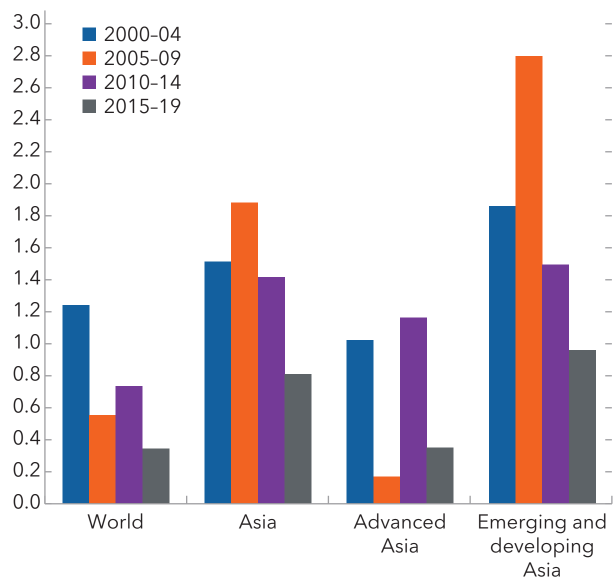
1. Introduction

Productivity growth in Asia was slowing before the COVID-19 pandemic. Productivity—whether measured in terms of labor productivity (output per worker) or as total factor productivity (TFP, a measure of economic efficiency)—has been on a downward trend worldwide, including in Asia. The slowdown, which started in the aftermath of the global financial crisis, has been particularly pronounced since 2015, impacting both advanced economies and developing countries alike in the Asia and Pacific region (Figure 1). Before the global financial crisis, productivity growth in emerging and developing Asia rose above that of advanced economies, leading to some catch-up effects. However, since the global financial crisis, productivity growth in emerging and developing countries in the region has significantly slowed toward advanced economies' levels. As a consequence, productivity levels in many Asian countries remain below the global productivity frontier (proxied by the productivity level of the United States).

Figure 1. Average Annual TFP Growth by Region
(Percent change, year-over-year)



Sources: University of Groningen; Penn World Tables; and IMF staff calculations.

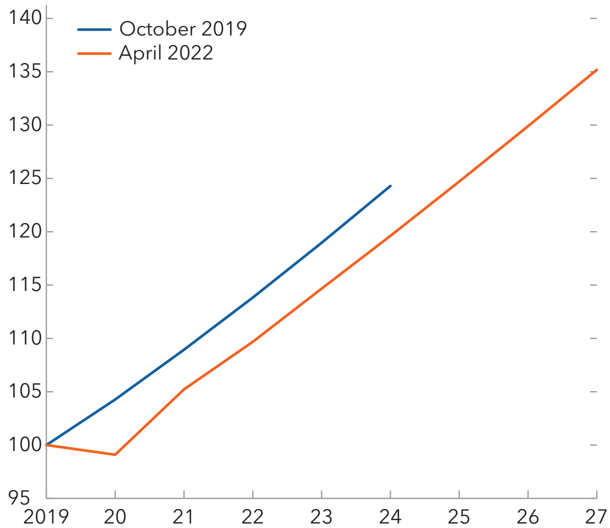
The productivity slowdown seems puzzling at first glance as it occurred concomitantly with noticeable advances in digital technologies and innovation in the region. Digital technologies allow firms to access new tools and ways to design, produce, and sell goods and services.[1] Advances in various areas such as artificial intelligence, robotics, computing power, and big data in the past decades have triggered a new wave of innovations and a rapid rise of digitalization across a range of sectors in recent years, from e-commerce, digital financial technology (fintech), ridesharing, and mobile app-enabled service.[2] Yet this surge in digital technologies and innovation has failed to offset the slowdown in aggregate productivity in many countries in Asia. A leading explanation of the inability of digital technologies to counter the slowdown in aggregate productivity to date lies in the sizeable dispersion in access to digital technologies across and within countries, and insufficient investment in enabling and complementarity factors such as organizational capital and management skills, human capital, and Information and Communications Technology-related (ICT-related) skills, and access to digital infrastructure (Brynjolfsson, Rock, and Syverson 2018; OECD 2021).

The pandemic has accelerated digitalization in the region, presenting a potential upside for productivity growth. The need to reduce in-person interactions and enhance social distancing experiences during the pandemic has put a premium on digitalization and accelerated its adoption. People and businesses turned to online platforms to make online purchases and pursue communication, education, and work. Digital

[1] Some studies have argued that while digital technologies offer a vast potential to boost productivity growth (Acemoglu and Restrepo 2020; Cette, Devillard, and Spiezia 2021; Mosiashvili and Pareliussen 2020), their full potential is yet to be realized.

[2] For instance, China accounted for less than 1 percent of global e-commerce retail transaction value about a decade ago, but that share has grown to more than 40 percent on the eve of the pandemic, and the penetration of e-commerce (as a share of total retail sales) stood at 15 percent, compared to 10 percent in the United States. A similar picture emerges for many other Asian countries, where e-commerce and fintech have grown rapidly (Dabla-Norris and others, 2021).

Figure 2. Asia and Pacific Region: Comparison of Pre-Pandemic and Latest Real GDP Projections
(Index, 2019=100)



Sources: IMF, *World Economic Outlook*; and IMF staff calculations.

solutions, including software and platforms, have surged to facilitate remote work, online platform activities, e-commerce, and online access to public services during lockdowns and to support safe distancing measures afterwards. For instance, spending on e-commerce rose by over 30 percent year-on-year in some countries in Asia.[3] Some consumer-based surveys have highlighted that technology adoption could remain strong in the near term and post-pandemic (Kinda 2021). If maintained, the recent boost in digitalization, and associated increase in investment in intangibles to fuel it could boost aggregate productivity.[4]

However, the pandemic could also present challenges for aggregate productivity growth. The slowdown in productivity growth could be exacerbated by the ensuing economic scarring as the health crisis has resulted in unprecedented output losses (Figure 2). Evidence suggests that previous epidemics (including SARS, Mers, Ebola, and Zika) had significant and persistent negative impacts on labor productivity (OECD 2020). While some sectors, in particular export-oriented sectors, have recovered from the health crisis, domestic-oriented sectors are still impacted, posing risks of hysteresis. In addition, the uneven diffusion of digital technologies, the concentration of digital investments and major innovations in a few large firms, and the resilience of highly digitalized firms during the pandemic could raise their market power, widen productivity divergence, and weigh on aggregate productivity over the longer run. The pandemic has also led to an erosion of human capital caused by the disruption of work, school, and university education as well as weaker investment that could delay broad-based digitalization and weigh on aggregate productivity growth. In addition, some of the policies implemented to cushion the economic fallout from the pandemic have reduced business exit and increased the survival likelihood of low performing firms (Barrero, Bloom, and Davis 2020).

The recovery offers the opportunity to redesign policies to durably accelerate a broad-based digital transformation and innovation that can lift aggregate productivity. While the pandemic and some of the policies implemented to dampen its impact on firms can exacerbate the uneven digital transformation and worsen firms' dynamism, it offers an opportunity to redesign policies to accelerate broad-based innovation and digitalization. This paper proposes a multipronged approach to durably accelerate the production and diffusion of digital technologies and foster innovation-led growth.

The innovation imperative across the region will require a differentiated response across countries, sectors, and firms. Innovation activity leads to technological progress in two distinct ways. Purposeful research and development (R&D) can result in the invention of completely new products and processes. This kind of innovative activity moves the global technological frontier and mainly occurs in developed Asian countries and China. But innovation also consists of the adoption and adaptation of existing technology, which closes

[3] Spending on e-commerce (in percent of total retail sales) also rose significantly in many countries in the region. For instance, in Vietnam small firms relied to a greater extent on e-commerce during the pandemic for business continuity (Dabla-Norris, Nguyen, and Zhang, forthcoming).

[4] Intangible capital includes all intangible assets such as formation expenses, research expenses, goodwill, development expenses, and all other expenses with a long-term effect.

the gap between countries converging towards the global technological frontier and those on the leading edge. As such, for emerging and developing countries in Asia with widely varying institutional, technological, and firm-level capacities, innovation entails not only the invention of new products and processes but also the diffusion and adoption of existing technologies or practices.

For all countries, the narrowing of productivity and digital/technological gaps across sectors and firms will be critical as this can have big payoffs in the aggregate. The productivity growth of countries is determined by the performance of individual firms in a country and by the reallocation of resources between the firms in that country. The latter results from business dynamism, that is, the growth of some (ideally the most productive and innovative) firms and the decline of other (ideally the least productive) firms. Firms in many advanced and frontier Asian economies, however, are well behind the technological frontier and some indicators suggest this gap is widening as firm-level productivity dispersion has increased. Firm-level evidence from OECD countries suggest that the economic impact of reducing this dispersion can be significant.[5] In emerging and developing Asia, such dispersion can be even larger across regions, sectors, and firms. In fact, the low average productivity in emerging and developing countries is mostly driven by a thick left tail of small and unproductive firms, while relatively productive firms exist even in the poorest countries (Hsieh and Klenow, 2009; Hsieh and Olken 2014).

Against this backdrop, the paper is structured as follows: Chapter 2 examines the landscape of innovation and digitalization in Asian countries before and during the pandemic and the extent of technology diffusion. Chapter 3 uses firm-level data for both advanced and developing economies in the region to investigate the role of innovation and digitalization for productivity growth and dispersion across firms and identify factors that impede faster innovation (for countries closer to the technological frontier) and broader technological diffusion (for countries farther from the frontier). Chapter 4 provides a detailed mapping of the policies and mechanisms, depending on where countries and firms stand, to foster broader-based innovation and boost aggregate productivity and longer-term growth prospects.

[5] For instance, firm-level evidence suggests that lifting the productivity of firms in the bottom 40 percent of the productivity distribution to median productivity level in OECD countries would have a sizeable macroeconomic impact by boosting aggregate output by up to 6 percent (Berlingieri and others 2020).

2. The Landscape of Innovation and Productivity in Asia

This paper adopts a broad view of innovation as the accumulation of knowledge and implementation of new ideas. It classifies innovation into four categories, based on the difference between product and process innovations, as well as innovation by discovery and innovation by diffusion.

- *Product innovation* leads to the introduction of new or improved goods and services. This type of innovation is usually easier to measure, as some of its outputs are observable (for example, patents or trademarks). In developing economies, product innovation often refers to the adoption of new or improved goods and services that differ from the firm's previously produced goods or services.

- *Process innovation* leads to novel or improved managerial practices or business operations that differ from the firm's existing business processes. This type of innovation typically increases the productivity of a firm by fine tuning the coordination between production processes or changing the way the firm operates (instead of through the adoption of new machinery or technology).

- *Innovation by discovery* concerns the invention of new ideas and is produced through R&D or other creative activities that push the technological frontier. The paper includes both basic and applied research into this category. This type of innovation is more prominent in advanced economies and in emerging economies such as China, where firms on the technology frontier typically have more incentive and resources to invest in R&D.

- *Innovation by diffusion* includes direct technology transfers, knowledge spillovers, or the adoption of existing business practices that were previously not used by a company. Most firms in emerging and developing economies are constrained to, or reap higher benefits from, this type of innovation.

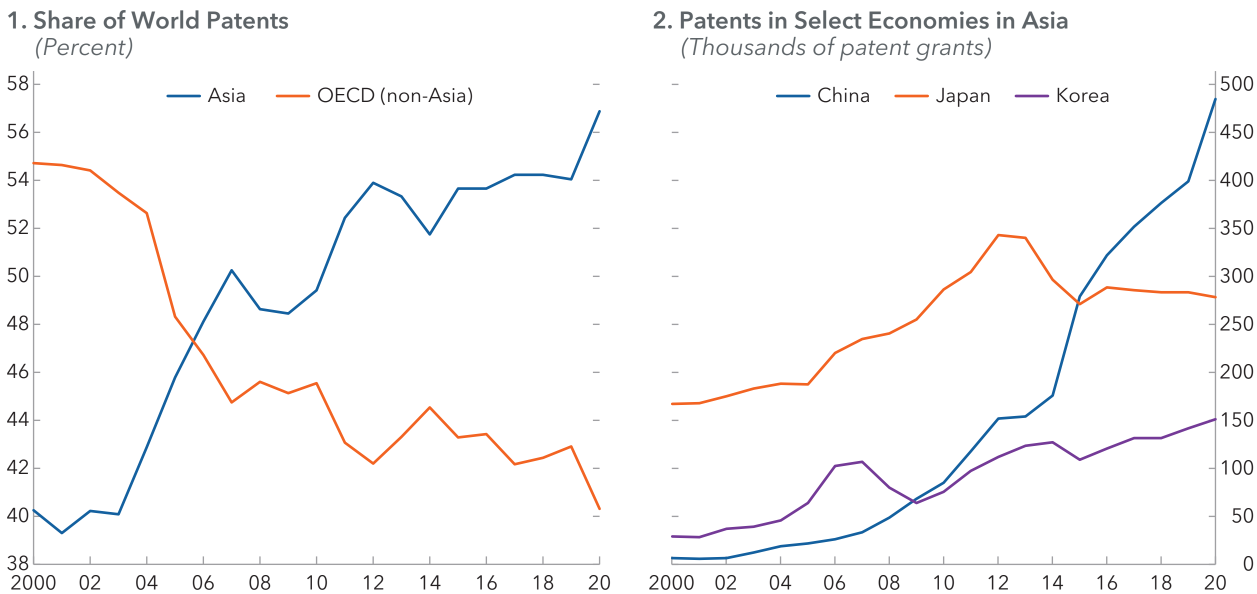
Advances in the digitalization of production involve all of the categories above. Invention of new digital technologies, typically through R&D, pushes the technology frontier. Growing adoption of digital technologies lead to new business processes and products. Digitalization also increases ease of diffusion of ideas, technologies, and practices. Higher degree of digitalization can be understood as both an output and an input of innovation. It is an output because new technologies tend to produce goods and services with a higher digital content. It is considered as an input because the digitalization or automation of production processes can increase the productivity of firms (process innovation) and are increasingly required to conduct the R&D that leads to the creating of new/improved goods and services.

In what follows, the paper presents a landscape of innovation across Asia by examining both outputs of and inputs into innovative activities. Outputs include patents based on both basic and applied research, while inputs into innovation including R&D spending and human capital, among others. Following IMF (2021b), we distinguish between basic research (undirected, theoretical, or experimental research), and applied research, which is directed and for practical purposes, such as bringing goods to markets. For this paper, we refer to all high-income countries in Asia and China as "frontier Asia," and to other countries as developing or "non-frontier" Asia. In the remainder of this chapter, we first provide an overview of progress achieved in innovation in recent decades in frontier and non-frontier Asia respectively, and then identify shifting trends of innovation toward accelerated digitalization since the onset of the COVID-19 pandemic. For non-frontier Asia, we present indicators that capture the diffusion of technology and innovation elsewhere. We conclude this chapter by discussing challenges in further advancing innovation and digitalization in Asia.

A. Asia as Innovation Powerhouse

Asia has become a powerhouse when it comes to applied research as measured by patents. Data on the spatial density of patents filed under the Patent Cooperation Treaty (PCT) of the World Intellectual Property Organization (indicate that less than 40 percent of world patents originated from Asia at the beginning of the century. In less than a decade, Asia's contribution to world patents increased to about 50 percent. By 2019, this share has reached 54 percent (Figure 3, panel 1). Asia is ahead of Europe and the Americas in terms of patent outputs, although in per capita terms it still trails Europe. The lion's share of patents in Asia are accounted for by a few countries, most notably China, Japan, and Korea, with China's rise being particularly striking in the past decade (Figure 3, panel 2). Other high-income countries in the region, such as New Zealand and Singapore produce significantly fewer patents due to their smaller scale but are nevertheless innovative relative to their size.

Figure 3. Outputs of Innovation: Patents in Asia

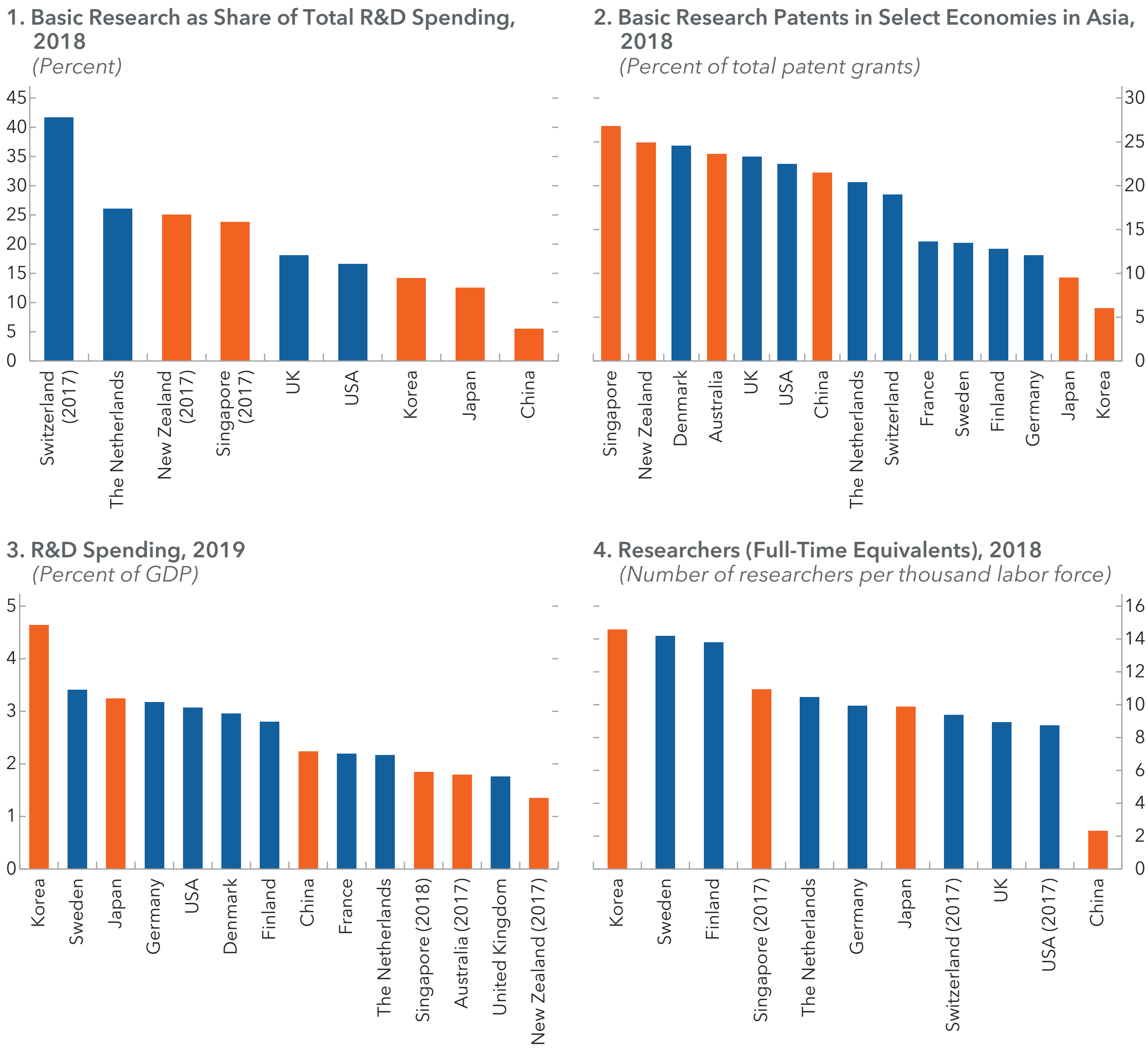


Source: World Intellectual Property Rights Organization.

Asia's focus on basic research—undirected, theoretical, or experimental work—is close to the most innovative economies worldwide. Basic research, as distinct from applied research, plays an especially important role in innovation. In frontier economies, between 10 to 25 percent of total R&D spending is devoted to basic research (except China), which is close to world leading innovators (Figure 4, panel 1). New Zealand and Singapore are among the countries that spend the most in basic research in percent of GDP. A higher share of frontier Asia's patents is related to or contribute to basic scientific research, compared with leading innovators in the world, with New Zealand and Singapore taking the top spots worldwide (Figure 4, panel 2).[6] Globally, while the United States remains the main source of cited works, citations to Chinese science have grown strongly since 2005 (albeit from a low base), as have citations across Asian countries (IMF 2021b).

[6] Calculated as the share of patents that cite scientific literature in total patents. Patents are counted equally for each country of origin of each of the patent applicants.

