CHAPTER 4

IS PRODUCTIVITY GROWTH SHARED IN A GLOBALIZED ECONOMY?

Introduction

Technology is a key driver of improvements in income and standard of living. Historically, technological developments have been concentrated in a few large industrialized economies (Figure 4.1). Therefore, the way technology diffuses across countries is central to how global growth is generated and shared across countries. Globalization has likely changed the diffusion process, with a large body of literature highlighting the importance of trade and foreign direct investment (Keller 2004, 2010).

Against this background, this chapter takes a closer look at the process of international technology diffusion. It examines whether globalization means that knowledge from technology leaders is spreading faster than it used to, and how this impacts the capacity of other economies to innovate and be more productive. The methodology also lends itself to discussing the influence of another aspect of globalization—increased international competition. Better understanding of how productivity growth is shared across the global economy can help explain cross-country differences in income per capita and technology and shed light on the policies that can influence them.

Specifically, the chapter will ask:

- How has the technological innovation landscape evolved?
- How strong is the diffusion of knowledge across countries? Has knowledge become more globalized?
- Do foreign knowledge flows increase domestic innovation and productivity both in advanced economies and emerging market economies?
- What impact does greater international competition have on innovation and technology diffusion?
- Which policies help increase inward technology diffusion?

To answer these questions, the chapter exploits a high-quality micro patenting data set, the Worldwide Patent Statistical Database (PATSTAT). The database, which is maintained by the European Patent Office, can be used to construct measures of technological innovation (patenting) and diffusion (cross-patent citations) across countries and across different sectors.[1]

Use of patent and research and development (R&D) data allows precise identification of knowledge generation and diffusion. At the same time, these data have limits in that not all innovations are patented. Innovations in services, for example, are less patentable and typically are protected through forms of intellectual property that tend to be more difficult to document across countries and over time. Therefore, the patent analysis in this chapter is complemented by an examination of productivity measures to establish whether the identified patterns of international technology diffusion are accurate indicators of productivity developments.

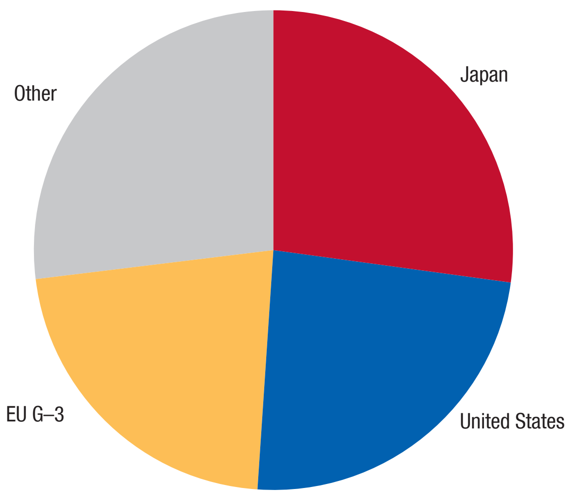
The first part of the chapter lays out a conceptual model for the production and diffusion of innovation. It also documents trends in R&D, patenting, and productivity, both at the technology frontier and in other advanced and emerging market economies. The strength of international technology diffusion and its effects on productivity are then examined, with estimates of the impact of technology leaders' knowledge flows on innovation and productivity in economies that are recipient of that knowledge. Because global value chains (GVCs) are a potentially important channel of knowledge spillovers, the analysis is complemented by a detailed look at their effect on technology diffusion in emerging market economies. The final part of the chapter discusses the complex relationship between international competition, market concentration, and innovation. It provides some evidence of the impact of such structural changes on innovation and technology diffusion.

The findings of the chapter show that globalization has intensified the diffusion of knowledge and technology across borders, helping to spread potential growth among countries and boost it at the global level. This productivity spillover is important because, until

The authors of this chapter are Aqib Aslam, Federica Coelli, Johannes Eugster, Giang Ho, Florence Jaumotte (team leader), Carolina Osorio Buitron, and Roberto Piazza, with support from Pankhuri Dutt, Chanpheng Fizzarotti, and Menexenia Tsaroucha.

