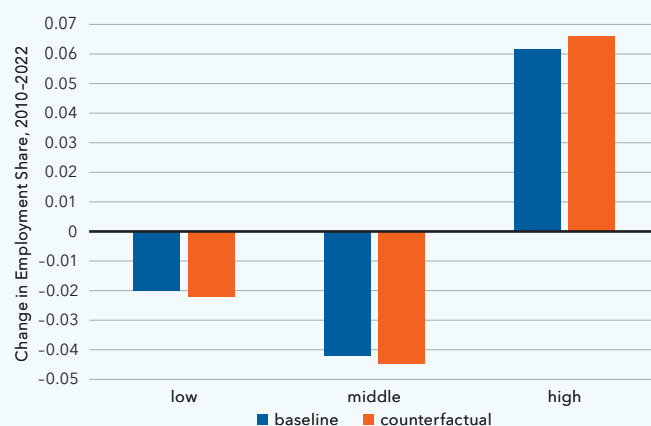
Source: Huang (2024, forthcoming).
Note: The figure shows the change in employment from 2010 to 2022 in low-, middle-, and high-skill occupations. The blue bars represent the baseline scenario, in which the economy experiences AI technological change during 2010–22. The red bars represent the counterfactual scenario, in which the economy continues IT technological change in 2010–22.

To address these issues, we group the 52 abilities from the Occupational Information Network (O*NET) into five task categories, broadly labeled as physical activities, information processing, language processing, visual processing, and reaction and problem-solving. We then structurally estimate the elasticity of substitution between human labor and machines for each of the task category and find that the level of complementarity is generally higher in AI than IT, except for physical activities. This is not surprising, as the use of AI allows for greater accuracy and dexterity in physical activities, which can thus replace human labor to a greater extent. For example, AI-trained massage robots can replicate the strength and delicacy of physical movements in a more subtle way. IT acts mostly as a substitute for human labor in all tasks, especially in language processing. AI, on the other hand, complements human labor in information processing and reaction and problem-solving.[1]

The labor market impact of IT vs. AI

Equipped with these estimates of complementarity and substitutability, we consider the following counterfactual scenario: What would happen to low-, middle-, and high-skilled workers if the technology progress during recent decade were in IT rather than AI?