Figure 4. Inputs into Innovation in Asia and Selected Countries

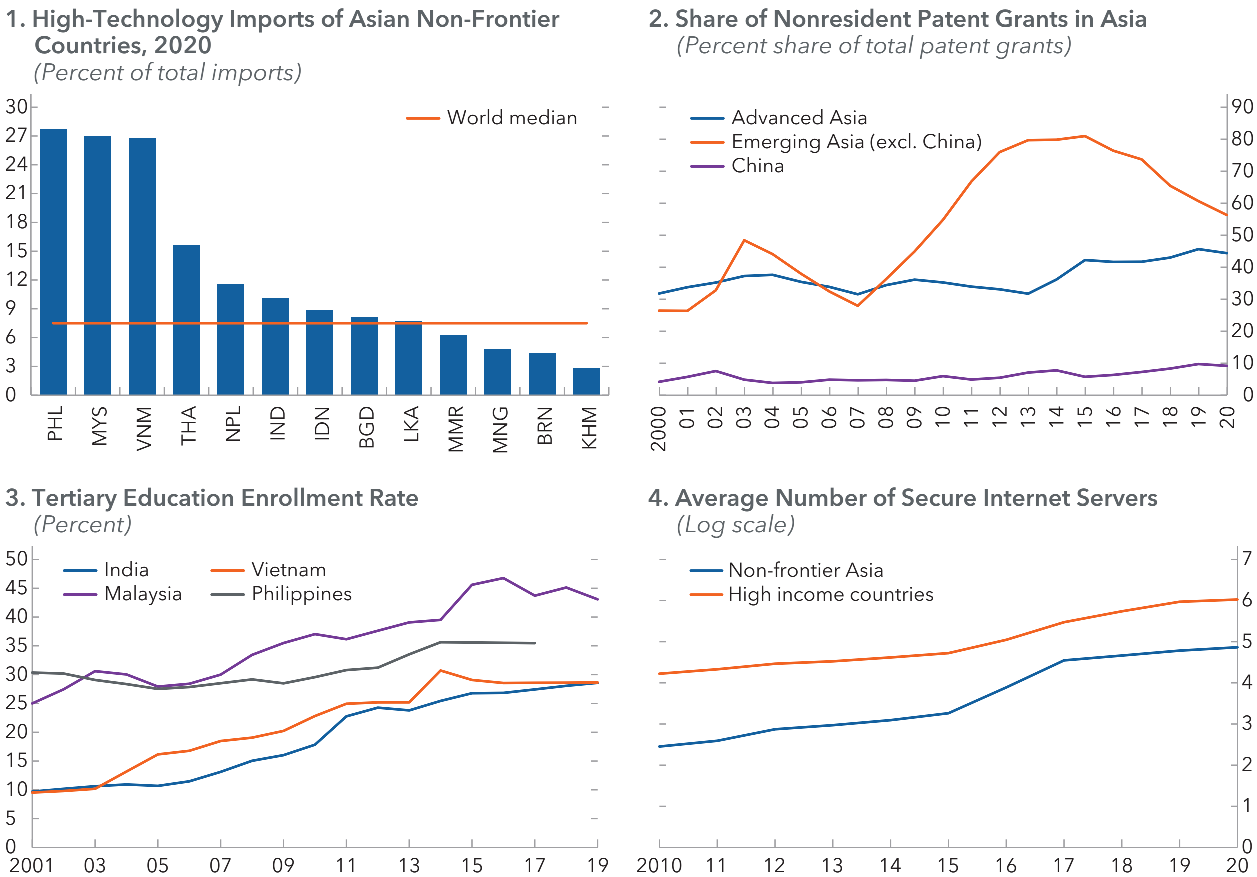


Sources: OECD; PATSTAT Global 2020; Reliance on Science in Patenting; UNESCO; and IMF staff calculations.

Frontier Asia has devoted large amounts of financial and human capital to R&D. Frontier Asia spends close to the most innovative economies elsewhere in R&D, with Korea being a world leader in R&D spending at 4.6 percent of GDP in 2019. Most other innovative economies spend between 2 to 3.5 percent of GDP in R&D (Figure 4, panel 3). The share of researchers in the labor force is also close to peers (except in China), with Korea again taking the leading spot at least in 2018 (Figure 4, panel 4).

Non-frontier Asia, while not engaging intensively in R&D activities, benefits significantly from international technology diffusion, supported by improvements in human capital and digital infrastructure. High-tech imports in most low-and-middle-income countries in Asia, particularly Bangladesh, India, Malaysia, Nepal, the Philippines, Sri Lanka, Thailand, and Vietnam are higher as a share of total imports than the world median (Figure 5, panel 1). Although many of these countries' participation in the trade of high-value added goods began with less-sophisticated components and assembly, these measures reflect the increased adoption of global technologies and production processes over time through FDI, creation of joint ventures, and

Figure 5. Indicators of Technology Diffusion in Emerging and Developing Asia



Sources: *Global Innovation Index 2021*; World Bank, World Development Indicators; World Intellectual Property Organization; and IMF staff calculations.

participation in trade and global value chains (GVCs).[7] In addition, foreign ideas started to diffuse more profusely since 2013, as non-frontier Asia accounted for an increasing share of patents granted from Asia to nonresidents (Figure 5, panel 2). At the same time, human capital improved significantly, especially in India, Malaysia, and Vietnam, where tertiary education enrollment rate has increased by more than 10 percentage points in the last two decades, enhancing firms' capacity for technology adoption and innovation, particular product innovation (Figure 5, panel 3).[8]

Digital infrastructure has also been significantly enhanced in non-frontier Asia. For example, the number of secure internet servers has seen a more than 200-fold increase, contributing to a much-reduced gap with high income countries (Figure 5, panel 4). India, in particular, has become a global information technology services powerhouse and a pioneer of "digital stacks" that bring together digital payments and identification services, among others, and upon which innovators can build additional services and applications (World Bank 2021b).

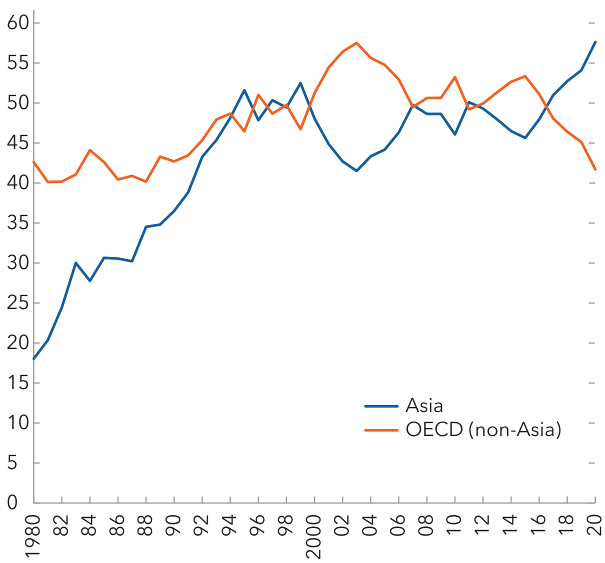
[7] For example, between 2000 and 2008, the share of the domestic content of exports in electronics grew significantly in Malaysia and Thailand, as well as in industrial machinery in Indonesia and the Philippines (World Bank 2021).

[8] See ADB (2020) for a study on the role of human capital in innovation in Asia.

B. The Pandemic and Innovation in Asia: A Boost to Digitalization

Innovation in digital/ICT technologies was advancing rapidly in Asia even prior to the pandemic. While the growth in patents in frontier Asia was broad-based, the increase was particularly prominent in digital and ICT technologies. Asia started to account for a higher share of world patents in these technologies than the rest of the world combined since 2017, representing about 60 percent of world total patents in digital and computer technologies by 2020 (Figure 6). Asia dominates all of the digital/ICT technology sub-categories in terms of the number of patents, including telecommunications, digital communication, basic communication processes, computer technology, and semiconductors (Figure 7). Not surprisingly, the ICT sector in Asia is among the world's largest. The sector accounted for more than 12 and 7 percent of total value added in Korea and India, respectively (Dabla-Norris and others 2021), comparable in size to most other OECD countries.[9] China's ICT sector is estimated to be about 6 percent of GDP (Herrero and Xu 2018).

Figure 6. Patent Grants for Digital Communication and Computer Technology
(Percent share of total patent grants in digital communication and computer technology)



Sources: World Intellectual Property Organization; and IMF staff calculations.

Many Asian economies were also at the frontier in terms of adoption of digital technologies, including robotics and e-commerce. In keeping with Asia's moniker of "manufacturing powerhouse," about two-thirds of the world's industrial robots are employed in the region. China alone is the single biggest user of robots (accounting for some 30 percent of the market), and China, Japan, and Korea each employed more robots than the United States on the eve of the pandemic. The rising trend of industrial robot use has been relatively broad-based in the region (Figure 8, panels 1 and 2). Online sales are also more common in some Asian economies than in other regions, including e-commerce exports, a trend that is expected to accelerate in the wake of the pandemic (Figure 8, panels 3 and 4). Business-to-Consumer (B2C) e-commerce in China and Korea is larger than in the United States. Cross-border e-commerce is also substantial, with B2C e-commerce exports from China exceeding that of advanced economies (Dabla-Norris and others 2021).

Asia stands out from other regions in having large home-grown tech giants. China has several of the largest e-commerce companies in the world, both measured in terms of market share and total sales. For instance, China's Alibaba Group and JD.com have nearly 40 percent of global e-commerce market share by merchandise volume (Dabla-Norris and others 2021), although the total value of Alibaba's transactions is smaller than that of Amazon.[10] Japan's Rakuten and Singapore's Sea Group (trading as subsidiary Shopee) are other major players in e-commerce as are Korea's Coupang and Indonesia's Go-Jek. These local firms generate

[9] Although fully comparable data are not available, McKinsey Global Institute (2019) estimate that India's ICT sector alone accounted for about 7 percent of GDP in 2017–18, mainly reflecting IT and digital communications services.

[10] Alibaba operates China's most visited online marketplaces, Taobao (Consumer to Consumer (C2C)) and TMall (Business to Consumer (B2C)), while JD.com's marketplace has a large in-house delivery network. OECD (2020) notes that the move of JD.com, now one of the largest online retailers in the world, from brick-and-mortar to online sales in 2004 was a direct response to the SARS crisis. The same crisis also provided the consumer base for Alibaba's business-to-consumer (B2C) branch Taobab, which was launched in 2003.

Figure 7. Patent Publications per Field of Technology by Region, 2020

Field of Technology	Asia	Europe	North and South America	Middle East and Central Asia	Africa
Electrical machinery, apparatus, energy	151,875	34,292	20,826	174	62
Audio-visual technology	68,650	8,161	13,983	28	17
Digital communication	102,593	19,986	39,792	124	19
Basic communication processes	10,510	3,326	4,034	17	7
Computer technology	227,971	24,159	64,379	233	43
IT methods for management	58,292	4,803	14,263	81	41
Semiconductors	66,278	8,025	13,494	81	7
Optics	52,284	9,530	9,926	53	7
Measurement	131,959	30,104	20,383	608	34
Analysis of biological materials	10,598	4,559	4,717	91	20
Control	55,254	10,217	11,421	84	21
Medical technology	77,108	37,220	47,268	276	91
Organic fine chemistry	34,946	16,545	13,559	174	25
Biotechnology	33,276	16,828	23,183	89	31
Pharmaceuticals	38,626	25,726	33,853	224	55
Macromolecular chemistry, polymers	34,053	8,749	6,318	102	16
Food chemistry	32,383	7,755	4,993	71	20
Basic materials chemistry	46,895	12,973	10,737	665	36
Materials, metallurgy	54,176	10,423	5,792	257	27
Surface technology, coating	34,095	7,580	6,003	78	6
Micro-structural and nano-technology	3,550	1,068	753	12	1
Chemical engineering	72,297	14,166	11,487	382	37
Environmental technology	49,558	7,737	5,544	197	12
Handling	72,311	17,971	11,221	71	32
Machine tools	83,563	13,504	7,836	44	14
Engines, pumps, turbines	33,003	18,330	9,219	200	7
Textile and paper machines	32,934	7,661	4,668	17	4
Other special machines	80,405	22,683	17,225	143	89
Telecommunications	37,485	7,061	10,869	60	9
Thermal processes and apparatus	41,830	7,973	4,464	102	10
Mechanical elements	46,996	21,491	8,998	81	34
Transport	83,078	41,358	19,065	128	44
Furniture, games	52,871	11,260	10,642	54	36
Other consumer goods	37,846	13,954	9,022	70	18
Civil engineering	88,843	20,738	15,561	765	110

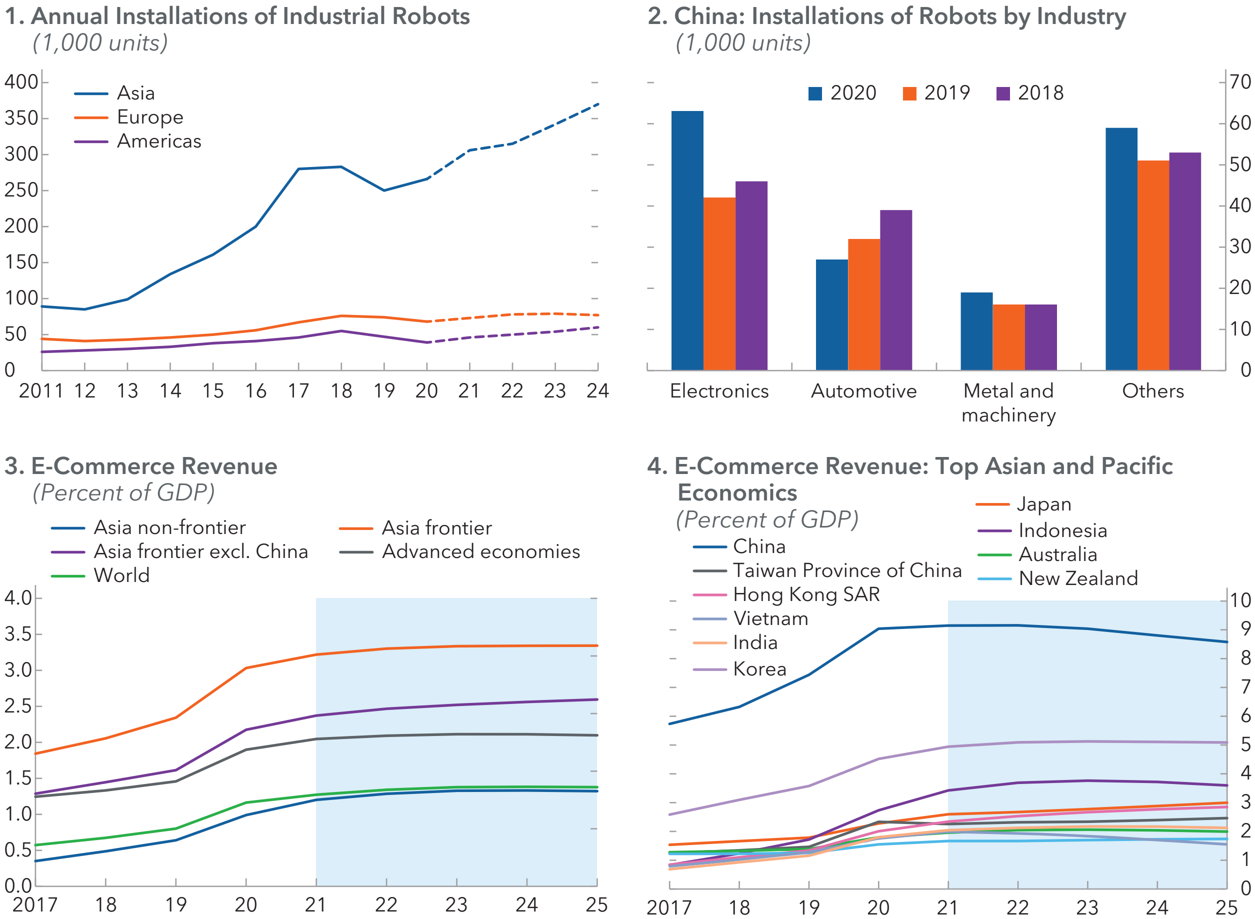
Rank 1 Rank 2 Rank 3 Rank 4 Rank 5

Sources: World Intellectual Property Organization; and IMF staff calculations.

similar levels of revenue in Asia to large firms in the United States, including Amazon, Walmart, and their local subsidiaries. Asia is also home to some of the world's largest providers of digital services other than e-commerce, such as China's Tencent (operating the WeChat communications, social media and payment platform) and Baidu (China's largest internet search engine).

The pandemic has changed innovation trends and accelerated digitalization and automation. As remote working has become more prevalent in many countries in the region, demand for digital solutions for work and life, including communication and shopping, have risen significantly and boosted innovation in digital technologies (Figure 9, panel 1). Patent application data suggest that the proportion of patent applications for remote work and e-commerce technologies have also increased substantially compared to pre-COVID times (Figure 9, panel 2), including by Asian countries (Asian Development Bank 2021). The use of e-commerce

Figure 8. Widespread Use of Robots and E-Commerce in Asia



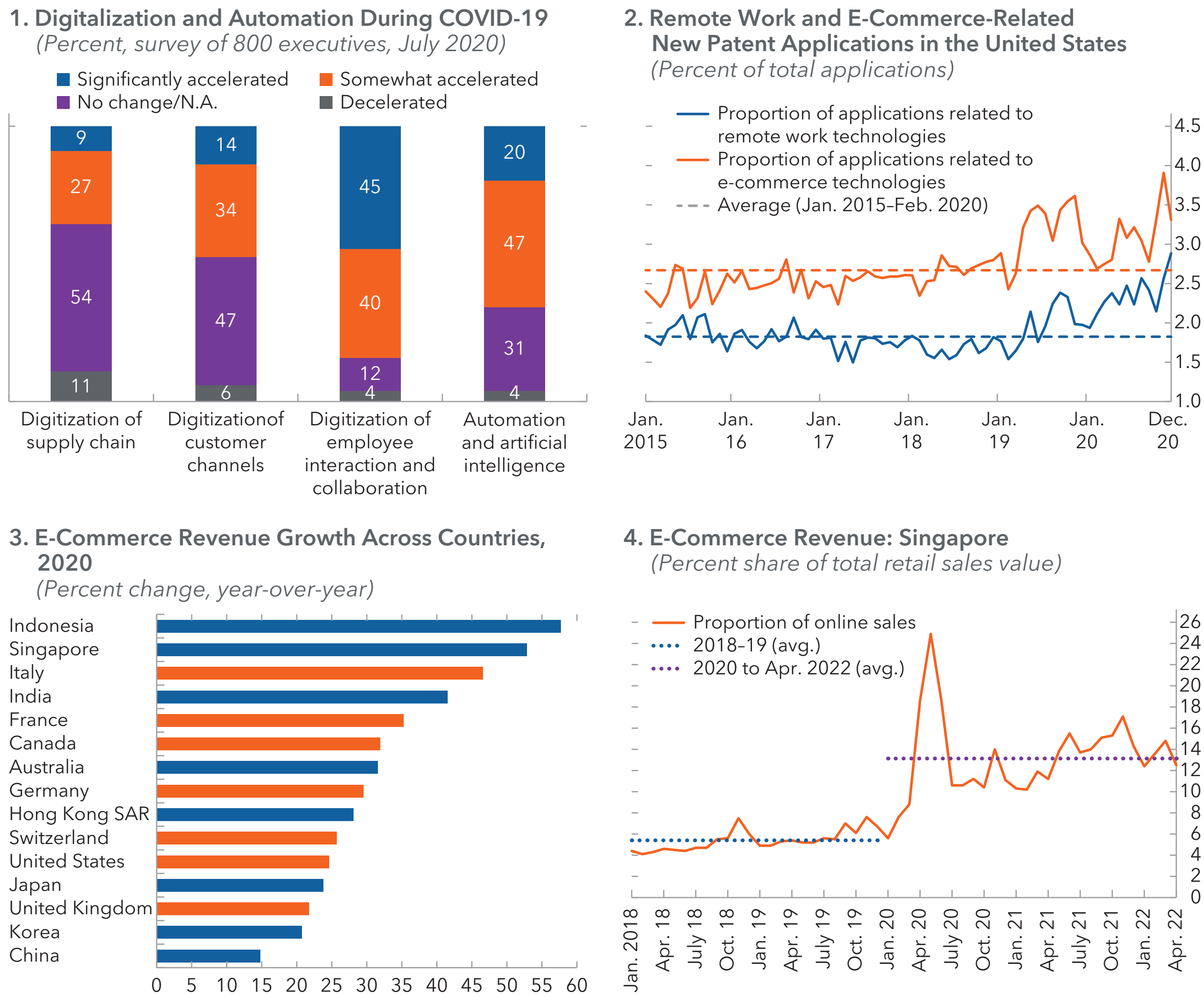
Sources: International Federation of Robotics; Statista Digital Market Outlook; IMF, *World Economic Outlook* Oct 2021; and IMF staff calculations.

has accelerated during the pandemic, with Asia now accounting for nearly 60 percent of the world's online retail sales. For instance, e-commerce revenues grew by 30–50 percent in many Asian economies in 2020, outpacing most countries in the world (Figure 9, panel 3). This rapid increase was driven by an increased reliance on e-commerce spurred by the ongoing trend away from cash payments and further development of new payment methods, particularly for e-wallets and prepaid cards.[11] Despite the pandemic's impact on global economic activities, robot installation in Asia increased in 2020 relative to other regions. In China, for instance, the installation of robots in electronics increased sharply, reflecting high demand for digital investment, including for 5G (IFR 2021). Going forward, the expected strong demand for electronics, digital infrastructure, and automation technologies could boost robot installation in Asia and further support digital commerce (Figure 9, panel 4).

Many countries in Asia actively promoted digitalization and innovation in the wake of the pandemic. In addition to leveraging technology resources for disease prevention and control, several countries in the region launched multi-faced initiatives to promote the digital economy as part of their stimulus packages.

[11] In many Asian countries, the expansion in e-commerce involved customers and firms that traditionally did not shop online. For instance, OECD (2020) notes that the increase in the share of online purchases in credit card transactions was highest for users in their 60s (from 15.4 percent in January to 21.9 percent in March 2020) and those in their 70s (from 10.9 percent to 16.4 percent). On the supply side, evidence from Vietnam shows that many operators of brick-and-mortar stores, including SMEs, that often were forced to completely shut down their physical business, adopted e-commerce ((Dabla-Norris, Nguyen, and Zhang, forthcoming).

Figure 9. Remote Work and E-Sales Growth in the Wake of the Pandemic



Sources: McKinsey Global Business Ececutive Survey, July 2020; Singapore Department of Statistics; Statista; USPTO; and IMF staff calculations.
Note: In panel 2, non-provisional utility and plant patent applications only. Based on methodology in Bloom and others (2021).