[1]For previous work using patents or citations data, see Branstetter (2001); Peri (2005); MacGarvie (2006); Madsen (2007); and Aghion, Howitt, and Prantl (2015).

Figure 4.1. International Patent Families by Publication Year
(Average 1995–2014)



Sources: European Patent Office, PATSTAT database; and IMF staff calculations.
Note: EU G–3 = France, Germany, and the United Kingdom.

recently, the production of knowledge and technology has been concentrated mostly in a handful of large industrialized economies. Innovation sharing has taken place through many channels, including the international use of patents and trade. Another mechanism through which globalization appears to have boosted the diffusion of knowledge and technology is by increasing international competition, which in turn has raised incentives to innovate and adopt foreign technologies.

By making increasing use of available foreign knowledge and technology, emerging market economies have boosted their own innovation activity and lifted productivity. Indeed, increased diffusion of knowledge to emerging market economies has partly offset the effects of the recent slowdown in innovation at the technology frontier. More intense diffusion of leading technologies to emerging market economies helps explain why their productivity growth has generally been stronger than in advanced economies, helping to drive cross-country income convergence for many countries in recent years. The effects have been substantial: over 2004–14, knowledge and technology flows from the global frontier explain about 40 percent of average sectoral productivity growth in emerging market economies.

Finally, knowledge and technology do not flow only in one direction—indeed, the chapter finds evidence that technology leaders themselves benefit from each other's innovation. This underlines the production and diffusion of knowledge and technology as a key mechanism through which globalization delivers global benefits. And even though until recently much of the production of knowledge and technology was concentrated in a small number of advanced economies, China and Korea have now emerged as significant contributors to the global technology frontier. Therefore, there may be scope in the future for spillovers from these new innovators to the traditional innovators.

This chapter is a contribution to the ongoing debate on the benefits and drawbacks of globalization. While the negative side effects of globalization have received much attention in public debates, the chapter highlights that there are upsides too: globalization helps the diffusion of knowledge and technology across borders, spreading their benefits more globally. From a policy perspective, greater global interconnectedness is thus key to maximizing inward technology diffusion and boosting economies' growth potential. But as economists have long emphasized, assimilating and productively using foreign knowledge often requires investments in domestic R&D and in human capital, which enhance absorptive capacity (for example, Cohen and Levinthal 1989; Griffith, Redding, and Van Reenen 2004).

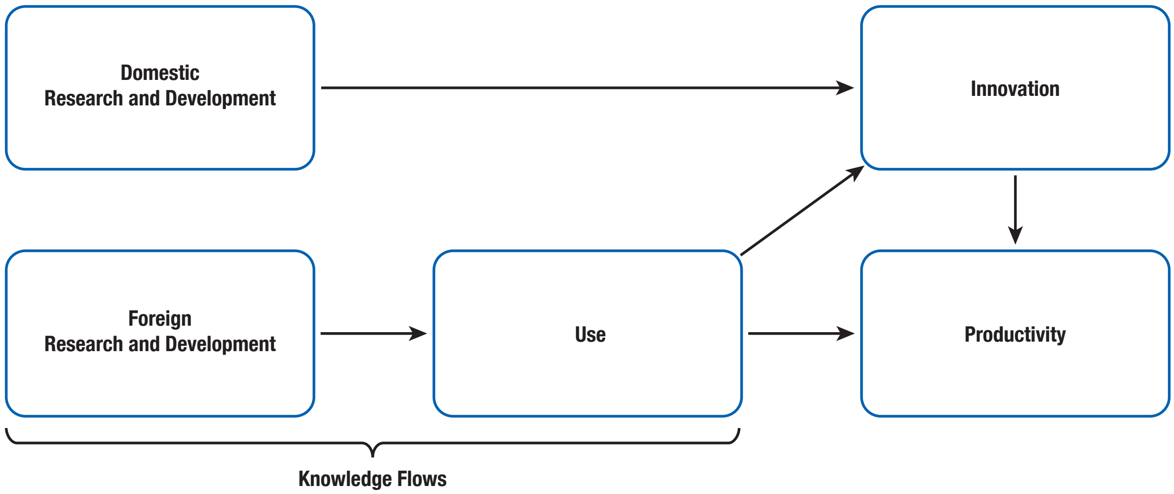
The chapter provides some evidence suggesting that strong institutions that uphold the rule of law benefit innovation, but it does not examine specifically the optimal extent of intellectual property rights protection, which includes patents. This is a complex issue and could not be dealt with conclusively at this chapter's broad level of analysis. Protection for innovators' ideas provides appropriate incentives and the ability to recover costs. But the policy design should maintain sufficient competition and allow for follow-on innovations by competitors, as well as prevent the abuse of power to the detriment of consumers. Finally, concerns that globalization may exacerbate inequality within countries also apply to the growth benefit from inward technology diffusion. It is therefore important for policymakers to ensure that these growth benefits are shared broadly across the population.