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[1] [Pizzinelli and others (2023)](#) also gauge the complementarity and substitutability of AI and labor, but at the occupational rather than the task level. They find that judges and lawyers are highly exposed but also highly complementary to AI, whereas telemarketers are highly exposed but have low potential complementarity and hence are more susceptible to replacement by AI.
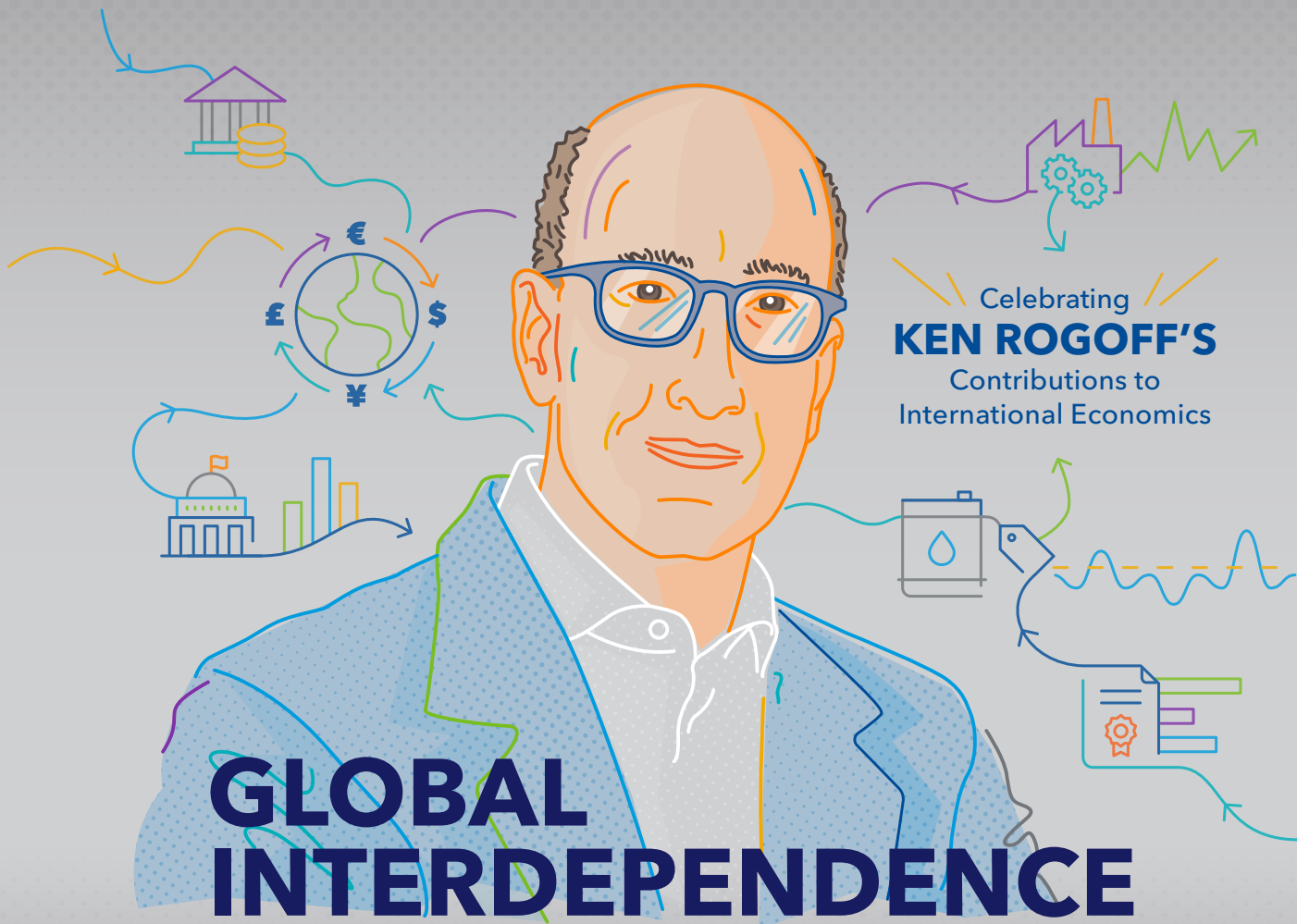
We show that even though high-skill occupations are more exposed to AI than IT, the high-skill employment share still increases, whereas low- and middle-skill employment shares remain in decline. This is because of differences in the occupational task structure for each skill type, coupled with differences in substitutability and complementarity between humans and machines for each technology. Low- and middle-skill occupations involve much more physical activity than high-skill occupations. Although physical activities are less exposed to AI than to IT, our estimates suggest that AI renders machines better able to substitute for humans in performing physical tasks. Occupations that use tasks such as language processing, information processing, and reaction and problem-solving the most are high-skill occupations. These tasks are now more complementary to human labor under AI than under IT. We also note that the changes in employment shares are less pronounced under AI than under IT because our structural estimates suggest that for now, machines are generally less productive under AI technology.

Conclusion

It is important to carefully assess the complementarity and substitutability of humans and machines in the discussion of the labor market impact of technology. Higher exposure to technology is not necessarily bad news for workers—if the technology complements rather than substitutes for them. Higher AI exposure in high-skill occupations does not guarantee that low- and middle-skilled workers are insulated from the AI revolution.

We may witness more AI technologies blended with IT in future applications; at the same time, AI may replace certain IT applications. For example, AI may revolutionize the way we prepare presentation slides, thereby replacing existing presentation software, developed during the IT revolution. Future research can investigate the degree of complementarity and substitutability between AI and IT and the economic implications.

Illustration: Stefan Lipsky

Celebrating
KEN ROGOFF'S
Contributions to
International Economics

GLOBAL INTERDEPENDENCE

Annual
Research
Conference

The IMF Research Department held the 24th Jacques Polak Annual Research Conference, November 9–10, 2023.

This year's conference focused on "Global Interdependence" and honored Ken Rogoff's contributions to economics. The conference provided a forum to discuss innovative research and facilitated the exchange of ideas among researchers and policymakers.

In the high-powered policy panel, titled "Monetary Policy Challenges in a Global Economy," Jerome Powell, Amir Yaron, Gita Gopinath, Ken Rogoff, and

Pierre-Olivier Gourinchas talked about the current global inflation episode, monetary policy spillovers, and central bank independence.

The Mundell-Fleming lecture was delivered by Mark Aguiar (Princeton University) and focused on sovereign debt. He used insights from data and theory to examine sovereign borrowing over the last half a century. It was a provocative lecture, in which he argued that sovereign debt has generated slower growth and more volatility and increased access to debt markets can be welfare reducing for private citizens. He stressed that his analysis focuses on highlighting costs and consequences of sovereign borrowing but is not designed to advocate specific policy proposals.

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