Tax incentives, public spending, and R&D loan programs have been used to support innovation and digitalization in the private sector. Countries in the region have also accelerated the deployment of fintech, digital public services, and provided support to SMEs for the adoption of digital technologies, including e-commerce platforms (Box 1). [12]

C. Challenges in Advancing Innovation and Digitalization

Despite these successes, Asian countries still face important challenges in fostering an innovation-led growth, with significant heterogeneity in performance across countries, sectors, and firms that weigh on aggregate performance. Inventions and new technologies offer the possibility for large increases in productivity in frontier economies, but this alone is not sufficient. What matters for a country's growth and productivity

[12] While platforms can magnify the benefits of e-commerce, they can raise competition issues. Exclusive access to information of platforms can pose anti-competitive concerns, particularly when these platforms become large. Network effects also make it challenging for retailers and vendors to switch platforms, reinforcing platforms' market power, and exacerbating risks of anticompetitive practices (Kinda 2019).

Box 1. Digitalization and Innovation Policies during the COVID-19 Pandemic

Many Asian countries have accelerated innovation and digitalization policies in the wake of the pandemic. These include policies to improve digital skills among SMEs, scale up digital infrastructure, promote cashless payment, and promote the digitalization of public services. Some countries formulated digitalization and innovation strategies to promote their post-COVID recovery.

Initiatives launched to promote digitalization. **Korea** unveiled a Digital New Deal as part of the Korean New Deal, with the aim to build a digital economy and promote growth in promising industries that rely less heavily on human contact. **Malaysia** announced the Twelfth Malaysia Plan, which aims to boost the digital economy and enhance broad-based productivity drivers. The government launched the Malaysia Digital Economic Blueprint (MyDIGITAL) to enable greater digital inclusiveness and promote growth of the digital economy. **Vietnam** announced the National Digital Transformation strategy to strengthen the online public services, accelerate non-cash payments, and e-commerce, and improve shared database for state management. India accelerated digitalization, including through increased digital payments, contactless payments, digital education.

Fiscal and financial support for digitalization and innovation. **Japan** introduced tax incentives for digital investments as part of the 2021 tax reform package. **Vietnam** has scaled up public investments in innovation and digitalization in the context of its Program for Recovery and Development. **New Zealand** introduced a one-off R&D loan scheme to support R&D investment of firms that have been severely affected by the pandemic.

Fintech. **Cambodia** introduced Bakong, a new payment system operated by the National Bank of Cambodia, using blockchain technology and providing real-time-gross settlement, to promote digitalization, cashless payment, and financial inclusion. The system provides e-wallets, mobile payments, online banking, and financial applications in a single interface.

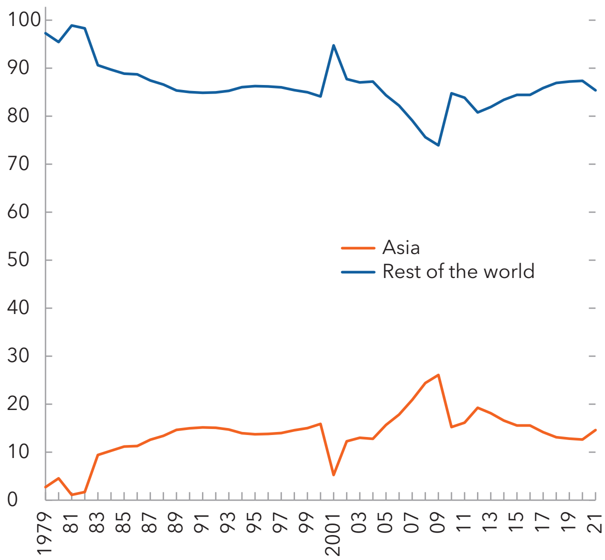
Public service. **Japan** established the Digital Agency to promote digitalization of the central and local governments, while supporting uptake of national ID cards (My Number). Philippines has digitalized revenue collection and has launched its digital ID system, which will support public service delivery such as social protection.

SMEs. **Singapore's** SMEs Go Digital program has supported SMEs' adoption and use of digital technologies through various channels. **China and Singapore** have actively supported SMEs in accessing e-commerce platforms with regional or global reach, to help them reduce costs or sell overseas through digital means. **New Zealand** introduced Digital Boost for SMEs to improve their digital skills and promote the take-up of digital technologies. **Japan** designed a business continuity subsidy to help firms diversify and expand their sales channels. **Korea** encouraged brick-and-mortar shops to open their business online through a dedicated support program.

performance is how rapidly technology and innovation diffuse across countries as well as across sectors and firms within a country.[13] Many countries in the region appear to underperform on several standard indicators of innovation for both diffusion and discovery. Further, limited spillovers from sectors that perform

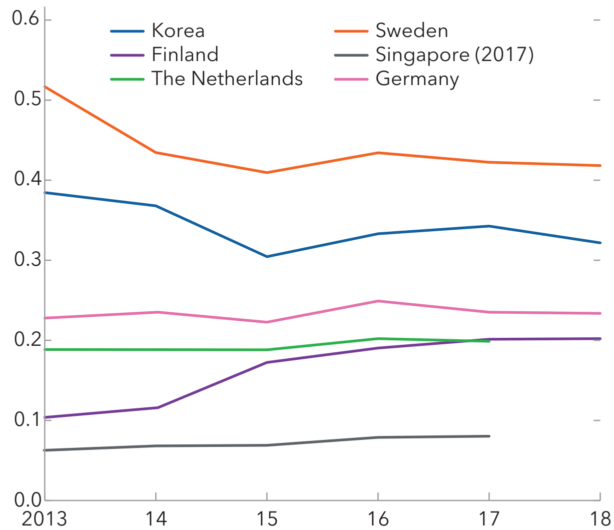
[13] IMF (2021b) finds that access to foreign research has a larger estimated effect on innovation in emerging markets and developing economies than in advanced economies, pointing to important international spillover effects.

Figure 10. Share of Total Patent Citations by Applicant Regions
(Percent share)



Sources: The Lens (lens.org); and IMF staff calculations.

Figure 11. Labor Productivity in R&D
(Patent per researcher)



Sources: World Intellectual Property Organization; UNESCO; and IMF staff calculations.

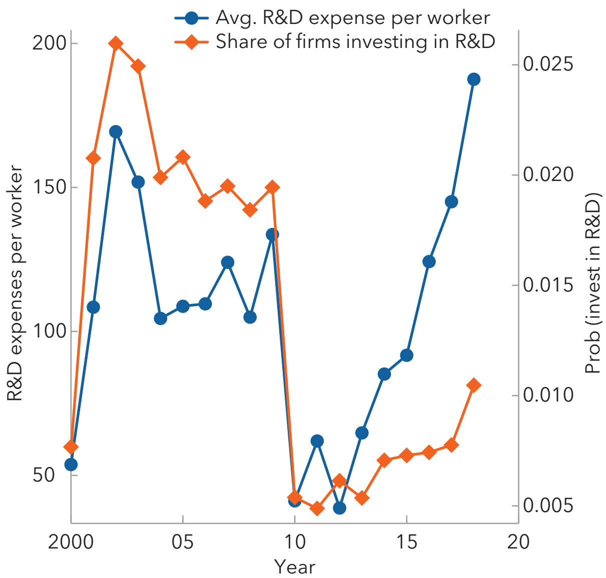
well relative to the rest of the economy constrain the contribution of innovation to overall growth. Within sectors, the large productivity and technological divides between the leading and lagging firms drives down aggregate productivity growth (see next chapter).

The quality and impact of R&D in Frontier Asia leave significant room for improvement. Despite the rapidly increasing number of patents generated in Frontier Asia, patent citations—a measure of the quality and impact of innovation—has been stagnant as a share of worldwide citations, reflecting the relative rarity of groundbreaking innovations originating from Asia (Figure 10). This could be related to weaknesses in basic research in the region. Basic scientific research in many frontier economies in Asia is underfunded, with significant heterogeneity across countries. For instance, the three countries with the most patent output in Asia, namely China, Japan, and Korea, are near the lower end in both spending in basic research and contribution to basic research in comparison with world leaders such as The Netherlands and Switzerland (Figure 4, panel 1). In addition, patents per researcher, a proxy for the productivity of R&D, has been stagnant or declining in recent years in some frontier countries in Asia (Figure 11).

Innovation in Asia is increasingly concentrated in a handful of firms. While R&D in frontier economies has increased in recent years, it has become more concentrated in a smaller set of firms since the global financial crisis. R&D spending per worker fell off the cliff in firms in Asia around 2009 but has since gradually recovered (Figure 12). However, the share of firms engaging in R&D, which has experienced a similar drop in 2009, has remained low, implying that a larger share of R&D activities is undertaken by a much smaller set of firms. A similar concentration of innovation in a minority of firms is seen in emerging and developing Asia. For instance, less than 30 percent of firms in developing Asia surveyed in the World Bank Enterprise Surveys (WBES) report having introduced any innovation over the previous three years. The concentration of R&D activity is likely to be a major drawback for the region's capacity to introduce breakthrough technology. Importantly, this concentration could result in divergence of productivity growth across firms and sectors, and ultimately weigh on aggregate productivity.[14]

[14] This concentration of R&D projects carried out by a handful of frontier firms is also found in other regions. For example, calculations using data from the European Union (EU) Industrial R&D Investment Scoreboard suggest that the top 10 public companies account for slightly less than 20 percent of aggregate private sector R&D spending in the United States (Hernández and others 2020).

Figure 12. R&D Expenditure Concentration in Asia



Sources: Orbis; and IMF staff calculations.

Access to cutting-edge technologies, particularly digital technologies, is also highly uneven across and within countries and across firms. Firm-level measures of innovation based on WBES data reveal significant heterogeneity in technology adoption in the region. For example, while 20 percent of Chinese firms license foreign technology, in Myanmar and Thailand only 5 percent of firms have any technology licensed from foreign companies (World Bank 2021b). In particular, SMEs face significant barriers related to access and use of digital technologies, preventing them from reaping the full rewards of participating in the new economy and reaching their full potential.[15] Low levels of digitalization and difficulties in accessing and adopting new technologies made it particularly difficult for those firms to change existing work processes, by introducing teleworking or an e-commerce sales channel.[16] Within sectors, the productivity and technological divide between the leading and lagging firms in both frontier and non-frontier Asia reflects the slow diffusion of technology. Insufficient investment in enabling and complementarity factors such as organizational capital and management skills, human capital, and ICT-related skills, hampers access to digital infrastructure as discussed below.

Diffusion of innovation remains a challenge. In developing Asia, despite notable achievements in accelerating innovation through the acquisition of technologies embedded in imports and FDI, this has not induced broad diffusion of new technologies and processes beyond export-linked firms. Even in the more advanced and frontier economies in the region, there is limited diffusion of innovation by the more frontier firms to other firms in the same country. Technology adoption and diffusion are determined by a range of factors, including access to finance, firm-level capabilities, and availability of skills, among others.[17]

- *Access to Finance*. Investing in new capabilities, such as skills, innovation, digital technologies, or machinery and equipment requires access to finance. Theory and empirical evidence suggest that the level of productivity and the likelihood of innovation, through invention or adoption, depend on the availability of financing (Hall and Lerner 2010). When asked explicitly about factors holding back business operations, about 20 percent of firms in emerging and developing Asia report financing constraints as the main obstacle in the WBES (Figure 13). By comparison, only 7 percent of firms in the non-Asia sample report credit constraints as the main obstacle. This is true for firms regardless of whether they innovate or not. Nearly half of SMEs and roughly one-third of large firms in emerging and developing Asia report difficulty in obtaining financing as a major barrier to technology adoption.[18] While purely descriptive, this evidence suggests that financing constraints may indeed be one of the factors holding back the diffusion of innovation in developing Asia.

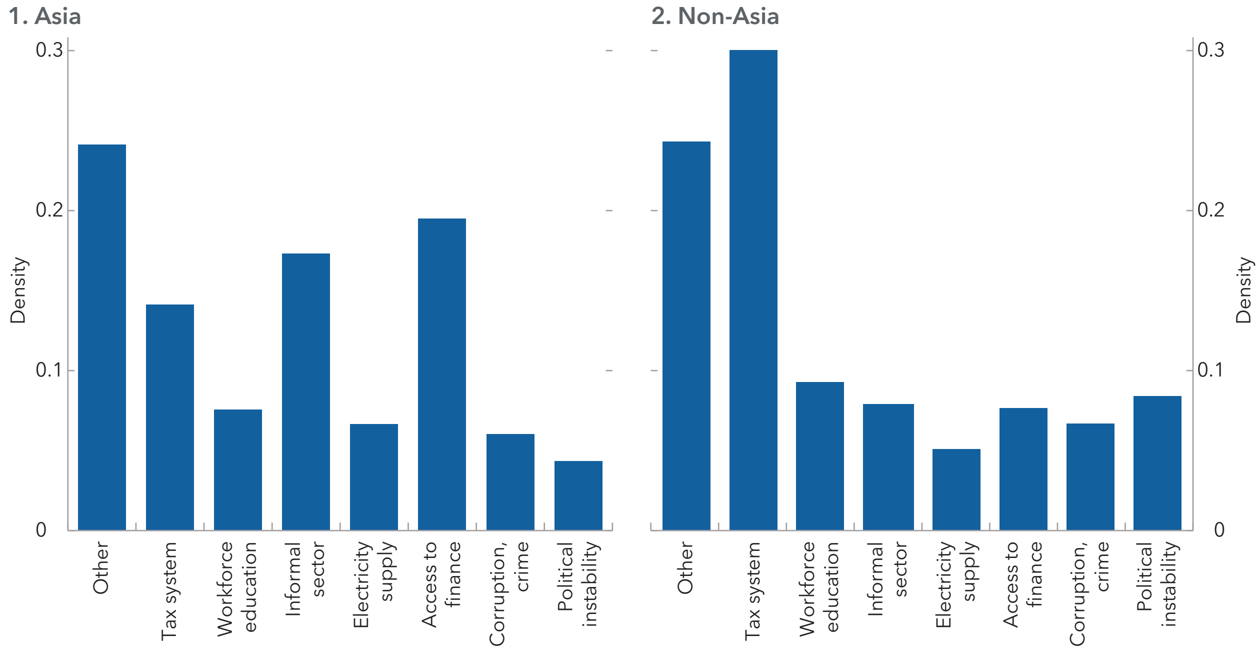
[15] As small firms tend to be more women-owned, uneven access to technologies could also affect women relatively more, worsening gender inequality.

[16] In 2017, the participation rate for SMEs in e-commerce was less than half the rate for large firms in a majority of OECD countries (OECD 2020). These gaps were exacerbated by the pandemic.

[17] Khera and Xu (2022) also show that factors such as (1) the degree of digitalization in the public sector, (2) user trust in digital technologies and consumer data protection, and (3) lack of digital literacy due to aging could play a role in the adoption of digitalization.

[18] Costs of government regulations and lack of adequate infrastructure (such as electricity or internet) are also cited by firms in developing Asia as barriers to technology adoption, albeit to a lesser extent.

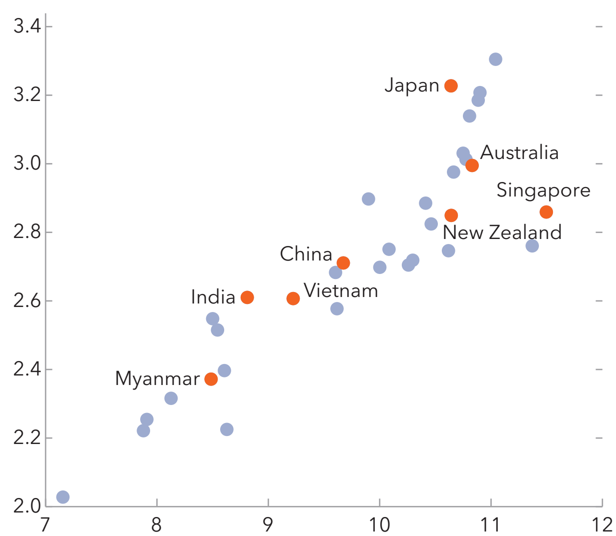
Figure 13. Major Reported Obstacles by Firms in Developing Countries



Source: WBES, 2006–20.
Note: Percentage of firms reporting any given option as the main obstacle to their business operations.

- *Management capabilities*. Adoption of new technologies and implementation of organizational changes require strong quality of management (Bloom and Van Reenen 2007). Results from the World Management Survey, however, highlight large variation in management quality across Asian countries, with some countries lagging behind peers at similar income levels (Figure 14) or those at the global frontier. Significant dispersion in management practices also exists within countries in both advanced and developing Asia, although weak management performance is more prevalent for smaller firms in developing countries (Figure 15). Large dispersion in management quality within Asian countries reflects underlying structural issues and firm specific characteristics.[19] This gap in management capabilities likely contributes to the innovation gaps between the region and the global frontier.

Figure 14. Management Scores
(Management scores in Y axis, logarithm GDP per capita in PPP in X axis)

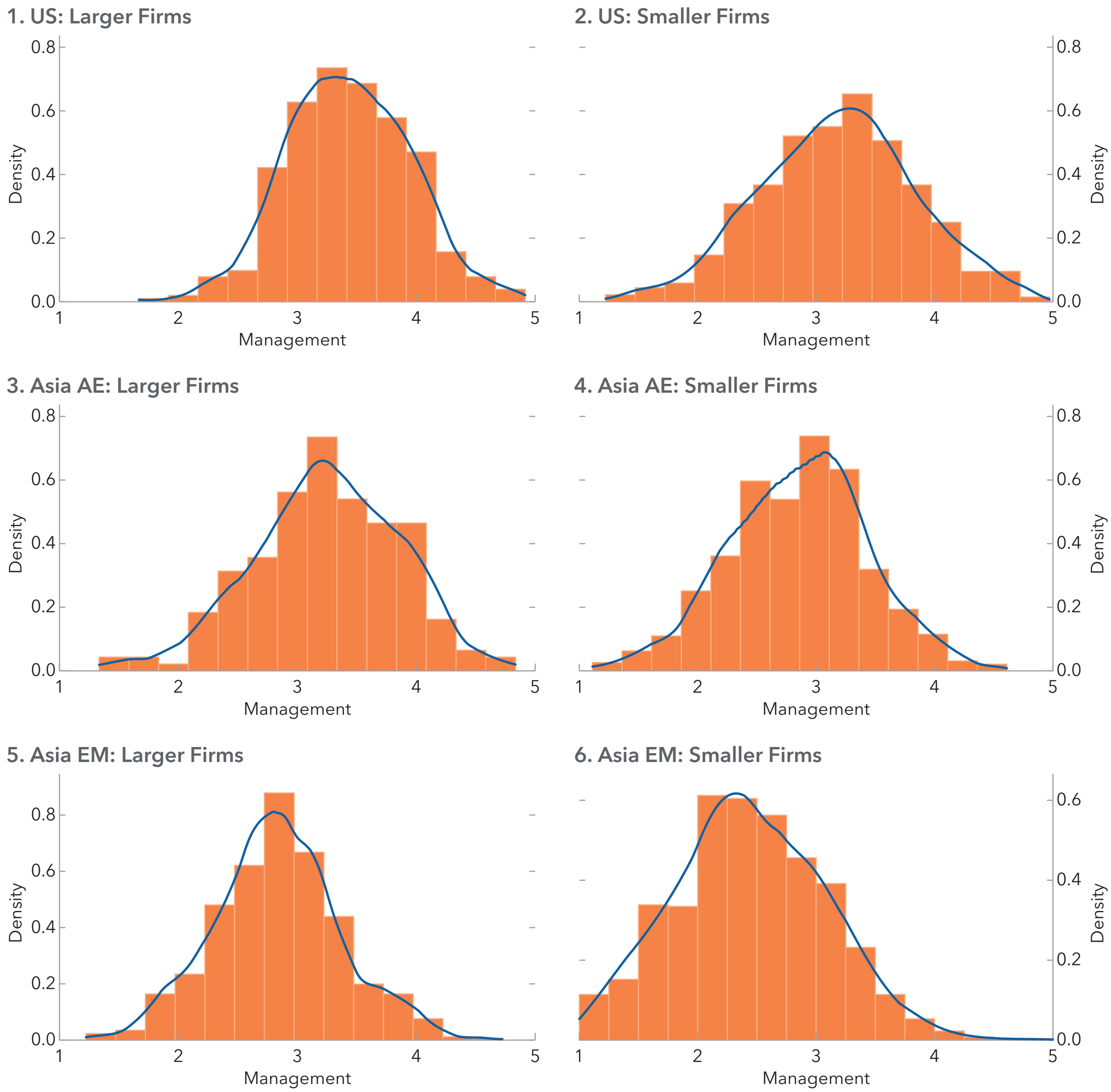


Source: IMF, World Management Survey.

- *Adequacy of skills*. A range of advanced skills are important in enabling innovation at the firm and country levels, with such skills becoming increasingly important as firms move from diffusion and technology adoption toward the technological frontier. However, firms in the region consistently report skills gaps

[19] For instance, firms exporting goods and services are exposed to global competition and tend to have better management practices compared to non-exporting firms. By contrast, family-owned and government-owned firms tend to be managed poorly.