Conceptual Framework

Domestic innovation draws on knowledge generated by domestic and foreign research efforts (Figure 4.2).[2]

[2]See Grossman and Helpman (1991) for models of endogenous growth, based on the idea that knowledge gained from past research efforts increases the productivity of current research efforts.

Figure 4.2. Technology Diffusion



Source: IMF staff illustration.

While domestic R&D can affect domestic innovation directly, it is useful to distinguish the steps through which foreign knowledge influences domestic innovation: the availability of foreign knowledge, the extent of its use domestically, and the impact of knowledge flows on domestic innovation and productivity more generally.

- *Available foreign knowledge:* A common measure is the cumulated stock of past R&D spending, corrected for the loss of some of the knowledge's relevance over time (see Annex 4.1). This is the main measure of foreign knowledge used in the analysis.
- *Extent of use of the stock of foreign knowledge:* Foreign knowledge is transmitted internationally through various channels. The strength of this transmission determines to what extent foreign knowledge is domestically usable. However, measuring transmission is difficult. The main channels mentioned in the literature are foreign direct investment (FDI), international trade, and migration (see Keller 2004 and 2010 for an extensive discussion of the empirical evidence).[3] Within these channels, knowledge flows can entail market transactions—for instance, trade or the licensed use of foreign patents—or occur through demonstration effects and outright copying of patented or nonpatented foreign innovations that have become domestically available. In this case, knowledge flows incorporate a significant externality component.
- *Impact of foreign knowledge flows on the production of domestic innovation and on the economy's productivity:* Foreign knowledge flows—as measured by the product of the available foreign knowledge and the extent to which that stock of knowledge is used—do impact domestic innovation. They can also contribute to raising domestic productivity, not only by boosting domestic innovation, but also directly through the adoption of foreign technologies in the production process (for example, through the licensing of foreign technology or technology embodied in imports or FDI).

Measuring Innovation

Measuring innovation is no simple task. This section discusses the advantages and limitations of the approach taken in the chapter. The analysis is centered on two variables widely used in the literature: R&D spending and patent data. These measures have two advantageous attributes:

- *Direct quantification of innovation activity:* R&D spending captures firms' research *input*. Patent data are a measure of the *outcome* of research activity. To be patentable, an idea needs to be *novel*, *inventive*

[3]Most empirical studies only test one channel at a time. In practice, all the channels are correlated, making it difficult to disentangle individual contributions. Testing for the role of trade or FDI is also subject to endogeneity concerns, as trade and FDI linkages with technology leaders will likely be influenced by the innovativeness or productivity of the country examined.