Figure 15. Firm-Level Overall Management Scores in Asian Countries, by Firm Size
(Scale 0 to 5, 5 is best)



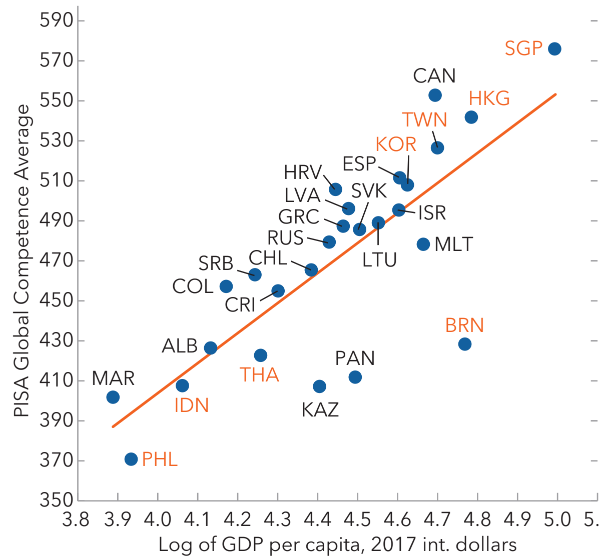
Sources: World Management Survey; and IMF staff estimates.
Note: The panels show distribution of firm-level management score from World Management Survey (2004-15). Lines represents kernel density estimation. Asia AE includes, Australia, Japan, New Zealand, and Singapore. Asia EM includes China, India, Myanmar, and Vietnam. Larger firms are firms that employ 500+ workers.

as serious impediments to their operations, as also reflected in variation in PISA scores in the region (Figure 16). More than 50 percent of innovating firms in ASEAN+3 countries cite a lack of managerial and leadership skills as a challenge when hiring new workers (World Bank 2021a). And more than half of all innovative firms in many of these countries cite the scarcity of interpersonal and communication, ICT, or technical skills as critical challenges when it comes to hiring. Educational achievement in developing Asian economies also tend to lag behind that of advanced economies.

- *Access to external knowledge and information.* Access to external knowledge—by using knowledge information services, tapping knowledge created in universities, or learning from other firms via trade flows or connections through global value chains—is an important driver of technology adoption. Flows of specialized information are particularly important for small businesses. Although firms in developing Asia can learn and improve their technological know-how through these different sources and have incentives to do so, access to information is oftentimes inadequate, particularly for small business, which tend to be less informed about the latest technologies available in the market. Filling this information gap is important to minimize entrepreneurs' uncertainty about technology adoption. As access to technology needs to be followed by its adoption to have the expected effects, facilitating information flows and reducing the perceived and actual cost of technological adoption, including through public policy, is key. Weaknesses in the legal environment in some developing countries, including lack of adequate legislations on data protection and cybercrime and ineffective enforcement mechanisms, hinder information sharing and confidence for technological adoption.

Figure 16. PISA Scores

(PISA scores in y axis, Log values in x axis)



Sources: OEDC; and IMF, *World Economic Outlook*.

3. How Can Innovation and Digitalization Help Close Productivity Gaps?

Aggregate TFP in an economy depends on not only the efficiency of individual firms or industries but also how inputs are allocated across them. Economic theory suggests that more productive firms should be more innovative and use more resources (capital and labor) than less efficient firms. Over time, less productive firms either become more efficient, or are replaced by more productive entrants. This process brings about capital and labor reallocation, which impacts measured TFP and output. Misallocation of resources, however, can arise if impediments exist to the movement of factors between heterogeneous firms (particularly young firms). This can give rise to persistent differences in the rates of return across firms and sectors, undermining aggregate TFP growth.

In this chapter, we focus on firm-level data, diving deeper into the determinants of productivity levels and innovation capacity across Asian firms prior to the pandemic. This can help shed light on longstanding structural challenges that have dragged down aggregate productivity growth and provide a roadmap of policies to address gaps. We begin by examining the relationship between innovation and productivity at the firm level in Asia and the rest of the world. We then turn to the drivers of productivity growth, discussing which characteristics lead some firms to be leaders in their sectors, and others to be laggards. In the third subsection, we zoom in on the drivers of firm-level innovation to identify which types of firms are more likely to push the technological frontier by introducing new products or processes. We conclude this chapter by reviewing its main takeaways.

To address these issues, we exploit different firm-level datasets, covering both frontier and non-frontier Asia. For advanced and emerging Asia, we rely on the Orbis database, covering firms in 16 different countries, distinguishing between Asia and rest of the world (see Appendix 1 for data sample). To capture the relationship between productivity and international trade (for example, due to imports of new technology or exposure to global competition, Keller 2004; Aghion, Bergeaud, and Van Reenen 2021), we merge the Orbis database with Zephyr to obtain information on FDI and mergers at the firm level. While allowing us access to detailed information, these data are skewed toward firms in more developed Asian economies. We complement this information by leveraging the latest waves of the WBES, which shed light on the link between innovation and productivity in emerging and developing Asia.[20]

A. Innovation and Digitalization as Engines for Productivity Growth

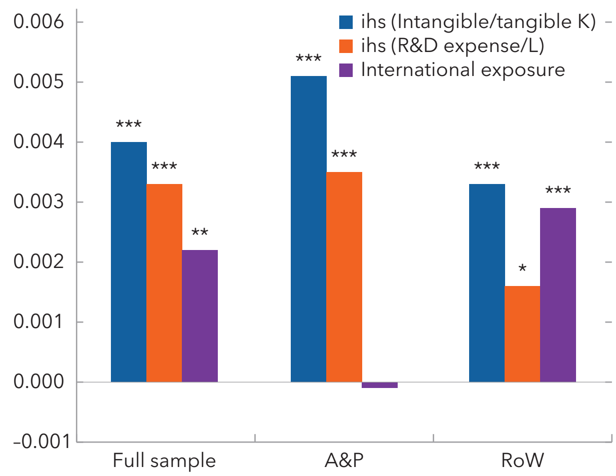
Firm-Level Evidence Focusing on Advanced and Large Emerging Market Economies

Innovation and digitalization are important drivers of firm-level productivity in Asia and elsewhere. The link between productivity and innovation intensity (measured as research and development expenses per worker) at the firm-level is well understood in the economic literature: higher R&D intensity leads to technological advances, which in turn increase TFP. Our results from a linear regression model (Figure 17, Annex Table 1.1) confirm this relationship. We also find that digitalization (proxied by the ratio of intangible to tangible

[20] The measures of TFP used in the paper are different across the two data sets due to differences in data availability. While Orbis allows for a better measure of firm-level TFP (as it tracks firms over time), WBES has a broader coverage across emerging market and developing economies. See Appendix 1 for more details on the data sets and a discussion on the different productivity measures used in the paper.

capital[21]) is a key driver of TFP, particularly for Asian countries. The digitalization of production processes can increase the efficiency of specific tasks, leading to gains in overall productivity. For example, Gal and others (2019) estimate that a 10 percentage point increase in the sector-wide adoption rate of cloud computing is associated with a 3.5 percent productivity increase for the average European firms after five years. Furthermore, complementary investment in skills and factors such as software and data, important parts of many firms' intangible capital, may be necessary to reap the benefits of digitalization (for example, van Ark 2016, Brynjolfsson and McAfee 2011). In contrast to physical capital, intangibles can be scaled-up easily at low costs and allow firms to grow rapidly. Studies from other regions have shown that firms that spend the most on intangible assets have the strongest productivity growth (see for example, Crouzet and Eberly 2018), and intangibles support the translation of technology into improved productivity (Mohnen, Polder, and van Leeuwen 2018).

Figure 17. Elasticity of Productivity (TFP) with Respect to Firm Characteristics



Sources: Orbis; Zephyr; and authors' calculations.
Note: $ihs(x) = ln(x + \sqrt{1 + x^2})$ indicates the inverse hyperbolic sine function. Because it quickly converges to $ln(2x)$, the coefficients can be interpreted as elasticities. Regressions include a firm and country-by-year fixed effects. Standard errors are clustered at the country-sector level and *, ** and *** indicate that coefficients are statistically significant at the 10%, 5%, and 1% levels, respectively (see Annex Table 1.1 for details).

Participation in international trade is positively associated with firm-level productivity, but this relationship is stronger for countries outside of Asia. This result confirms a positive correlation between international exposure (that is, firms that export their production or have received FDI) and higher productivity for a sample of firms in non-Asian countries, while the results are statistically insignificant for the sample of firms in Asia. There are several channels through which exposure to international trade can affect productivity, including self-selection (only productive firms choose to participate in international markets, since they possess the capacity to produce at larger scale); competition (unproductive firms entering a competitive market are eventually driven out); or learning (firms learn from foreign companies in the same market).[22] The smaller coefficient for Asian countries could be due to weaker spillovers from international participation. Another possibility is that firms compete in a different institutional environment, whereby the selection of firms that export their production is less related to productivity. Yet a third explanation could be that Asian companies are more (or less) likely enter and exit international markets, depending on the costs and benefits of doing so.[23]

Firm-level evidence for emerging and developing Asia also shows that innovative firms tend to be more productive than other firms. This evidence is based on regression analyses using firm-level data from the WBES, covering more than 8,000 firms in 19 emerging market economies and developing countries over 14

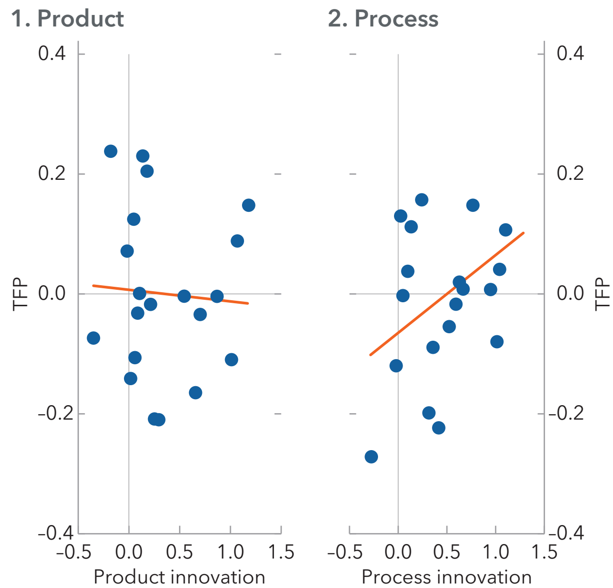
[21] We recognize that digitalization and the adoption of intangible capital are not necessarily the same. Digitalization encompasses the use of digital processes—including software and the adoption of new technologies—to increase the efficiency of production. Intangible capital is a broader concept that also includes brand value, some forms of innovation, marketing and managerial skills, and others. However, it remains the best proxy for digitalization as no direct evidence on the adoption of digital processes is currently available.

[22] See also Melitz (2003) and De Loecker and Warzynski (2012).

[23] Note that the presence of firm fixed effects and country-specific time effects imply that the coefficients shown here are identified using within-firm variation only. As a result, the impact of international exposure cannot be estimated for firms are either always or never exposed to international competition.

Figure 18. Innovation and Productivity

Figure 19. Productivity and Different Types of Innovation



Source: WBES, 2006–2020.
Note: Charts represent OLS regressions, with productivity as an outcome variable and innovation as a dependent variable. Firm age, size, location, R&D expenditure, share of high-skilled workers, imports/exports as a share of sales are included as controls, as well as country and year fixed effects. Each dot represents 50 data points.

years.[24] The outcome variable is firm-level productivity, regressed on a variable indicating whether the firm has innovated over the previous three years.[25] Innovation here is defined broadly as the introduction of new production processes or product lines, so that it includes firms adopting existing technology. In general, product and process innovation, including both new-to-market and new-to-firm innovation, is associated with both higher labor productivity and higher revenue TFP, controlling for firm-level and market characteristics (Figure 18 and Annex Table 2.1). The findings for this sample confirm earlier results using the WBES, focusing on a different subset of countries (Dabla-Norris and others 2012).

In developing Asia, the association between innovation and productivity level is stronger for process innovation than for product innovation (Figure 19, Annex Table 2.1). Product innovation is defined as the introduction of new products, new to the firm or even to the reference market, over the previous three years. Process innovation, by contrast, is the introduction of new means of production: the adoption of new technologies, machinery, ways of organizing business, managerial capabilities. Importantly, process innovation includes digitalization processes, for example the adoption of IT or e-commerce practices. E-commerce, in particular, has been shown to be a key driver of productivity growth in Asia (Kinda 2019). This result suggests firms in developing Asia do not need to be at the cutting-edge of innovative processes or produce innovation by discovery to benefit from innovation. The adoption of existing technologies and processes can lift many firms up the productivity ladder.

Productivity also depends on the share of workers with higher educational attainment and on the degree of R&D expenditure at the firm level (Annex Table 2.1). These variables can be considered as proxies for the likelihood of introducing non-imitative, cutting-edge innovation, or innovation by discovery. A range of advanced skills are important in enabling innovation at the firm and country levels. While R&D activities tend

[24] The sample includes the following Asian countries, surveyed in different years between 2006 and 2020: Cambodia, China, Fiji, India, Indonesia, Lao P.D.R., Micronesia, Mongolia, Myanmar, Nepal, Papua New Guinea, Philippines, Samoa, Solomon Islands, Sri Lanka, Thailand, Timor-Leste, Vanuatu, Vietnam.

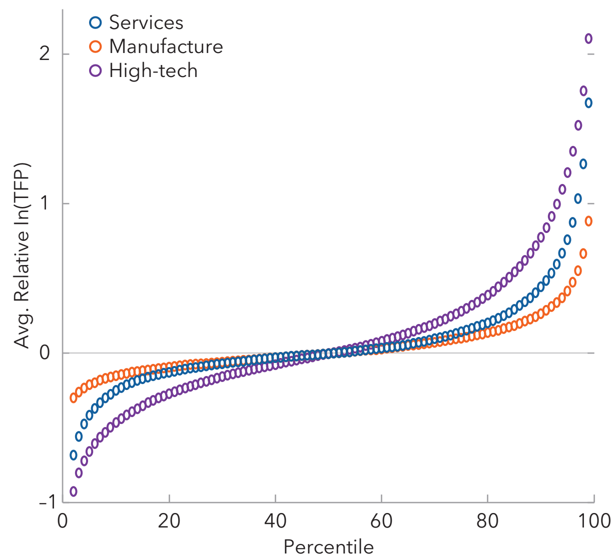
[25] See Appendix 1 for details on the construction of the TFP measure using the WBES.

to be concentrated at the very top of the productivity distribution, the availability of a skilled workforce has the potential to create gains across a broader spectrum of firms, including by raising managerial competence and the firms' capacity to absorb positive spillovers from innovative and higher-performing firms.

B. Firm Heterogeneity and Aggregate Productivity Growth in Asia

Aggregate productivity growth depends on both expanding the technology frontier and closing productivity gaps across firms. The previous section shed light on the characteristics that differentiate between high- and low-productivity firms, with a focus on innovation. However, a country's productivity growth performance depends on not only the TFP growth of firms at the technological frontier, but also how rapidly technology and innovation diffuse across firms within a country. Indeed, the productivity and technological divide between the leading and lagging firms in Asia is likely the consequence of slow diffusion within countries. In this context, assessing the extent of productivity dispersion and understanding its driving factors, including over time, are important policy issues. In what follows, we first examine the determinants of productivity dispersion within sectors, and the characteristics of laggard firms in Asian countries.

Figure 20. TFP Dispersions across Sectors



Sources: Orbis; and authors' calculations.

Large dispersion in productivity exists within narrowly defined industries, particularly in high-tech sectors and services. TFP in the most productive firms can be up to seven (≈ exp(2); see Figure 20) times bigger than in the median firm, even within narrowly defined sectors.[26] In addition, productivity dispersion in high-tech sectors and in services is considerably larger than in manufacturing (Figure 20).[27] This dispersion is not unique to Asian countries but could be an important contributor to the relatively low aggregate TFP growth observed in recent years. For instance, Andrews, Criscuolo, and Gal (2016) show that the aggregate productivity slowdown in many OECD countries reflects weaker productivity growth of firms outside of the top 5 to 10 percent of companies with the highest productivity. By contrast, productivity growth of top firms has been strong across many OECD economies, suggesting weaker technology diffusion from the "best to the rest."

Productivity dispersion tends to be higher in more digitalized sectors, and in sectors less exposed to international markets. To analyze the determinants of productivity dispersion in more detail, we look at the ratio between the 90th and 10th percentiles of the TFP distribution within 4-digit sectors, country, and year (90/10 TFP ratio). Consistent with the results above, productivity dispersion is considerably higher in high-tech sectors, followed by services and manufacturing. TFP dispersion tends to be larger in sectors where firms have a higher intangible-to-tangible capital ratio, and are less exposed to international competition, with both effects stronger in Asia than in the rest of the world (Table 1). One potential explanation for those results

[26] The relative ln(TFP) for each firm in our sample is defined by the difference between the firm's log productivity and the median log productivity in the firms' (4-digit) sector each year: $ln(TFP_i) - ln(TFP^{med}_{s(i)})$. All firms are then sorted according to their relative ln(TFP) and binned into percentiles, which are illustrated Figure 20.

[27] High-tech sector is defined as ICT; professional, scientific, and technical services; manufacturing of computers and electrical/electronic products; manufacturing of chemicals; and manufacturing of pharmaceuticals.

Table 1. Regression of 90/10 TFP Ratio (by country-sector-year) on Sector Characteristics

	(1) A&P	(2) A&P	(3) RoW	(4) RoW
Services	0.5552*** (0.0958)	0.5298*** (0.0959)	0.0024 (0.0902)	0.0769 (0.0953)
Manufacture	−0.5424*** (0.0719)	−0.5545*** (0.0730)	−1.1494*** (0.0765)	−0.9813*** (0.0842)
High-tech	0.9193*** (0.1274)	0.8176*** (0.1291)	1.5476*** (0.1326)	1.6216*** (0.1342)
Invests R&D		−0.1181 (0.3289)		0.0428 (0.4990)
Digitalization (ihs[Intangible/Tangible K])		0.1246*** (0.0321)		−0.0694** (0.0295)
International Exposure		−1.4188 (1.2702)		−0.8006*** (0.1785)
Observations	25,919	25,875	53,480	53,480
Within R^2	0.1846	0.1897	0.1795	0.1839

Sources: Orbis; Zephyr; and authors' calculations.

Note: All specifications include country and year fixed effects. Standard errors are shown in parenthesis and clustered at the country-sector (4-digit) level. *, ** and *** indicate that coefficients are statistically different from 0 at the 10%, 5%, and 1% levels, respectively. ihs represents the inverse hyperbolic sine function, $ihs(x) = ln\left(x + \sqrt{1 + x^2}\right)$. A&P = Asia and Pacific; RoW = rest of the world.

is that higher digitalization provides larger benefits for firms that are already highly productive, leading to an increase in TFP dispersion. In contrast, exposure to international markets might force unproductive firms out of the market, decreasing the TFP dispersion. In both cases, however, we would see an increase in average productivity, as predicted by our results in the previous section.

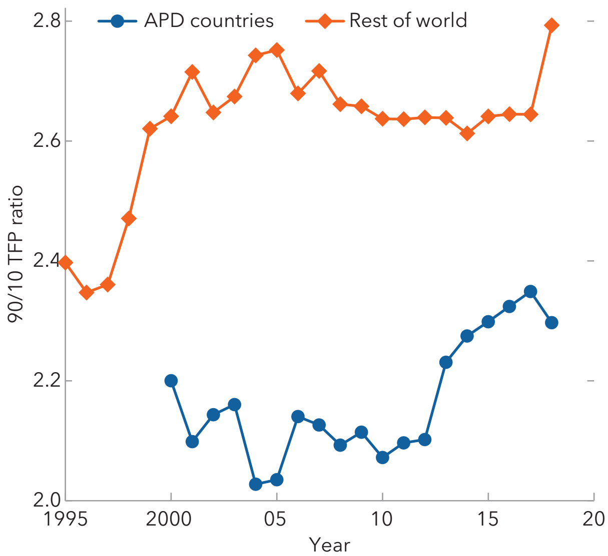
Productivity dispersion has increased over time. Plotting the 90/10 TFP ratio over time highlights the fact that productivity dispersion in Asia, despite being lower than in our sample of advanced economies, has increased in recent years (Figure 21). In addition, this increase has been much more pronounced in high-tech sectors, compounding on its already higher levels of dispersion (Figure 22). Given that large dispersion in firm-level productivity can hold back aggregate productivity, it is important to understand what characteristics are associated with the firms at the bottom of the TFP distribution. We discuss this in the next chapter.

Who Are the Laggard Firms Holding Back Aggregate Productivity?

Understanding the characteristics of "laggard" firms can help shed light on the impediments to firm growth and productivity in frontier and emerging Asia. Following OECD (2020), this paper defines laggard firms as those in the bottom 40 percent of the productivity distribution within each country-year-sector. To understand the characteristics that are most associated with laggard firms, we estimate a linear probability model, where the dependent variable is a firm-level indicator for whether each firm is classified as a laggard in any given year. This allows us to determine the extent to which different features affect the likelihood that a firm is classified as a laggard. We discuss our findings below.

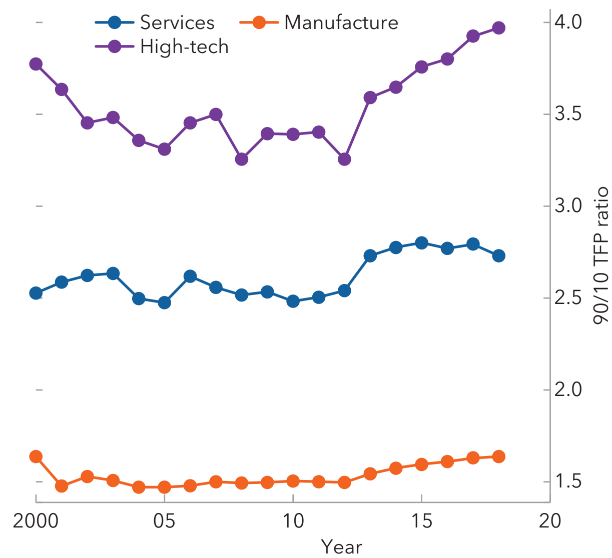
Laggard firms tend to be smaller and older. Our empirical results highlight that laggard firms tend to be small and old, both in Asia and in the rest of the world (Table 2). Plotting the average size (number of employees) and age of firms in each percentile of the relative productivity distribution shows that productivity and size are closely linked, but productivity and age have a nonlinear relationship (Figure 23). Very

Figure 21. TFP Dispersion over Time



Sources: Orbis; and authors' calculations.