("non-obvious to persons skilled in the art") and *capable of industrial application* (OECD 2009). Both variables are available internationally and at disaggregated levels and can be used to study the strength of the innovation link between industries and across countries.
- *A proxy for the domestic use of foreign knowledge:* Patent citations provide a direct way to quantify the strength of international knowledge flows—the extent to which recipient countries actually make use of the available stock of global knowledge. Citation data are readily available, thanks to the need for precise and comprehensive citations for patent registration.

Nevertheless, patent and R&D measures have their limitations. First, patenting can be a noisy measure of innovation capacity. There are multiple reasons why the incentive to patent an innovation can differ between countries and across time, including differences in the procedures and requirements of patent offices. As a result, the number or economic value of ideas per patent can vary significantly, which makes international comparison of simple patent counts harder. To improve comparability, this chapter follows the practice developed in the literature to construct quality-adjusted patent measures (Box 4.1 discusses the concepts and measurement issues related to patent indicators). The preferred measures focus on international or top three patent "families," which group individual applications for the same underlying technology.

An international patent family features one patent application in at least two distinct patent offices. The idea is to exclude many patents with lower economic value, as the low expected payoff would not warrant the extra cost of application, examination, and maintenance in a foreign country. The approach also reduces the impact of possible idiosyncrasies in patenting activity across patent offices.

The top three patent families include an application to at least one of the top three patent offices (European Patent Office, Japan Patent Office, United States Patent and Trademark Office). Relative to the previous measure, this implies more consistency as it involves a very limited number of patent offices. The drawback is that count measures tend to favor inventors and applicants from Europe, Japan, and the United States.

In recognition that there is no perfect measure, the empirical analyses—which use sector- or firm-level data for each country—include country-year fixed effects to absorb the fiscal, institutional, cultural, and legal factors that affect incentives to patent or cite other patents across countries and time.[4]

A second drawback of using patent data is that not all innovations are patentable. Certain sectors, such as manufacturing, display more patentability than others—such as services, which rely more on forms of intellectual property protection that are less systematically recorded.[5] This and related data issues make it hard to investigate technology diffusion in nonmanufacturing activities, focusing the analysis mostly on manufacturing sectors. Therefore, the degree to which this chapter's results extend to other sectors depends on how well patenting correlates with overall innovation activities, including those that do not lead to patenting. While impossible to test precisely, some support is found for this assumption.[6] Nevertheless, macroeconomic interpretation requires some care.

Despite some limitations, patents are an attractive measure to capture innovation, which is also reflected in their frequent use in the economic literature. Patents are related to new ideas with the objective of, or at least potential for, economic exploitation. The key advantage is, however, the precision with which the idea can be attributed to its creator at a particular moment and to other ideas through the link of citations.

Technology diffusion can stimulate innovation, but may also affect productivity directly through simple adoption of existing technology. To test for this more direct channel, various productivity indicators are examined. This provides a broader, albeit less precise, measure of technological progress and complements the patent-data analysis. The disadvantages of these

[4]This would also address the case where local firms have a lower propensity to patent either domestically, because the actual protection of patents in the domestic economy is weak, or internationally, because the domestic market is large enough that they do not need to patent abroad. Similar points can also be made for R&D spending, since incentives to precisely measure and classify innovation efforts are subject to significant heterogeneity across sectors and countries, including their tax treatment; differing public support systems; and other legal, institutional, and cultural differences.

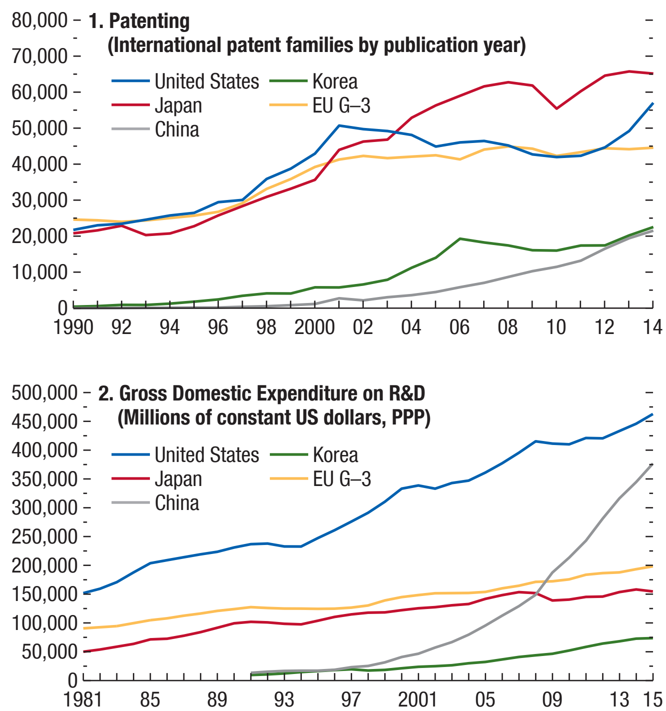
[5]For example, copyrights, which are used to protect the intellectual ownership of texts, software, and other expressions of creative work, do not generally require registration, which complicates record keeping even if the information is public. By definition, this also holds for trade secrets. Open-source software is another example of technology diffusion that does not involve patents or patent citations.

[6]For instance, recent country rankings based on broader measures of innovativeness by Bloomberg Finance L.P. correlate strongly with those based on the patent measures used in this analysis.

measures compared with patent counts are that their quantification is subject to significant measurement uncertainty (especially for total factor productivity) and that they include components extraneous to innovation (for example, labor productivity increases with investments in physical and human capital). Their main advantage is that all innovations, regardless of their specific channel of diffusion, are expected to translate into changes in productivity eventually. Use of productivity measures also helps to disentangle the effect of foreign R&D on domestic innovation (patents) from its contribution to the efficiency of domestic production (productivity).

A final issue is whether patent citations are a good proxy for the extent to which foreign knowledge becomes available for domestic use through the various transmission channels. For instance, a popular alternative proxy is the intensity of international trade. This approach has its own drawbacks, however, as a significant fraction of trade in goods is not associated with any technology diffusion. Indeed, a key advantage of using the propensity to cite foreign patents is that it provides a direct measure of knowledge use and, at the same time, correlates well with other indirect measures, such as the propensity to import.[7] On balance, patent citations are the more attractive indicator of the extent of use of foreign knowledge, but the chapter also offers estimates based on the intensity of trade as a robustness check.

Figure 4.3. Patenting and Research and Development at the Frontier



Sources: European Patent Office, PATSTAT database; Organisation for Economic Co-operation and Development; and IMF staff calculations.
Note: EU G–3 = France, Germany, and the United Kingdom; PPP = purchasing power parity.

The Innovation Landscape

The evolution of innovation can be tracked by examining data across different measures, countries, and time periods, which confirms that global technological advances have been concentrated in a few large industrialized countries.

The United States, Japan, Germany, France, and the United Kingdom (henceforth the G5) accounted for about three-fourths of international patent families during 1995–2014 (see figure 4.1). They are also responsible for the bulk of R&D spending over those years (Figure 4.3). For this reason, the aggregated activity of the G5 is used as a proxy for the global technology frontier and as the main source of technology diffusion worldwide in the chapter's analysis.