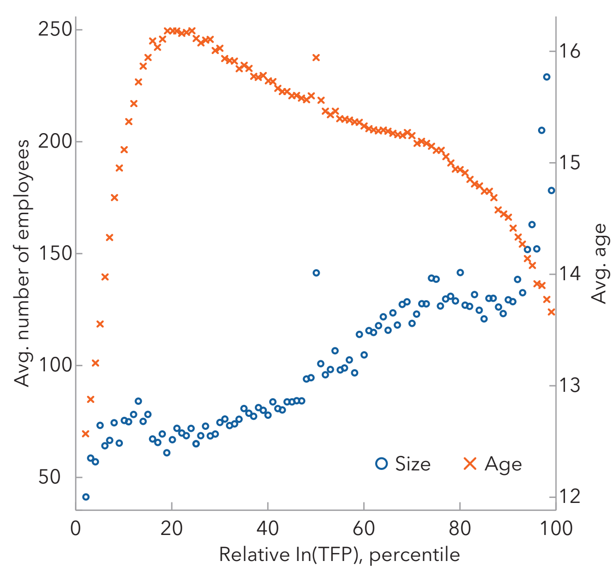
Figure 22. TFP Dispersion by Sector



Sources: Orbis; and authors' calculations.
Note: Includes only Asia and Pacific countries.

young firms tend to be financially constrained and often fail, as they are unable to realize productivity growth (Haltiwanger and others 2017). However, the relationship between age and productivity quickly peaks, and we see a negative correlation between the two variables outside of the bottom quintile of the TFP distribution: as firms age, they can become less innovative, which can lead to them eventually being replaced by younger competitors (Akcigit and Kerr 2018).

Figure 23. Firm Size and Age by Relative Productivity



Sources: Orbis; and authors' calculations.

C. Closing Productivity Gaps

What Drives Innovation (by discovery) at the Frontier?

Innovation by discovery is a matter of selected few. Only a small share of firms registers any R&D expenses across all years. In fact, only about 1 percent of firms have positive R&D expenses in the sample of countries.[28] Given the relevance of R&D to productivity growth, it is worthwhile investigating which firms invest in R&D and the drivers of such investments. We follow a similar empirical approach as above, estimating a linear probability model in which the dependent variable is a firm-level indicator that equals one if a firm has registered positive R&D expenses in at least one year during our sample.

[28] This share increases to about 1.5 percent in Asian countries.

Table 2. Regression of Laggard Indicator on Firm Characteristics

	(1) A&P	(2) A&P	(3) RoW	(4) RoW
ln(Employment)	−0.0212*** (0.0047)	−0.0112** (0.0053)	−0.0209*** (0.0035)	−0.0168*** (0.0035)
Age	0.0042*** (0.0005)	0.0050*** (0.0006)	0.0015*** (0.0003)	0.0012*** (0.0003)
ln(Employment) X Age	−0.0004*** (0.0001)	−0.0005*** (0.0001)	−0.0003*** (0.0001)	−0.0002*** (0.0001)
International Exposure		−0.0334*** (0.0106)		−0.0481*** (0.0053)
R&D investment (ihs[R&D Expense/L])		−0.0168*** (0.0012)		−0.0084*** (0.0009)
Digitalization (ihs[Intangible/Tangible K])		−0.0221*** (0.0015)		−0.0095*** (0.0006)
Number of Observations	7,245,791	6,595,033	12,212,401	12,157,864
Within R^2	0.0077	0.0184	0.0039	0.0080

Source: Orbis; Zephyr; and authors' calculations.

Note: All specifications include a sector fixed effect and a country-by-year fixed effect. Standard errors are shown in parenthesis and clustered at the country-sector (4-digit) level. *, ** and *** indicate that coefficients are statistically different from 0 at the 10%, 5%, and 1% levels, respectively. ihs represents the inverse hyperbolic sine function, $ihs(x) = ln\left(x + \sqrt{1 + x^2}\right)$. A&P = Asia and Pacific; RoW = rest of world.

Firms that invest in R&D tend to be larger and pay higher wages. The estimates show a positive correlation between the probability of investing in R&D and employment as well as wages in a firm (Appendix Table 1.3). This suggests that firms with a large and qualified workforce are more likely to invest in R&D, which is not surprising. It also suggests that one important bottleneck for firms to invest in innovation is the ability to attract qualified workers into their ranks, as suggested by Van Reenen (2021). We also note that this relationship is robust to the inclusion of gross profits, equity, and debt (as proxies for financial or cash constraints) for each firm in the regression, as well as the inclusion of our direct measure of TFP.

R&D-intensive firms also tend to have higher capital intensity, be more digitalized, and are more likely to operate in international markets. This result corroborates the fact that R&D tend to be more prevalent in high-tech sectors, highlighting the close association between innovation and digitalization. R&D-intensive firms are more likely to be exposed to international markets, either through exports or through FDI. This association could happen through many channels. These include: (1) selection, as high productivity firms self-select into expanding their market to other countries; (2) learning/technology transfer from other firms, for example through FDI, partnerships, or by participating in a larger production chain; and (3) competition from foreign companies, which might push firms to innovate in order to move ahead of their competitors (*escape competition*).[29]

Tax incentives and macroeconomic stability can encourage innovative investment. The literature points to the effectiveness of government support measures in stimulating private innovative investment. In their survey of literature, Hall and Van Reenen (2000) and Becker (2015) find that R&D tax credits have a positive

[29] Competition could also have the opposite effect on innovation, as it increases the likelihood that firms are replaced by competitors, which decreases the expected gains from developing a new product (Aghion and others 2005, Akcigit and Melitz 2021).

and significant effect on R&D expenditure.[30] Akcigit and others (2018) argue that such policies in the United States were an effective response to foreign competition, leading to much higher welfare gains than the introduction of tariffs would. In addition, R&D tax credits can be used as an incentive for inventors and firms to locate in the same places, benefitting from agglomeration spillovers and increasing aggregate innovation (Sollaci 2022). An empirical analysis using Australian firm-level data finds heterogenous effects of tax incentives across firm groups (Box 2).[31] Specifically, tax incentives tend to have higher stimulative effects on innovative investment for smaller firms and those in the manufacturing sector. Recent studies have also highlighted that having well-designed R&D tax incentives is important to benefit from their positive effects (Guceri and Liu 2019, Chen and others 2020).[32] In contrast, macroeconomic uncertainty tends to weigh on innovative investment, particularly for fast-growing companies.

Box 2. Firm-Level Determinants of Intangible Investment: Evidence from Australia

This box uses Australian firm-level data to shed light on the heterogenous impact of uncertainty and government tax incentives on intangible investment of different firm groups. The Australian government has offered R&D tax incentives since 1985, with a major change of the scheme in 2011 (Bakhtiari and Breunig 2018). A number of changes in the R&D tax incentives were also introduced in 2021, which include the increase in R&D expenditure ceilings. In this box, we employ an R&D investment model similar to Bloom (2007) and augment it with the R&D tax incentive, interacted with firm characteristics. The model can be written as follows:

$$
\begin{aligned}
ITA_{i,t} = {} & \alpha_i + \alpha_t + \beta_1 \Delta Sales_{i,t} + \beta_2 \sigma_{i,t} + \beta_3 \sigma_{i,t} * \Delta Sales_{i,t} + \beta_4 ITA_{i,t-1} + \beta_5 \sigma_{i,t} * ITA_{i,t-1} \\
& + \beta_6 ExternalFinance_{i,t} * Incentive_{t-1} + \beta_7 Manufacturing_{i,t} * Incentive_{t-1} + \beta_8 Small_{i,t} \\
& * Incentive_{t-1} + \beta_9 High\ Future\ Growth_{i,t} * Incentive_{t-1} + \varepsilon_{i,t}(X)
\end{aligned}
$$

where $ITA_{i,t}$ denotes the growth rate of intangible capital for firm i at time t, $\Delta Sales_{i,t}$ denotes the growth rate of sales, $\sigma_{i,t}$ denotes firm-level uncertainty proxied by the volatility in weekly stock returns of the firm (annualized). In addition, the model incorporates lagged government tax incentives as a share of GDP $Incentive_{t-1}$, interacted with various dummy variables capturing firm characteristics. $ExternalFinance_{i,t}$ dummy takes value 1 if firms have higher external finance dependence (above median), and $Manufacturing_{i,t}$ and $Small_{i,t}$ are dummy variables for the manufacturing sector and smaller firms (asset size below 25th percentile of the sample). High future growth firms ($High\ Future\ Growth_{i,t}$) are proxied with firms with higher-than-median Tobin's Q. We employ annual Australian firm level data obtained from IMF Corporate Vulnerability Unit Database, which is based on the Thomson Reuters Worldscope database. Data are from 2001 to 2018 and include the nonfinancial sector.

[30] Estimates of the effect R&D tax incentives on welfare require a cost-benefit analysis. While many studies show a net positive impact of R&D tax credit (for example, Foreman-Peck 2013 and Russo 2004) some studies point to limited or potentially negative effects of R&D tax incentives, depending on assumptions (Parsons and Phillips 2007). This suggests the need for careful design of these schemes and continuous cost-benefit analyses.

[31] Using cross-country data on the manufacturing sector of nine OECD countries for 1979–97, Bloom, Griffith, and Van Reenen (2002) estimate a long-term elasticity of R&D with respect to its user cost and find that R&D tax incentives are generally effective. Using European firm-level data, Hussinger (2008) and Cerulli and Potì (2012) find positive effects of government-funded R&D on private R&D investment. Other strands of literature point to adverse effects of uncertainty on R&D investments, including Bloom (2007).

[32] Tax incentives should also be assessed against their costs. For instance, they may not be the most effective instruments in developing countries with limited fiscal space and facing structural issues such as weak infrastructure or low human capital.

Box 2. Firm-Level Determinants of Intangible Investment *(continued)*

The results point to positive impacts of tax incentives, with some heterogeneity across firm groups. The firm-level regression suggests that the effects of tax incentives depend on firm size, sectors, financing structures, and viability (Box Table 2.1). In particular, when aggregate tax incentives are higher, these tend to benefit smaller firms who increase intangible capital by a larger amount. This result is consistent with the existing literature, such as Lach (2002), OECD (2020), and Bakhtiari (2021), which finds that subsidies for small firms have a strong stimulative effect after the first year of subsidies. Hall, Lotti, and Mairesse (2009) argue that SMEs that have not conducted R&D before are

Box Table 2.1. Determinants of Firm-Level Intangible Investments in Australia

	(1)	(2)	(3)	(4)	(5)
Dependent Variable: Growth Rate of Intangible Capital					
Sales Growth	.2464*** (.0609)	.2486*** (.0610)	.2510*** (.0612)	.2509*** (.0611)	.2497*** (.0612)
Uncertainty	−0.0251 (.0516)	−0.0333 (.05067)	−0.0230 (.05072)	−0.0360 (.05094)	−0.0186 (.0514)
Sales Growth* Uncertainty	−.3318*** (.1071)	−.3347*** (.1071)	−.3354*** (.1076)	−.3332*** (.1075)	−.3358*** (.1076)
Uncertainty* Lagged Dependent Variable	1.5171*** (.0655)	1.5174*** (.0653)	1.5183*** (.0653)	1.5212*** (.0654)	1.5173*** (.0653)
High Ext. Finance Dep.* RD tax incentives (–1)	.3279*** (.1094)	.3267*** (.1097)			
Manufacturing* RD tax incentives (–1)	1.1048* (.6241)		1.1420* (.6479)		
Small* RD tax incentives (–1)	1.0199*** (.4211)			1.1134*** (.4310)	
High Exp. Growth* RD tax incentives (–1)	0.2529*** (.1221)				0.2823*** (.1245)
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
R^2	0.7597	0.7614	0.7588	0.7606	0.7623
Sample Period	2001–18	2001–18	2001–18	2001–18	2001–18
Number of Observations	4,006	4,006	4,006	4,006	4,006

Source: IMF staff estimates.

Note: Data are from IMF CVU firm database. Reports results for estimates of the equation described in the box and its variants for Australian firms. R&D tax incentives are in percent of GDP. High External Finance Dependence is a dummy variable for firms with higher external finance dependence (measured as Rajan-Zingales finance dependence index), Manufacturing is a dummy variable for manufacturing firms, Small is a dummy variable for smaller firms (sales size below 25 percentile of the sample), and High Expected Growth is a dummy variable for firms with higher expectations for future growth (Tobin's Q above median of the samples). The regression controls for the lagged dependent variable. Some outliers of dependent variables and independent variables are excluded. Standard errors are clustered at firm level. *, **, and *** indicate significance at the 10, 5 and 1 percent level, respectively.

Box 2. Firm-Level Determinants of Intangible Investment *(continued)*

more likely to start investing in R&D if they receive a subsidy. Quantitatively, our results suggest that the positive impact of increasing tax incentives by 0.1 percentage point of GDP (nearly doubling) on the growth of intangible capital next year is about 10.2 percentage points stronger for SMEs. The results also suggest that industry type and financing structures play a role, with the manufacturing sector and firms more dependent on external financing seeing a larger increase in intangible capital when aggregate incentives increase. In addition, firms with higher expectations for growth (proxied by higher Tobin's Q) tend to increase intangible investment more in response to government tax incentives than less viable firms.

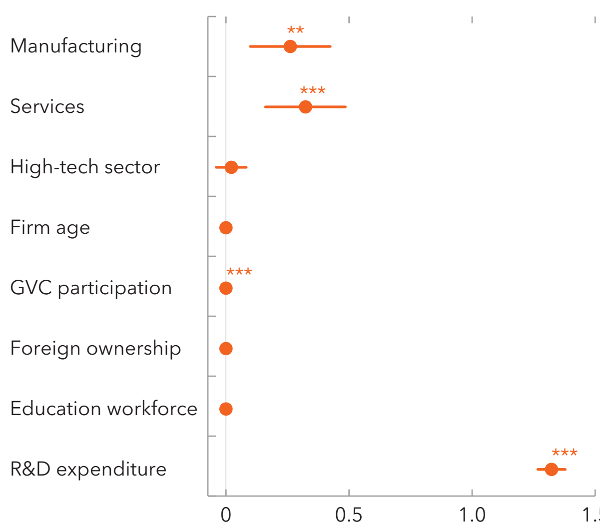
In addition, the results highlight some effects of uncertainty on intangible investment. As Bloom (2007) suggests, uncertainty tends to make intangible investment less responsive to changes in business situations and makes firms reluctant to change their investment plans, leading to more persistent intangible investment.

What Drives Adoption (Innovation by Diffusion) in Developing and Low-Income Asia?

As in advanced and emerging Asia, R&D investment is a strong predictor of the likelihood of innovating in developing Asia (Figure 24, Appendix Table 2.2). While R&D aims at the development of new products, or innovation by discovery, innovation can also occur via the adoption of existing processes or technologies. This distinction is particularly relevant for developing Asia, where not all firms may have the capital, adequate access to financing or skills to introduce products which are new to their reference markets. In fact, technological diffusion via the adoption of existing technology (or licensing from foreign firms) may be a more cost-effective path to the improvement of productivity levels, especially for financially constrained SMEs (World Bank 2021b).

Both product and process innovation are more likely to occur in larger firms, particularly those located in capital cities (Figure 25; Appendix Table 2.2). Geographic concentration of innovative activity is a feature of developing Asia, with high degrees of spatial clustering of startups and venture capital investment.[33] Firms located in cities are also more likely to benefit from agglomeration effects, including positive spillovers such as technological diffusion by proximity and imitation. This implies that despite a level of technological achievement in major cities that might rival that of higher-income countries, low

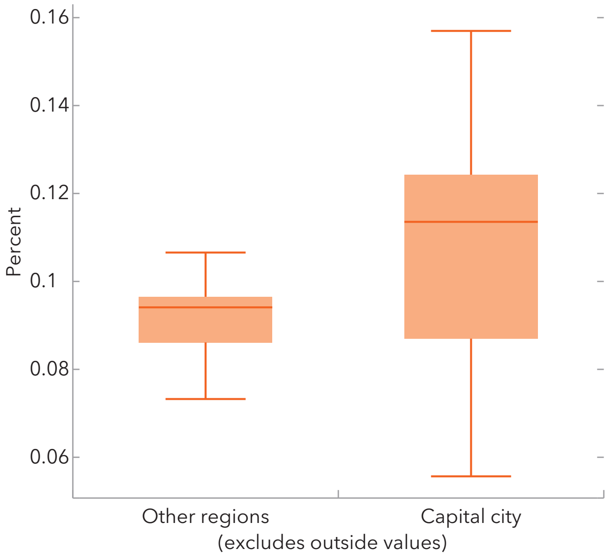
Figure 24. Characteristics of Innovators in Emerging Market Economies and Developing Countries



Source: WBES, 2006–2020.
Note: Regressions results based on a linear probability model, with innovation as a dependent variable. Additional controls include country and year fixed effects.
*$p<.05$, ** $p<.01$, *** $p<.001$.

[33] Prud'homme and Zhang (2019) discuss spatial concentration of innovation in China.

Figure 25. Share of High-Productivity Firms
(Proportion of firms in the region)



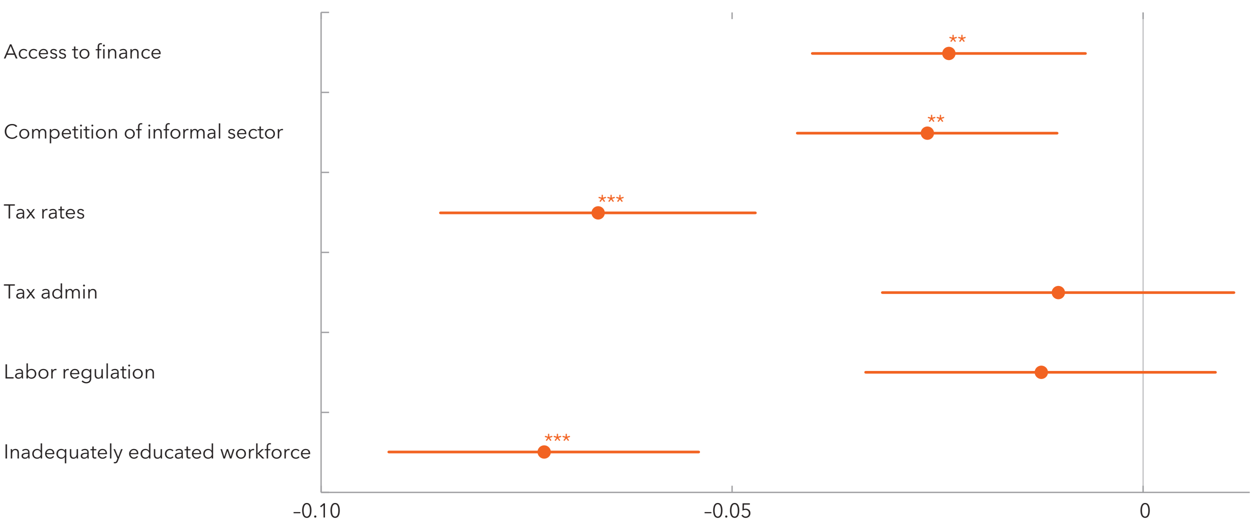
Source: WBES, 2006–20.
Note: High-productivity firms are defined as those in the top decile of the country-year productivity distribution.

levels of technological advancement in lagging areas mean that, in aggregate, emerging market economies and developing countries in Asia are not as technologically advanced as high-income economies in Asia or elsewhere in the world.

Innovation in emerging and developing Asia is associated with higher trade integration and participation in GVCs (Figure 24, Appendix Table 2.2). Firms more integrated in GVCs, proxied by the value of imports and exports as a share of annual sales, are also more likely introduce product and process innovation. As in advanced economies, greater exposure to competition from abroad and dynamics of agglomeration and diffusion originating domestically may be important drivers of productivity growth in emerging and developing Asia (Amiti and Konings 2007; Goldberg and others 2010; Aghion and others 2018, 2019; Coelli and others 2022).

Inadequate access to financing opportunities, lack of a skilled workforce, and competition from the informal sector are frequently cited as the strongest impediments to growth by firms that do not innovate (Figure 26). Many firms also report that high tax rates are an obstacle to their business operations.[34] While the survey questions do not elaborate on the channels underlying these obstacles, it is possible to infer that a lack of financing opportunity and high

Figure 26. Innovation: Obstacles in Developing Asia



Sources: WBES, 2006–20.
Note: Regressions results based on linear probability model; innovation as a dependent variable. Additional controls include country and year fixed effects, firm age, sector, size, R&D expenditure, ownership status, and GVC participation.
p*<.05, ** *p*<.01, * *p*<.001

[34] The obstacles variables are categorical variables, taking value 1 if the firm reports a specific item (such as high tax rates) as a main obstacle to business operations; 0 otherwise.

tax rates may reduce resources available for exploring opportunities to grow and innovate. Self-reported constraints, or firms' subjective perceptions of impediments to growth are a good meter to identify areas of potential policy intervention.

Closing Productivity Gaps: Which Factors Matter Within Countries and Sectors?