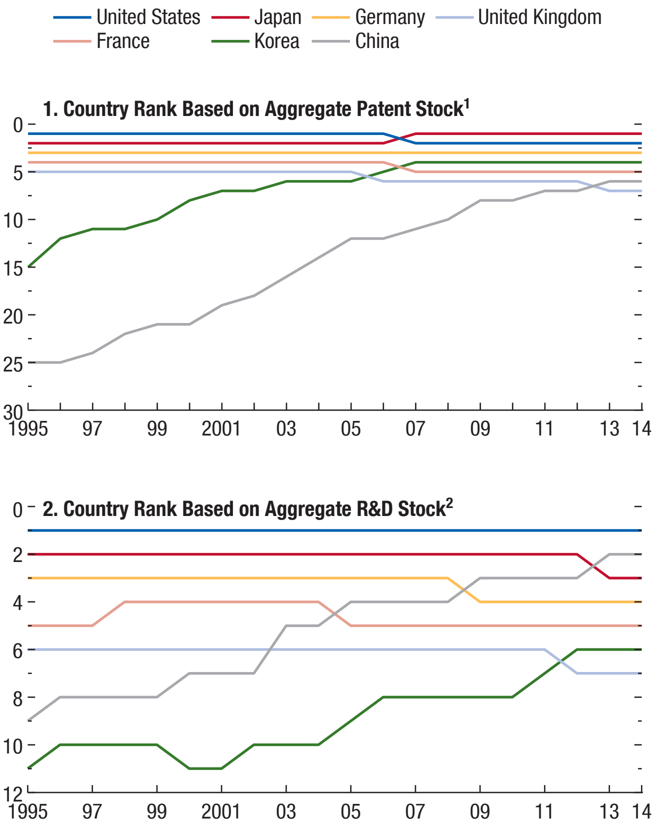
However, this is not to imply that other emerging market or advanced economies have not contributed to the evolution of global knowledge. For example, in recent years Korea and China have joined the top five leaders in a number of sectors, either based on the stock of R&D and/or the stock of international patents (Figure 4.4). Their rise is particularly pronounced in the electrical and optical equipment sector and, for Korea especially, in machinery equipment.

The dynamics in innovation between economies at the technology frontier and others are diverging (Figure 4.5). Since the early 2000s, the G5 has experienced a pronounced slowdown in growth of patenting—and to a lesser extent R&D—mirroring the well-documented slowdown in labor productivity and total factor productivity.[8] The slowdown was much milder in advanced economies outside the G5 and in emerging market economies. Growth in innovation and productivity held up much better, especially in

[7]See for example MacGarvie (2006).

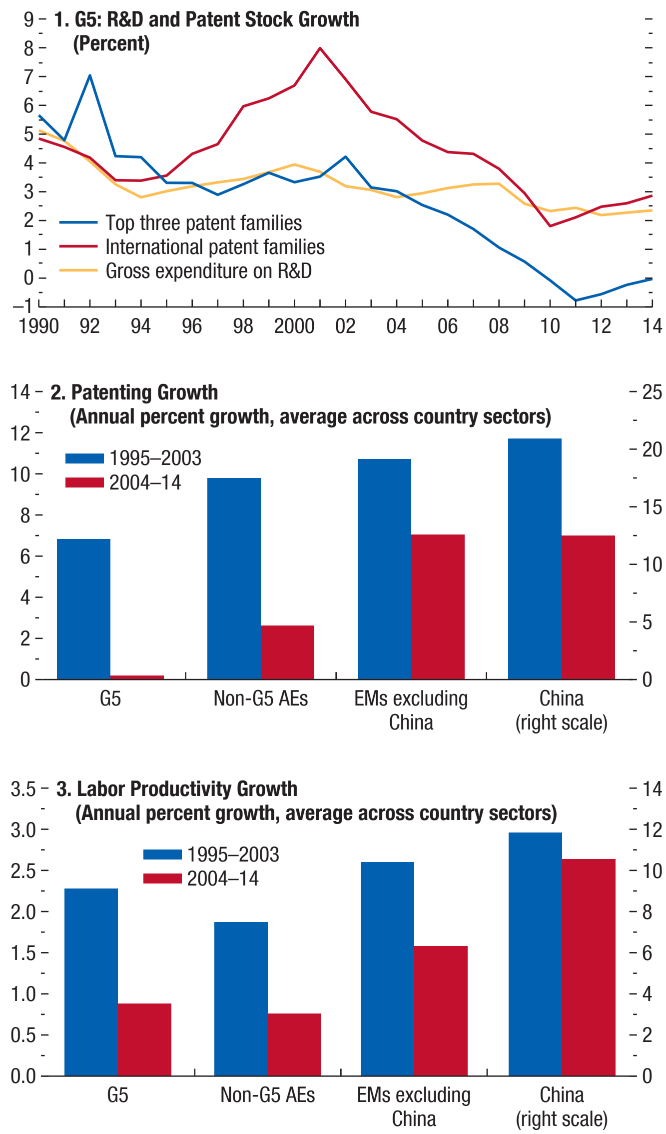
[8]Patenting in the United States has picked up in recent years, however.