Assessing the factors that impact TFP growth at different points of the firm productivity distribution can help identify policies for closing productivity gaps. As illustrated above, productivity dispersion across firms within our sample is large, suggesting potential resource misallocation (Hsieh and Klenow 2009). As a result, we examine how firm-specific characteristics, including a firm's distance to the technology frontier (Aghion and Howitt 2006; Acemoglu, Aghion, and Zilibotti 2006), can affect its productivity growth each year. The key intuition is that firms that are farther away from the global technological frontier tend to grow mainly through technology adoption and imitation, whereas firms closer to the frontier rely more on innovation. Therefore, the set of policies aimed at sustaining productivity growth across firms, industries, and countries could vary depending on their locations vis-à-vis their technological frontiers. To capture those heterogeneous effects, we split firms into groups based on their position in their country-sector-year-specific distribution of TFP and allow all coefficients to vary by group. Frontier firms are defined as those in the top decile of the TFP distribution of their sector, while non-frontier firms are split into 3 subgroups: top (90th–60th percentiles), middle (60th–30th percentiles), and bottom (below the 30th percentile).[35]

Firms tend to benefit from productivity spillovers from their peers at the frontier, and there is some evidence of convergence. TFP growth across firms is spurred by developments at the technological frontier (captured by the positive coefficient of TFP growth at the frontier), suggestive of significant productivity-enhancing knowledge spillovers from the technological leaders (Table 3).[36] Spillovers seem to be strongest for the top (non-frontier) firms, indicating that these firms are better positioned to take advantage of innovation and growth at the frontier. Furthermore, we find evidence that productivity growth across firms is driven by a catching-up process associated with the gradual adoption of newer technologies. In particular, the pace of convergence of non-frontier firms increases with the distance to the technological frontier (measured by the positive coefficient of the TFP gap). However, this effect is nonlinear: as firms grow farther from the technological frontier, they also become more likely to lack the capacity to effectively adopt new technologies created by firms in the frontier. At this point, increasing the TFP also decreases productivity growth, as captured by the negative coefficient on the TFP gap squared. Indeed, this is how the data can simultaneously support increasing TFP dispersion (Figure 21) and catching-up of non-frontier firms. Note that this non-linearity is particularly pronounced in non-Asian countries.

Digitalization and international competition foster TFP growth, but largely for non-frontier firms at the top group. Our results show that an increase in digitalization (intangible capital) is associated with higher productivity growth, but the impact is largest for non-frontier firms that are closer the technology frontier (that is, top group, followed by middle group, and finally no discernible effect for the bottom group; see Table 3).[37] Looking at how exposure to international markets affects productivity growth, we find a positive effect for non-frontier firms in the top group, but negative effects for firms in the middle and bottom groups of the country-specific firm productivity distribution. This result again corroborates the idea that firms in the bottom of the productivity distribution are somehow worse at learning from more productive firms

[35] The details of the analysis, as well as the different regression specifications, are discussed in Appendix 1 (see also Appendix Table 1.3).

[36] Our regressions include both firm fixed effects and country-by-year fixed effects, which control for permanent firm-specific differences and country-specific trends in TFP growth. However, we cannot rule out that our results are contaminated by country-and-sector specific trends, as their measure of productivity growth at the frontier varies at this same level. In other words, we are unable to distinguish between the effects of spillovers from frontier firms and unobserved country-by-sector trends that might impact both frontier and non-frontier firms at once.

[37] These productivity gains are more than doubled for high productivity firms in comparison to low productivity firms.

Table 3. Distance to the Frontier and Firm Productivity Distribution

Variable	Firm Group	Asia and Pacific			Rest of World		
		(1)	(2)	(3)	(1)	(2)	(3)
TFP growth rate at frontier	Top	***	***	***	***	***	***
	Middle	***	***	***	***	***	***
	Bottom	***	***	***	***	***	***
Gap relative to frontier	Top	***	***	***	***	***	***
	Middle	***	***	***	***	***	***
	Bottom	***	***	***	***	***	***
Gap relative to frontier - squared	Top				***	***	***
	Middle	***	***				**
	Bottom	***	**	*			
International exposure	Top		***	***		***	***
	Middle		***	***		***	***
	Bottom		***	***		***	***
Intangible/tangible capital ratio	Top		***	***		***	***
	Middle			***		***	***
	Bottom		***			**	
Sectoral std. deviation: log-TFP	Top			***			***
	Middle			***			***
	Bottom			***			***
Number of observations		7,556,396	6,939,968	6,900,854	14,448,480	14,407,254	14,401,055
R^2		0.2	0.1992	0.2418	0.2	0.2005	0.2351

Positive Zero Negative Not included in specification

Sources: Orbis; Zephyr; and authors' calculations.
Note: *, ** and *** indicate that coefficients are statistically different from 0 at the 10%, 5%, and 1% levels, respectively. All regressions include a firm fixed effect and a country-by-year fixed effect. Standard errors are clustered the country-sector (4-digit) level.

or adapting to tougher competition, compared to firms at the top. It also strongly suggests that policies that foster greater international integration might have radically different effects on firms belonging to different groups.

Lower resource misallocation is beneficial for firms of all types. Exploring how productivity growth at the firm level might be affected by the sectoral productivity dispersion yields stark results: increasing the standard-deviation of log-productivity by 0.01 (equivalent to a 3.7 percent increase in log-standard deviation for the median sector[38]) would reduce the average firm's TFP growth by 1.5 to 2.1 percentage points (see Appendix Table 1.3). Following Hsieh and Klenow (2009), we interpret this productivity dispersion as a measure of resource misallocation.[39] As such, this result suggests that firms in sectors with higher resource misallocation grow considerably more slowly, potentially because capital and/or labor are locked up in unproductive firms. In addition, note that this effect is more pronounced for non-frontier firms in the middle and bottom groups, suggesting that small (and possibly young) firms are less able to adapt to the market distortions that generate resource misallocation. Finally, we caveat our findings by noting that there are

[38] This number is obtained by calculating, for each country-sector-year, the value of a constant k such that $k_{c,s,t}\, sd(ln(TFP_{c,s,t})) = sd(ln(TFP_{c,s,t})) + 0.01$. After obtaining the distribution of such constants, we find that the median value of k is approximately 1.037.

[39] Intuitively, the argument proposed by Hsieh and Klenow (2009) is as follows: if all firms are operating in a frictionless market, then the marginal product of all factors should be equated across firms. However, market distortions (for example lack of access to capital) will drive a wedge between those marginal products, as some firms will face higher input costs than others. Importantly, those distortions generate a higher dispersion in firm-level productivity, which is what allows us the use TFP dispersion as an indicator of resource misallocation. Mathematically, it can be shown that a firm's measured TFP is proportional to the wedges W_i (representing the market distortions) that it faces. Thus, the standard deviation of log-TPF is in fact a measure of the extent to which resources are misallocated across firms: $sd(ln(TFP_i)) = sd(ln(C \times W_i)) = sd(ln(W_i))$.

other potential sources of productivity dispersion, such as firm-specific shocks and varying degrees of market power across firms. However, the patterns we see in the data are decidedly consistent with the misallocation interpretation.

D. Conclusions and Key Takeaways

Using firm-level data from a broad spectrum of Asian economies, the paper has identified some of the mechanisms linking innovation, digitalization, and productivity in the region. The following are their key findings:

- Asian firms that are more innovative tend to be more productive: this result holds at all levels of development, and sectors and controlling for various firm characteristics. Preliminary evidence indicates, however, that firms do not need to be at the technological frontier to benefit from innovation: the adoption of existing technologies is often sufficient to increase productivity levels, at least for firms operating in emerging and developing Asia.

- The productivity distribution within countries in Asia is often bimodal, with a few top performers coexisting with a much larger share of laggard firms. Laggard firms tend to share a few characteristics: they are smaller, older, and less likely to participate in international trade. They are also less likely to invest in research and development and to digitalize their activities.

- Innovation is highly concentrated in a narrow subset of firms: across all levels of economic development, innovation tends to be a prerogative of larger and more capital-intensive firms, which invest in R&D and have strong links with foreign markets through international trade. A number of key areas for policy intervention are identified. Improving access to financing opportunities and increasing educational attainment emerge as keys to foster innovation in the region. To make the most of existing and emerging technologies, it will be important for firms in emerging and developing Asia to continue strengthening their innovation capabilities—first by upgrading their processes using digital technologies, and then by adopting more sophisticated technologies. The dividends from doing so, in terms of productivity gains, can be large.

- Significant productivity-enhancing spillovers accrue from the technological leaders (frontier firms) in Asia and benefit most firms that are positioned at the next level (top non-frontier firms). In the same vein, the impact of digitalization on productivity growth is higher for non-frontier firms closer to the technology frontier. However, laggard firms in Asia appear to be falling further behind. This highlights the importance of participation in international trade, including GVCs, and strengthening supplier linkages to facilitate technology diffusion. In addition, policies should focus on facilitating greater firm entry and exit, capitalizing on the potential of new firms while reducing the presence of stagnant and unproductive ("zombie") firms in the economy.

4. Supporting Productivity Growth with Innovation and Digitalization

Innovation and digitalization will be paramount to promote post-pandemic durable growth in Asia. Building on the findings above, this chapter provides a comprehensive policy toolkit to help policymakers achieve this goal, taking into consideration country circumstances and firms' positions in the innovation and productivity distribution. Many countries in Asia have already introduced policy measures to revive productivity growth and avoid scarring from the pandemic, but more can be done.

Post-pandemic recovery offers an opportunity to boost productivity. Although Asian frontier economies have become a global powerhouse of innovation, there is scope to further push the technology frontier and improve the quality of innovation. In non-frontier economies, innovation is still constrained by institutional and infrastructure bottlenecks. Furthermore, cross-border and within-country innovation spillovers have slowed, calling for increased efforts to speed-up technology diffusion. Policy actions are also needed to accelerate digitalization and address digital inequalities in the wake of the pandemic. Countries and firms at different stages of innovation ladder require customized policies to foster innovation and promote resource reallocation (Figure 27). This chapter aims to provide a comprehensive toolkit for policy makers.

A. Overarching Policy Priorities

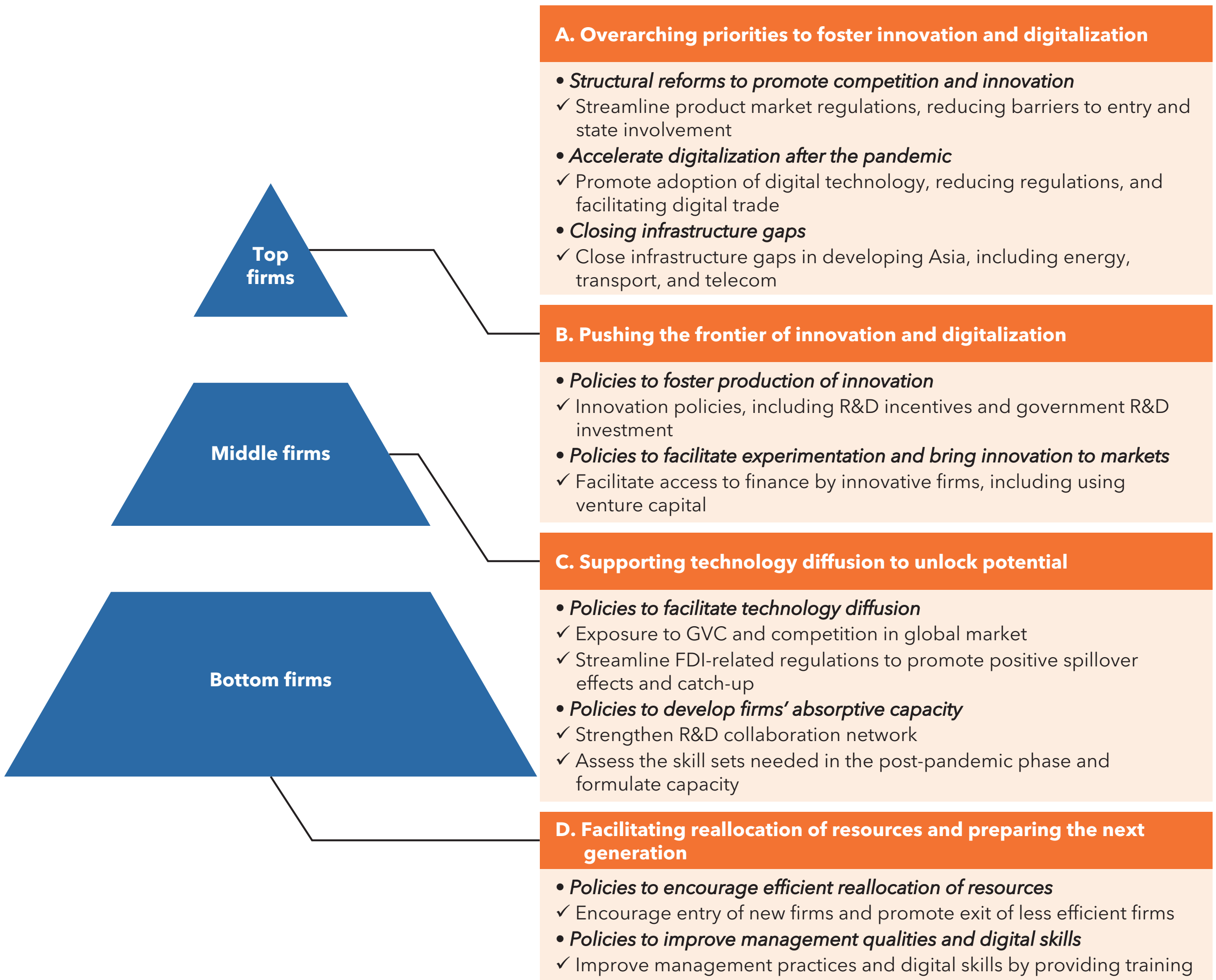
Reforms should center on regulatory reforms that promote competition, innovation, and needed digitalization after the pandemic. A large body of literature suggest that product market deregulation would promote innovation and boost overall growth potential of the economy (for example, IMF 2016 and references therein). It would promote competition and more efficient allocation of resources, thereby reducing misallocation in Asian economies identified in the previous chapters. Product market regulations in many Asian economies are more restrictive compared to international best practices (Figure 28), particularly in the area of state involvement and barriers to entry, suggesting scope for improvement. In addition, regulations in the upstream network sectors tend to be restrictive, including in e-communications, which could be an impediment for further digitalization in Asia (Figure 29). Reducing restrictions in the upstream sectors could boost productivity in highly dependent downstream sectors.

Post-pandemic recovery offers a tremendous opportunity for further digitalization. As highlighted in Chapter 2, the COVID-19 pandemic has provided a unique opportunity for digital innovation and many policymakers in Asia are taking actions to accelerate digitalization (Box 1). To fully reap the benefits of digitalization, policymakers need to facilitate firms' adoption of digital technology by reducing regulation, modifying supervision in line with the evolving digital industry, and facilitating digital trade (Figure 30). Private sector digitalization should be matched by a similar drive in the public sector, where Asia still lags behind OECD countries in GovTech.[40]

Closing large infrastructure gaps in Asian developing countries will be paramount to support digitalization over the long term. In developing Asia, large infrastructure gaps remain in areas such as energy, transport, and telecommunications, and additional spending on digital infrastructure would be required to accelerate digitalization. Filling the infrastructure gaps, particularly in digital infrastructure, would also enhance

[40] See the World Bank's 2020 GovTech Maturity Index and database.

Figure 27. Policy Priorities to Promote Innovation and Digitalization



Source: ???.

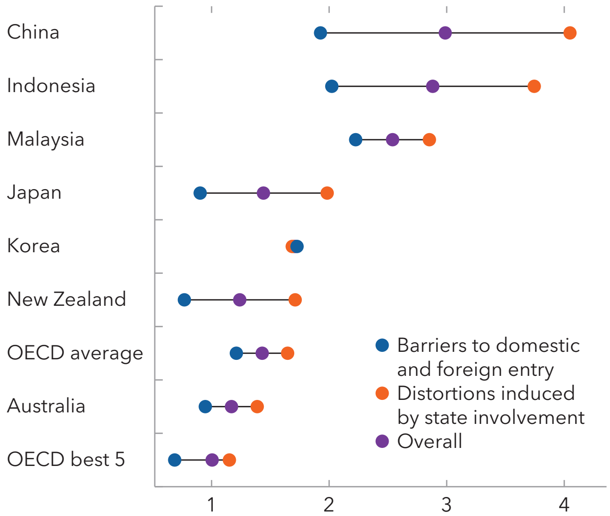
information flows and facilitate technology diffusion and adoption by the private sector. Every 10 percent increase in broadband penetration increases GDP in developing countries by 1.4 percent and doubling broadband speed leads to 0.3 percent increase in per capita GDP growth (AIIB 2020).

B. Pushing the Frontier of Innovation and Digitalization

Policies to Foster Production of Innovation

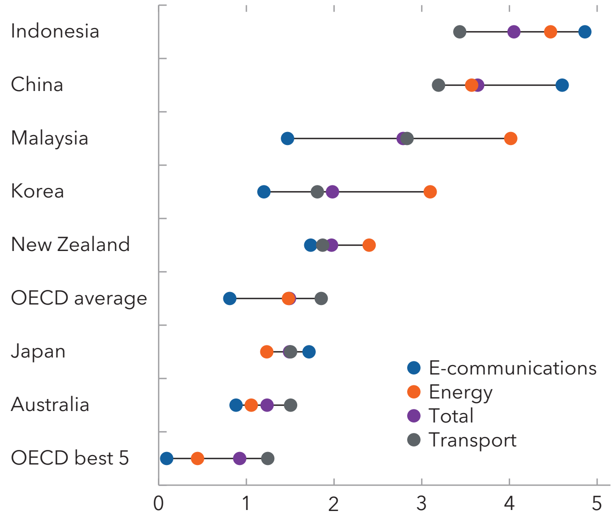
Tax incentives and well-targeted grants can stimulate innovative investment in the post-COVID recovery. In Asia, R&D spending declined since the onset of the pandemic and has not recovered to the pre-pandemic trend in many countries. Fiscal incentives targeted at R&D activities, such as R&D tax credits and allowances, could be used to stimulate innovation by increasing the return to R&D. Numerous studies have confirmed the effectiveness of R&D tax incentives in boosting R&D investment and its qualities (Bloom, Van Reenen, and Williams 2019; Akcigit and others 2018; Sollaci 2022). Asian economies could consider increasing the generosity of tax credits to boost innovative investment by firms in the post-pandemic recovery phase, in an effort to limit scarring. In doing so, the targeting and design of schemes will be critical in maximizing

Figure 28. Product Market Regulation
(0 to 5, 1 is most restrictive)



Source: OECD.

Figure 29. Network Sector Regulations
(0 to 5, 1 is most restrictive)



Source: OECD.

the effectiveness of tax credits, and careful cost-benefit analysis is warranted. Well-balanced intellectual property rights (neither too restrictive nor too loose), that reward disruptive innovations more than incremental improvements would also support cutting-edge innovation at the frontier.

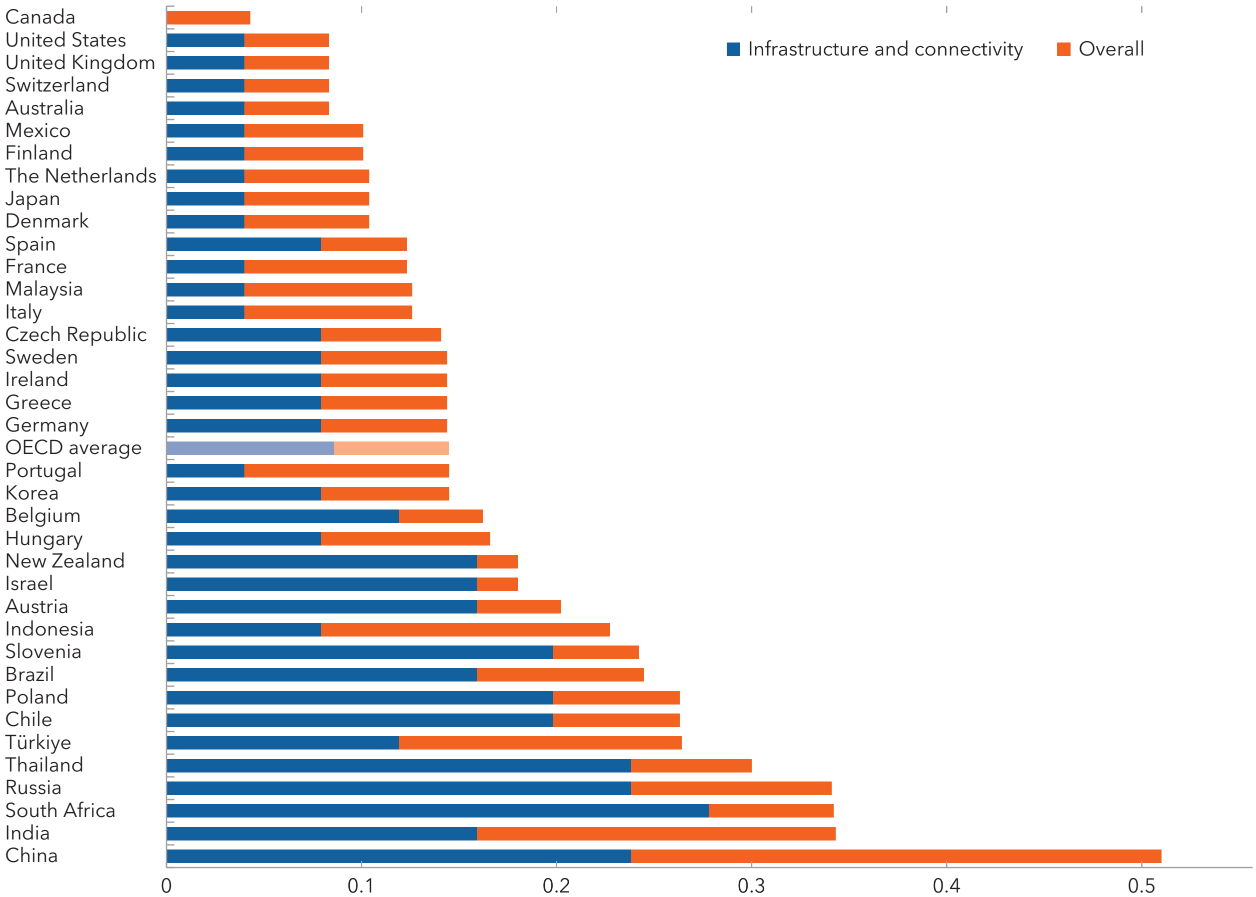
Government investment would also promote innovation, including in basic research. Recent literature suggests that government R&D would stimulate, rather than crowd out, private R&D (Becker 2015). Government can also play a pivotal role in basic research given its positive externality and longer development cycle. Recent studies point to a declining trend of public funding for basic research in advanced economies, which may have contributed to the global productivity growth slowdown (IMF 2021b). Asian economies, though becoming increasingly important as a source of basic knowledge, could still improve compared to top performers. To push the technology frontier, government spending for research institutes could be scaled up, together with grants and subsidies targeting basic research and firm-academia cooperation (Figures 31 and 32).

Policies to Facilitate Experimentation and Bring Innovation to Markets

Access to finance by new, small, and digital firms needs to improve. Small and young firms can play a pivotal role in innovation as the literature shows that large firms tend to focus more on improving existing innovations, while small firms tend to contribute to more radical innovations (Akcigit and Kerr 2018). Cross-country data suggest that loan interest rate spreads between SMEs and large firms in Asian countries are relatively wide compared to other countries (Figure 33). Alleviating financing constraints faced by SMEs and young innovative firms can help productive firms grow and adopt new technologies. Measures aimed at improving matching between businesses and investors and enhancing financial literacy among SMEs through training can help in this regard (OECD 2018). To facilitate market-based financing, developing a deep and diversified capital market to provide various financial instruments to SMEs and new entrants is key. Government R&D loan or credit guarantee schemes, adopted in some Asian countries like Indonesia, Malaysia, and New Zealand, could alleviate financing constraints by addressing the lack of collateral.

Venture capital (VC) could become an important funding source for startups and innovative firms. VC is specialized in addressing the asymmetric information issue for new and intangible-intensive firms. Evidence from the United States suggest that the overall efficiency of VC-backed firms is higher than non-VC-backed

Figure 30. Digital Service Trade Restrictiveness Index
(0 to 1, 1 is most restrictive)



Source: OECD.

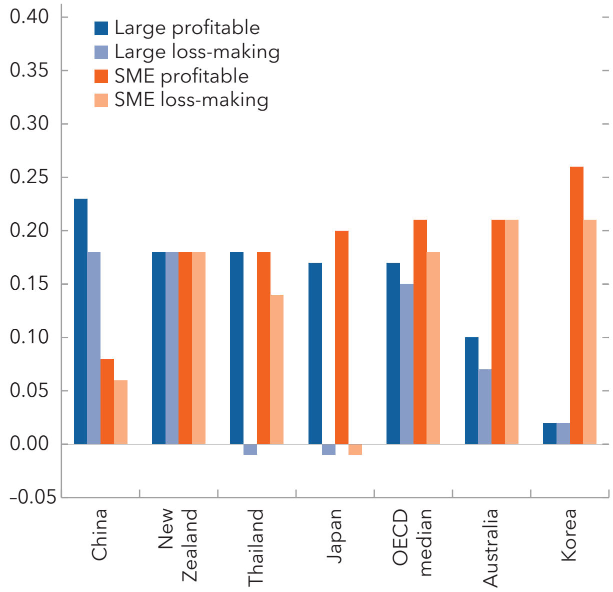
firms and the difference arises from both screening and monitoring effects that VC can bring (Chemmanur, Krishnan, and Nandy 2011). Corrado and others (2021) suggest that early-stage VC helps lower productivity dispersion by facilitating knowledge diffusion and helping new firms to catch up. Scope remains for Asian countries to further deepen VC markets, both for early and later stage investment (Figure 34). VC market can be expended, for example, by introducing government-sponsored funds or co-investment funds and removing potential barriers to investment, which could improve young firms' access to finance while promoting productivity growth.

Policies to Facilitate Technology Diffusion

Participation in international trade and the global value chain accelerates technology diffusion and adoption. There is room to promote participation in global trade, including GVC, for some Asian countries (Figure 35, panel 1). Policy options include reducing tariff and nontariff trade barriers, facilitating access to trade finance, and investing in international logistics infrastructure.[41] These policies could also help promote cross border e-commerce, further boosting technology diffusion and adoption. At the same time, a proper regulatory framework should be implemented to avoid excessive market power to large domestic and foreign corporations. This includes enforcing merger controls in product markets, as well as curtailing market power in labor

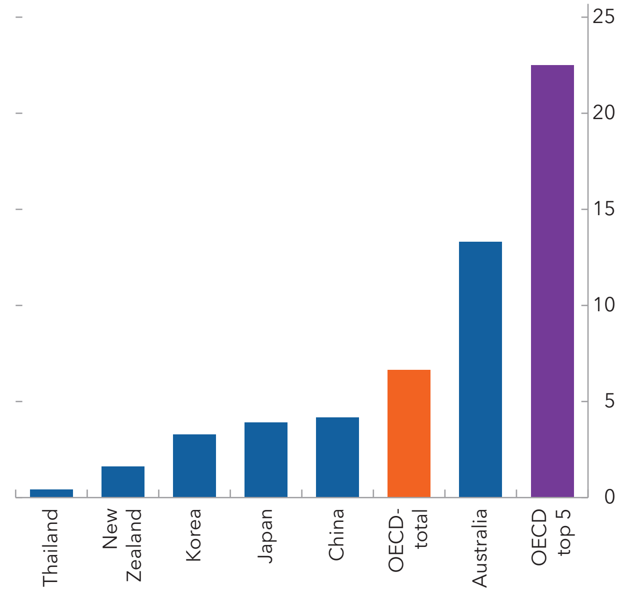
[41] See IMF (2021b) for the impact of reduction in nontariff barriers on trade, GVC participations, and productivity.

Figure 31. Implied R&D Tax Subsidy Rates
(Percent)



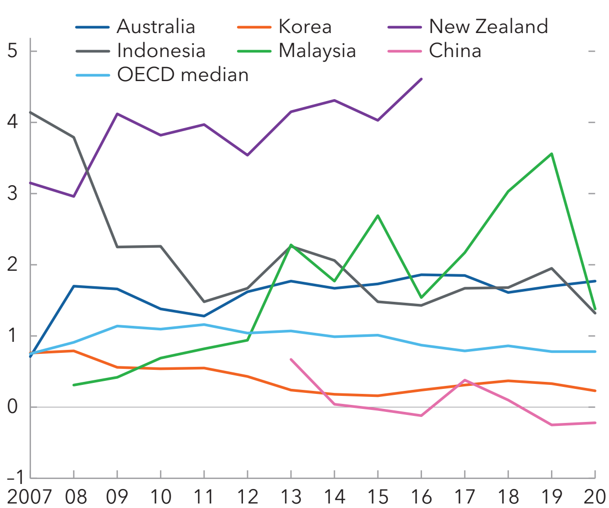
Source: OECD.

Figure 32. R&D Tax Support
(Percent of business enterprises R&D)



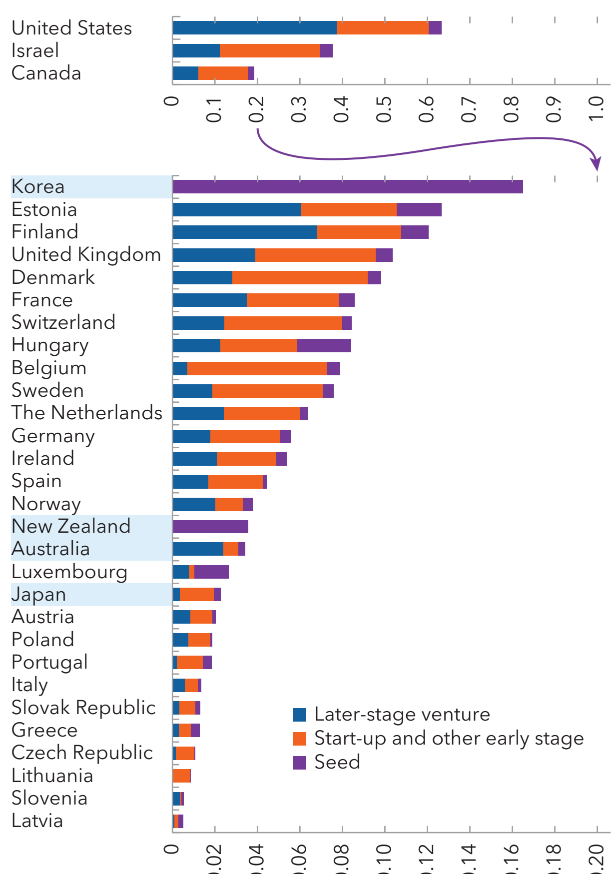
Source: OECD.

Figure 33. Loan Interest Rate Spread between Large and SMEs
(Percentage points)



Source: OECD.

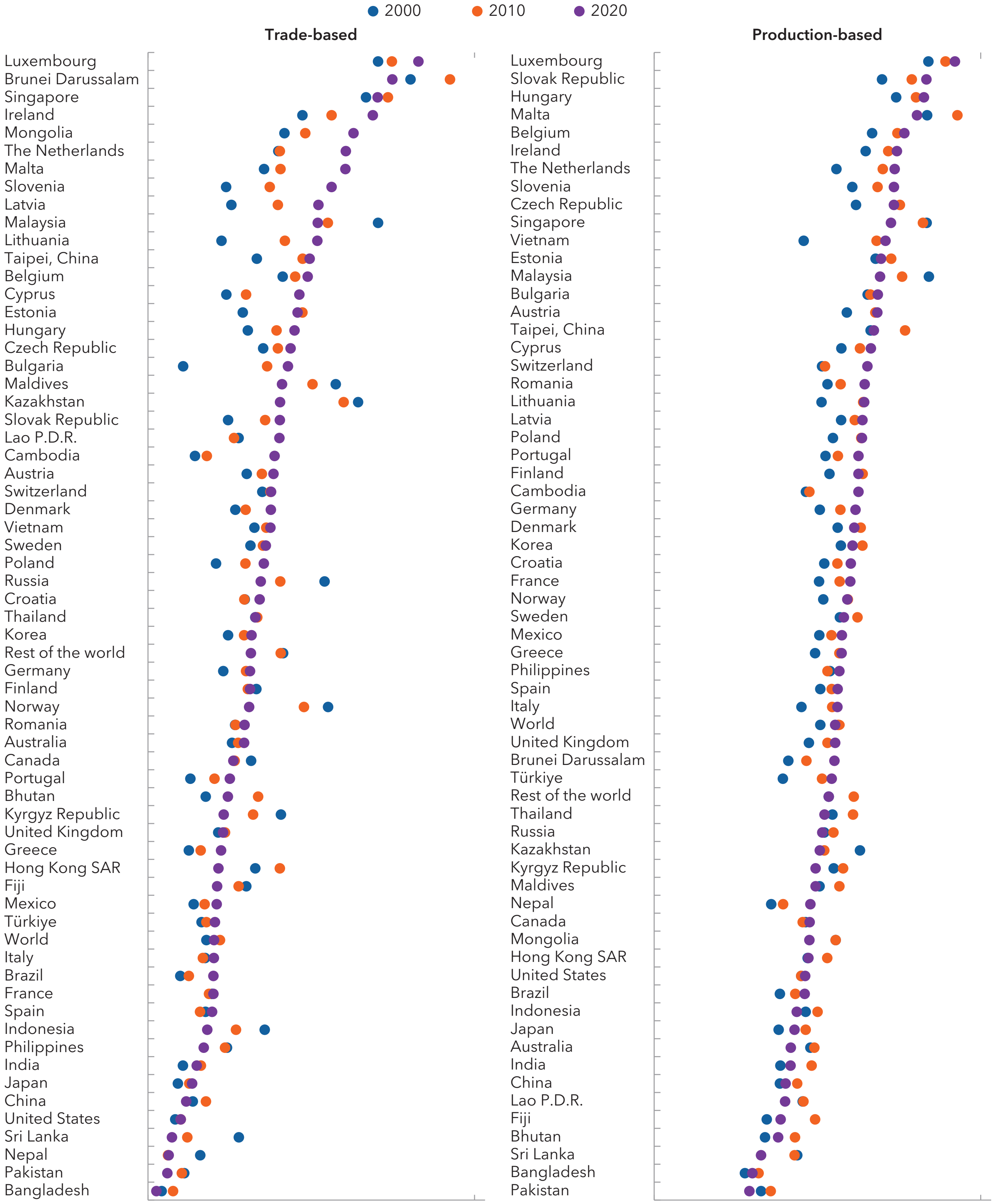
Figure 34. Venture Capital Investment
(Venture capital as percent of GDP, 2019 or latest available year)



Source: OECD.

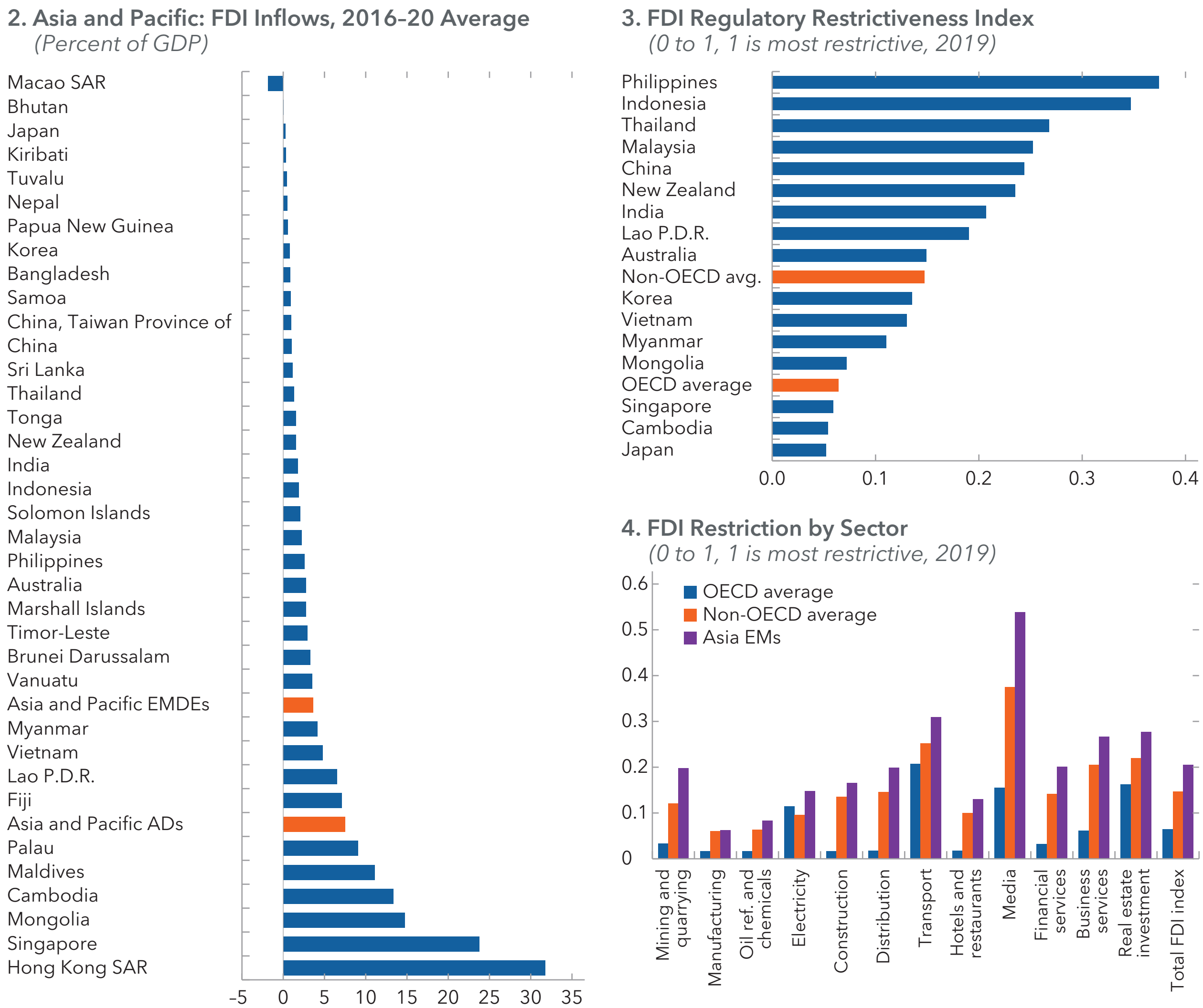
Figure 35. GVC Participation and FDI Flows in Asia and Select Economies

1. Measures of Global Value Chain Participation, 2000, 2010, 2020



Source: Asia Development Bank.

Figure 35. (Continued) GVC Participation and FDI Flows in Asia and Select Economies



Sources: OECD; UNCTAD; and IMF staff calculations.
Note: In panel 2, the aggregate values presented are simple averages.

markets. In addition, given the fast pace of the digital economy, authorities should consider making use of interim measures (imposed before a final decision is reached) and developing specific expertise by building digital economy units (IMF 2021a).

Streamlining FDI-related regulations could also support entry of foreign firms and enhance knowledge transfers and productivity growth, including in services. The literature finds that liberalizing FDI-related restrictions would boost FDI, bringing positive spillover effects and promoting competition (Javorcik 2004; Haskel, Pereira, and Slaughter 2007; and Mistura and Roulet 2019). Relative to their economic size, FDI inflows in many developing Asian countries are smaller than peers (Figure 35, panel 2). For these countries, regulatory barriers to FDI tend to be high, with relatively stringent restrictions on services, suggesting scope for further deregulation (Figure 35, panels 3 and 4). In particular, greater FDI in the service sectors would offer opportunities for laggard firms in Asia to catch up with industry leaders (Fernandes and Paunov 2012). Facilitating cooperation between foreign and local firms, for instance by developing a network of providers, would also support knowledge transfer.

Policies to Develop Firms' Absorptive Capacity

Strengthened collaboration among firms, academia, and government could help reduce the costs of searching for external technology. Bloom and others (2011) argue that informational barriers are the primary factor explaining the lack of technology adoption. An open and collaborative innovation network, consisting of firms, academia, and relevant government agencies, could help firms in the middle and bottom quickly obtain information of new technologies and adopt them. Such a collaboration network could take various forms, including industry-academia collaborative projects, government consulting services to small and new businesses, national or international product expositions, and digital platforms. Economies of agglomeration could also be explored, particularly in the knowledge intensive high-tech industries, to facilitate knowledge diffusion among firms in the same industry and generate synergy effects. Enhancing the legal environment, including legislations on data protection and cybercrime together with effective enforcement mechanisms, will also help lower barriers to information sharing and support technological adoption.

Broadening and deepening the skill base will allow better exploitation of new technology. The literature has long demonstrated the importance of a well-educated workforce for firms to absorb new technology (Van Reenen 2021). The paper's analysis finds that the education level of the workforce is positively related with firms' productivity. Without adequate supply of qualified human capital, firms would be unable to exploit new technologies. However, many firms in developing Asia are reporting difficulties in hiring workers with adequate skills, especially foreign language, managerial, and IT skills (World Bank 2021a). Policymakers should assess the skill sets most needed for their countries to boost innovation and digitalization in the post-pandemic phase and formulate a holistic human capital development strategy accordingly.

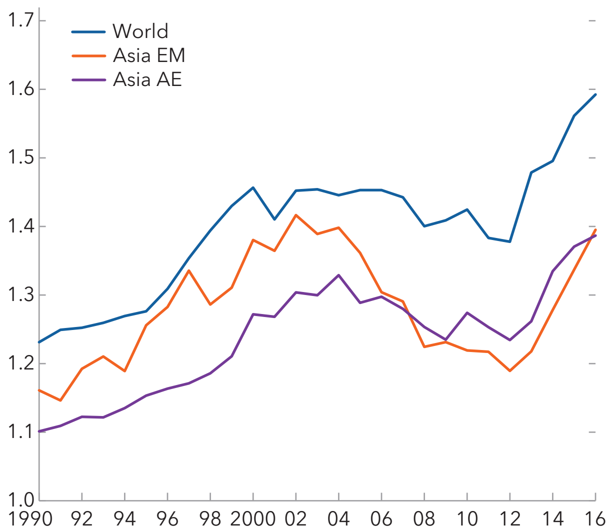
Improving management practices and digital skills of laggard firms can play a pivotal role in promoting long-term growth. As discussed in Chapter 2, a large portion of Asian firms, especially in developing countries, have weaker management qualities. There is significant room for improving management practices of less efficient firms, for example by providing training, thereby boosting overall productivity performance. Promoting uptake of new digital technologies by less productive firms, including firms in services, and supporting training of digital skills would help improve their productivity.

C. Facilitating Reallocation of Resources and Preparing the Next Generation

Policies to Encourage Efficient Reallocation of Resources

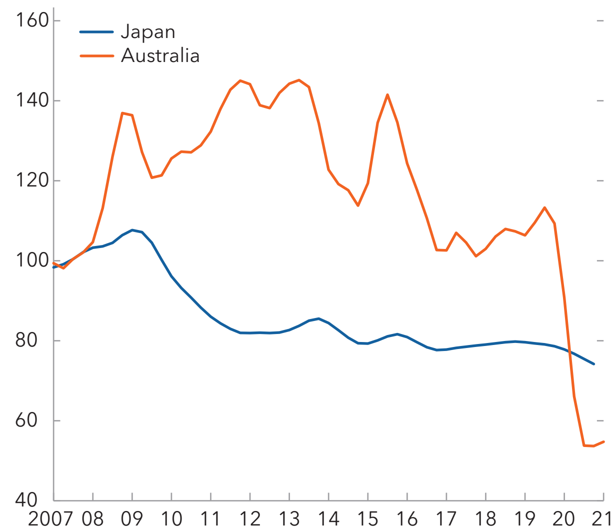
Healthy competition and strong firm dynamism could facilitate needed resource reallocation after the pandemic and limit scarring effects of the pandemic. Chapter 3 identified a large dispersion of productivity among Asian firms and identifies laggard firms, which are often small and old. Strong firm dynamism helps resource allocation through creative destruction, allowing inefficient firms to exit and young innovative firms to enter (Aghion and Howitt 1992). In Asian countries, market concentration, as measured by markups, appears to have been increasing in recent years (Figure 36), which could be an impediment for growth as it may reflect barriers to entry, lower investment, and weaker innovation. In addition, despite the pandemic's large economic impacts, firm exit remains low (Figure 37), in part due to lifeline measures deployed at the onset of the pandemic (Vandenberg 2021). This could have adverse effects on productivity by preserving less productive and zombie firms. Supporting exit of such firms, for example by simplifying the insolvency framework, would reduce misallocation by freeing up resources to be used by more productive firms.

Figure 36. Markup in Asia and World
(Markup)



Source: De Loecker and Eeckhout (2021).
Note: Asia EM includes China, India, Indonesia, Malaysia, Philippines, and Thailand. Asia AE includes Australia, Hong Kong SAR, Japan, Korea, New Zealand, Singapore, and Taiwan Province of China.

Figure 37. Exit of Firms
(Exit of firms, index, 100 in 2007)



Source: OECD.

Annex 1. Orbis and Zephyr

Data

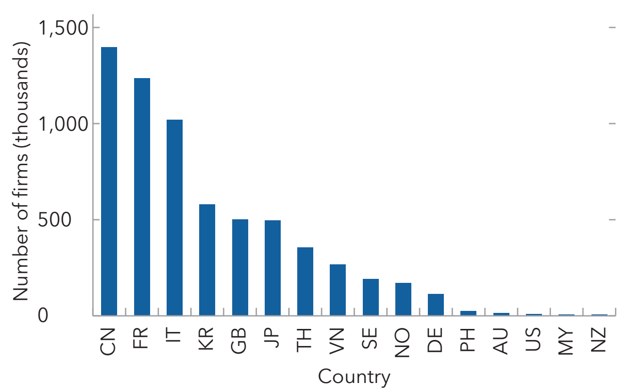
The paper uses the Orbis and Zephyr databases (both maintained by Bureau van Dijk) for extensive coverage of firm-level data. Orbis contains detailed data on each firm's accounting data, while Zephyr provides information on mergers & acquisitions and FDI deals (which we use, along with export revenues, to construct our measure of exposure to foreign markets). We closely follow Diez and others (2021) for the data cleaning and firm-level TFP calculations in Orbis. In the Zephyr database, we only keep completed, cross-border deals with a single acquiror (both single and multiple target deals). When companies have multiple deals in a single year, all of their values are summed to obtain the total amount invested. We merge Orbis and Zephyr using unique firm identifiers, along with each firm's country of origin and the year of the observation.

The paper's final data set contains more than 34 million observations on 6.4 million individual firms, between 1995 and 2018, and across 16 countries. We split countries into two comparison groups: Asia and Pacific (A&P) and Rest of World (RoW). Asia and Pacific countries can also be further classified into frontier and non-frontier, based on their levels of development and production of innovation. The table accompanying Annex Figure 1.1 details the countries included in each category, and Annex Figure 1.1 shows our data coverage by firm origin.

Asia and Pacific		Rest of World
Frontier	**Non-frontier**	**Frontier**
Australia, China, Japan, Korea, New Zealand	Malaysia, Philippines, Thailand, Vietnam	France, Germany, Great Britain (UK), Italy, Norway, Sweden, United States.

Source: ???.

Annex Figure 1.1. Data Coverage



Measuring Productivity

The paper estimates productivity at the firm-level following the control function approach proposed by Ackerberg, Caves, and Frazer (2015) but using turnover revenue as the output measure and the cost of goods sold as the measure of variable inputs. Specifically, we assume the following production function:

$$y_{it} = \beta_0 + \beta_v v_{it} + \beta_k k_{it} + \omega_{it} + \varepsilon_{it}$$

where y_{it} it is turnover revenue, v_{it} are variable inputs (measured by the cost of goods sold), k_{it} is the value of physical capital used in production (in US dollars), and ω_{it} it is TFP (all variables measured in logs). We assume that TFP is an increasing function of both variable costs and capital, $\omega_{it} = h(v_{it}, k_{it})$, so the production function becomes

$$y_{it} = \phi_t(v_{it}, k_{it}) + \varepsilon_{it}$$

We estimate ϕ_t non-parametrically in the first stage. Assuming that TFP follows a AR(1) process $\omega_{it} = \rho\omega_{it-1} + \xi_{it}$ it, we can write our second stage equation

$$y_{it} = \beta_0 + \beta_v v_{it} + \beta_k k_{it} + \rho\left(\widehat{\phi}_{t-1} - \beta_v v_{it-1} - \beta_k k_{it-1}\right) + \xi_{it} + \varepsilon_{it}$$

Plugging in the first-stage estimate ϕ_{t-1}, we can estimate the parameters in this equation using the moment condition $E\left[\varepsilon_{it} + \xi_{it} | I_{t-1}\right] = 0$ where I_{t-1} is the information set in year *t-1*. Each elasticity—and therefore TFP—is estimated at the country-industry level, and country-industry pairs that contain less than 300 observations are dropped from the data to increase precision of the estimates.

Note that we do not include intangible capital as an input into the production function of firms. This is mainly driven by two features of the data. First, by its definition, intangible capital includes brand value, some forms of innovation (patents, trademarks), marketing and managerial expenses, among others. All of those can influence the level and growth of productivity but are not usually thought of as direct inputs. Second, many firms in the data have no intangible capital at all, suggesting that the role of intangible capital in the production process of a firm has a different nature than that of labor or physical capital. Having said that, the decision to not include intangible capital directly into the production function is not innocuous: if some components of intangible capital are indeed better described as inputs to the production function, and at the same time are correlated with the firm's productivity, then our estimated TFP could be overstated.

Comparing TFP Measures

Multiple observations of the same firm across time are not always available in datasets, including the World Bank Enterprise Survey (WBES), which we also explore in this report due its better coverage of developing economies. When using WBES data, we construct a different measure of productivity we regress log-sales for the year on firm-level labor (log-head count), log-capital, and fixed effects for the firm's country, sector, and year. TFP is defined as the residual of this regression.

This method raises concerns related to biased elasticity estimates and whether this is an accurate representation of TFP at the firm level. We test whether this concern might drive any of our results by computing this measure in the Orbis data set and comparing the results with the TFP measured using the method above. We find that, except for the extremes of the residual-TFP measure, it correlates very strongly with the control function TFP measure, yielding more credibility to our results concerning productivity in the WBES.

Dealing with Zeroes

Due to the large number of firms that do not record any expenditures on R&D, or have no stock of intangible capital, the paper uses the inverse hyperbolic sine function to obtain the elasticities between those variables and the outcomes of interest. This function is defined as $ihs(x) = ln\left(x + \sqrt{1 + x^2}\right)$ which has equals zero when $x = 0$, but quickly converges to $ln(2x)$ as x increases.

Since R&D intensity (R&D expenses/employment) tends to be on the hundreds or thousands for most firms that invest in R&D, the difference between the ihs and ln functions is very small. However, the intangible-to-tangible capital ratio is frequently smaller than 1, even after conditioning on the firms have some intangible capital. As a result, we adjust the scale of the intangible capital ratio by a factor of k, defining a slightly modified function $ihs(x; k) = ln\left(kx + \sqrt{1 + (kx)^2}\right) - ln(k)$, where $k = \dfrac{mean(R\&D\ intensity \mid R\&D\ intensity > 0)}{mean(intangible/tangible\ K \mid intangible/tangible\ K > 0)}$

Annex Table 1.1. Regression of ln(TFP) on Firm Characteristics

	(1) Full Sample	(2) A&P	(3) Rest of World
ihs(R&D Expense/L)	0.0033*** (0.0004)	0.0035*** (0.0003)	0.0016* (0.0008)
ihs(Intangible/Tangible K)	0.0040*** (0.0003)	0.0051*** (0.0008)	0.0033*** (0.0002)
International Exposure	0.0022** (0.0010)	−0.0001 (0.0021)	0.0029*** (0.0010)
Number of Observations	15,322,552	3,776,025	11,546,527
Within R^2	0.0167	0.0556	0.0401

Sources: Orbis; Zephyr; and authors' calculations.

Note: All specifications control for capital intensity (K/L) and average wages paid by the firm (as a measure of human capital in the labor force). The paper also includes a firm fixed effect and a country-by-year fixed effect. Standard errors are shown in parenthesis and clustered at the country-sector (4-digit) level. *, ** and *** indicate that coefficients are statistically different from 0 at the 10%, 5%, and 1% levels, respectively. ihs represents the inverse hyperbolic sine function, $ihs(x) = ln\left(x + \sqrt{1 + x^2}\right)$. A&P = Asia and Pacific; RoW = rest of world.

Annex Table 1.2. Regression of I(R&D expenses > 0) on Firm Characteristics

	(1) Full Sample	(2) A&P	(3) RoW
International Exposure	0.0143*** (0.0020)	0.1543*** (0.0079)	0.0079*** (0.0014)
ihs(Intangible/Tangible K)	0.0013*** (0.0002)	0.0067*** (0.0010)	0.0005*** (0.0001)
ln(K/L)	0.0018*** (0.0002)	0.0041*** (0.0007)	0.0009*** (0.0001)
ln(Wages)	0.0034*** (0.0004)	0.0171*** (0.0019)	0.0015*** (0.0002)
ln(Employment)	0.0065*** (0.0006)	0.0232*** (0.0028)	0.0026*** (0.0002)
Number of Observations	2,800,409	643,697	2,156,712
Within R^2	0.0114	0.0505	0.0076

Sources: Orbis; Zephyr; and authors' calculations.

Note: All specifications control for firm age, debt and equity (both measures of financial access), and include country-by-sector fixed effects. Standard errors are shown in parenthesis and clustered at the country-sector (4 digit) level. *, ** and *** indicate that coefficients are statistically different from 0 at the 10%, 5%, and 1% levels, respectively. ihs represents the inverse hyperbolic sine function, $ihs(x) = ln\left(x + \sqrt{1 + x^2}\right)$. A&P = Asia and Pacific; RoW = rest of world.

The empirical evidence on the distance to frontier regressions relies on the following baseline equation:

$$\Delta ln(TFP_{isct}) = \sum_{g \in G} I(i \in g)\left\{\beta_1^g \Delta ln(TFP_{sct}^f) + \beta_2^g gap_{isct} + \beta_3^g gap_{isct}^2 + \beta_4^g X_{isct}\right\} + \delta_i + \delta_{ct} + \varepsilon_{isct}$$

where $\Delta ln(TFP_{isct})$ is the change in log-productivity for firm i (in sector s and country c) between years t and *t + 1*; $\Delta ln(TFP_{sct})$ represents the average change in log-productivity for firms in the frontier (defined as the firms in the top 10 percent of each sector-country-year); gap_{isctis} the productivity gap for firm $ln(TFP_{sct})$ – $ln(TFP_{sct})$; X_{isct}; is a collection of firm-level characteristics; and δ_i and δ_{ct} are firm and country-year fixed effects.

We allow for each of those variables to have a different effect on TFP growth depending on each firm's group g: top firms (which are between the 60th and 90th percentiles of the sector-country-year productivity distribution), middle firms (between the 30th and 60th percentiles), and bottom firms (below the 30th percentile). Firm-level characteristics included in the vector X_{isct} are international exposure, intangible capital ratio, the mean intangible capital ratio in the firm's sector, and the standard deviation of ln(TFP) in the firm's sector.

Annex Table 1.3. Regression of Change ln(TFP) on Policy and Firms Characteristics

Variable	Group	(1) A&P	(2) A&P	(3) A&P	(4) RoW	(5) RoW	(6) RoW
Δ Frontier ln(TFP)	Top	0.2651*** (0.0077)	0.2687*** (0.0078)	0.1064*** (0.0051)	0.2503*** (0.0074)	0.2510*** (0.0074)	0.0959*** (0.0050)
	Middle	0.2386*** (0.0073)	0.2439*** (0.0078)	0.0774*** (0.0048)	0.2359*** (0.0072)	0.2355*** (0.0072)	0.0812*** (0.0044)
	Bottom	0.2401*** (0.0089)	0.2462*** (0.0095)	0.0761*** (0.0059)	0.2437*** (0.0078)	0.2428*** (0.0078)	0.0906*** (0.0045)
ln(TFP) Gap	Top	0.4185*** (0.0210)	0.4289*** (0.0213)	0.6549*** (0.0121)	0.3378*** (0.0181)	0.3416*** (0.0179)	0.5042*** (0.0102)
	Middle	0.5013*** (0.0176)	0.4831*** (0.0184)	0.6410*** (0.0126)	0.4112*** (0.0164)	0.4081*** (0.0166)	0.5155*** (0.0148)
	Bottom	0.5418*** (0.0169)	0.5130*** (0.0197)	0.7968*** (0.0178)	0.4530*** (0.0157)	0.4463*** (0.0160)	0.6987*** (0.0173)
[ln(TFP) Gap]^2	Top	−0.0029 (0.0107)	−0.0082 (0.0107)	−0.0058 (0.0052)	0.0275*** (0.0103)	0.0259** (0.0103)	0.0170*** (0.0045)
	Middle	−0.0329*** (0.0084)	−0.0247*** (0.0085)	−0.0071 (0.0048)	0.0004 (0.0084)	0.0013 (0.0085)	0.0112** (0.0047)
	Bottom	−0.0318*** (0.0084)	−0.0206** (0.0093)	−0.0100* (0.0058)	−0.0049 (0.0073)	−0.0032 (0.0073)	0.0035 (0.0046)
International Exposure	Top		0.0098*** (0.0014)	0.0086*** (0.0013)		0.0130*** (0.0014)	0.0110*** (0.0013)
	Middle		−0.0036*** (0.0011)	−0.0038*** (0.0009)		−0.0025*** (0.0006)	−0.0018*** (0.0005)
	Bottom		−0.0161*** (0.0016)	−0.0154*** (0.0015)		−0.0119*** (0.0010)	−0.0101*** (0.0009)
ihs(intangible K ratio)	Top		0.0021*** (0.0002)	0.0020*** (0.0002)		0.0021*** (0.0002)	0.0022*** (0.0001)
	Middle		0.0001 (0.0002)	0.0007*** (0.0001)		0.0006*** (0.0001)	0.0009*** (0.0001)
	Bottom		−0.0009*** (0.0003)	0.0002 (0.0002)		−0.0003** (0.0002)	0.0001 (0.0001)
Std Dev[ln(TFP)]	Top			−1.7397*** (0.0429)			−1.4706*** (0.0445)
	Middle			−1.7050*** (0.0393)			−1.4663*** (0.0465)
	Bottom			−2.1339*** (0.0428)			−1.9496*** (0.0442)
Number of Observations		7,556,396	6,939,968	6,900,854	14,448,480	14,407,254	14,401,055
Within R^2		0.2000	0.1992	0.2419	0.2000	0.2005	0.2351

Sources: Orbis; Zephyr; and authors' calculations.

Note: All specifications include a firm fixed effect and a country-by-year fixed effect. Standard errors are shown in parenthesis and clustered at the country-sector (4-digit) level. *, ** and *** indicate that coefficients are statistically different from 0 at the 10%, 5%, and 1% levels, respectively. ihs represents the inverse hyperbolic sine function, $ihs(x) = ln\left(x + \sqrt{1 + x^2}\right)$. A&P = Asia and Pacific; RoW = rest of world.

Annex 2. World Bank Enterprise Survey

Innovation is defined as a dummy, which takes value 1 if the firm has introduced any new products or processes over the previous three years; 0 otherwise. The paper uses two measures of productivity levels: Annual sales divided by the number of workers, and a residual (TFP) based on a Cobb-Douglas with log sales/worker as output, log capital and labor as controls (plus year and country FE). $log(Sales_{icst}) = \alpha + \beta_1 log(K_i) + \beta_2 log(labor_i) + \theta_s + \varphi_c + \theta_t + \varepsilon_{icst}$. We obtain predicted values based on this regression $log(\widehat{Sales_{icst}})$ and then compute residuals $TFP = log(Sales_{icst}) - log(\widehat{Sales_{icst}})$

Annex Table 2.1. Drivers of Productivity

	(1) TFP	(2) Sales/Worker	(3) TFP	(4) TFP
Innovation	0.095*** (0.034)	0.096*** (0.024)		
Size: Medium (20–99)	−0.006 (0.032)	0.057** (0.023)	0.002 (0.032)	−0.009 (0.032)
Size: Large (100 And over)	0.107** (0.043)	0.282*** (0.030)	0.122*** (0.043)	0.098** (0.043)
Manufacturing	−0.463*** (0.050)	−0.024 (0.096)	−0.453*** (0.055)	−0.460*** (0.050)
Services	−0.647*** (0.187)	0.016 (0.096)	−0.639*** (0.188)	−0.629*** (0.189)
High-tech sector	0.055 (0.038)	0.244*** (0.029)	0.056 (0.038)	0.058 (0.038)
Firm age	0.000 (0.000)	−0.000 (0.000)	0.000 (0.000)	−0.000 (0.000)
GVC participation	0.002*** (0.000)	0.001*** (0.000)	0.002*** (0.000)	0.002*** (0.000)
Foreign ownership	0.000 (0.001)	0.001* (0.001)	0.000 (0.001)	0.000 (0.001)
Education workforce	0.012*** (0.003)	0.010*** (0.003)	0.011*** (0.003)	0.012*** (0.003)
Credit constrained	−0.081*** (0.030)	−0.127*** (0.021)	−0.080*** (0.030)	−0.083*** (0.030)
Capital city	0.230*** (0.048)	0.237*** (0.033)	0.231*** (0.048)	0.229*** (0.049)
R&D expenditure	0.048 (0.038)	0.180*** (0.026)	0.093** (0.039)	0.032 (0.038)
Product innovation			−0.019 (0.032)	
Process innovation				0.130*** (0.034)
Year FE	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
Number of Observations	8,431	18,721	8,422	8,411
R^2	0.144	0.593	0.143	0.145

Source: WBES, 2006–20.

Note: OLS regression. The dependent variable in columns 1, 3, and 4 is firm-level TFP. In column 2, the dependent variable is sales per worker in nominal NCU. These variables are regressed on a set of firm-level characteristics : firm age, sector, size, R&D expenditure, ownership status, GVC participation, proxied by the ratio of imports of imports and exports to annual sales. Columns 1 and 2 include also controls for firm-level innovation, measured as the introduction of new processes or products over the previous three years columns 3 and 4 instead include an indicator variable for product and process innovation, respectively. Country and year fixed effects are included. The sample includes Cambodia, China, Fiji, India, Indonesia, Lao P.D.R., Micronesia, Mongolia, Myanmar, Nepal, Papua New Guinea, Philippines, Samoa, Solomon Islands, Sri Lanka, Thailand, Timor-Leste, Vanuatu, Vietnam.

Annex Table 2.2. Drivers of Innovation

	(1) Innovation	(2) Product	(3) Process
Size	0.081*** (0.007)	0.066*** (0.008)	0.087*** (0.007)
Manufacturing	−0.012 (0.010)	−0.032*** (0.010)	−0.010 (0.010)
High tech sector	0.006 (0.009)	0.035*** (0.010)	−0.007 (0.009)
Firm age	0.000 (0.000)	−0.000 (0.000)	0.000 (0.000)
GVC	0.060*** (0.010)	0.031*** (0.010)	0.046*** (0.010)
Foreign ownership	−0.000 (0.000)	−0.000 (0.000)	−0.000* (0.000)
Education workforce	−0.001* (0.001)	0.001 (0.001)	−0.001* (0.001)
Credit constrained	0.019*** (0.007)	0.011* (0.007)	0.017** (0.007)
Capital city	0.036*** (0.009)	0.068*** (0.009)	0.021** (0.009)
R&D expenditure	0.385*** (0.007)	0.388*** (0.008)	0.402*** (0.007)
Country FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Number of Observations	19,701	19,681	19,648
R^2	0.255	0.195	0.263

Source: WBES, 2006–20.

Note: Linear probability model. The dependent variables are indicator variables taking value 1 if the firm has introduced any innovation over the previous 3 years (column 1), 0 otherwise; columns 2 and 3 split between product and process innovation. These indicators of innovative activity are regressed over firm level characteristics: firm age, sector, size, R&D expenditure, ownership status, GVC participation proxied by the ratio of imports of imports and exports to annual sales. Controls include year and country fixed effects. The sample includes Cambodia, China, Fiji, India, Indonesia, Lao P.D.R., Micronesia, Mongolia, Myanmar, Nepal, Papua New Guinea, Philippines, Samoa, Solomon Islands, Sri Lanka, Thailand, Timor-Leste, Vanuatu, Vietnam. Standard errors in parentheses are robust to heteroskedasticity *** p <0.01, ** p <0.05, * p <0.1

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