Figure 4.4. Countries at the Technology Frontier



Sources: European Patent Office, PATSTAT database; Organisation for Economic Co-operation and Development; and IMF staff calculations.
Note: R&D = research and development. Data labels use International Organization for Standardization (ISO) country codes.
[1]Based on international patent families.
[2]Cumulated gross domestic expenditure on R&D (in millions of constant US dollars at purchasing power parity).

Figure 4.5. Slowing Patenting and Productivity



Sources: European Patent Office, PATSTAT database; KLEMS database; Organisation for Economic Co-operation and Development; United Nations Industrial Development Organisation; and IMF staff calculations.
Note: AEs = advanced economies; EMs = emerging market economies; G5 = France, Germany, Japan, the United Kingdom, and the United States; R&D = research and development.

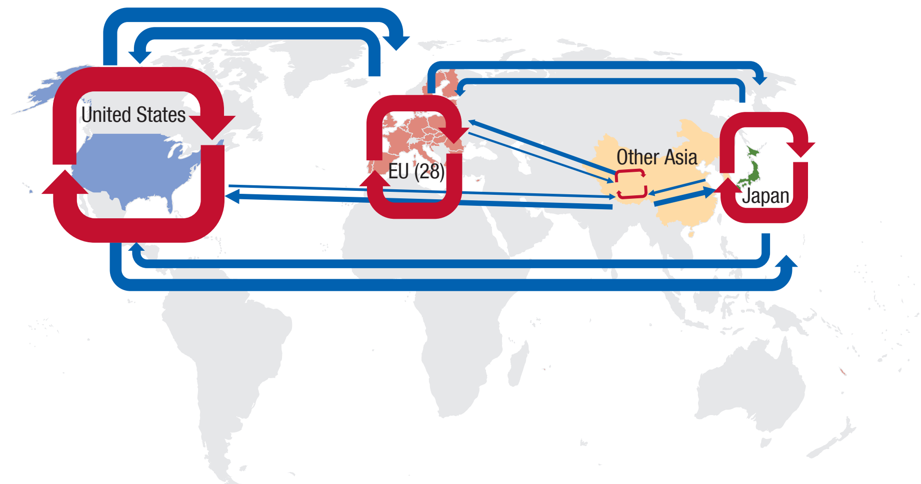
emerging market economies. Diverging dynamics could reflect issues particular to the frontier and/or changes in the way innovation is diffused from the frontier to other regions. To elaborate:

- *Issues specific to the frontier:* There are two main hypotheses behind the slowdown at the frontier. One proposes that the impact of the most recent large wave of innovation related to advances in information and communication technology (ICT) is fading, while ongoing progress in the digital domain, artificial intelligence, automation, and machine learning will be felt some years after their introduction (Brynjolfsson, Rock, and Syverson 2017) because the benefits take time to materialize as new general-purpose technologies. More pessimistic views (for example, Gordon 2012, Bloom and others 2017) contend that really good ideas become harder to come by over time, leading to a secular decline in productivity growth. Keeping productivity growth constant would require increasingly larger R&D investment in this scenario.[9]

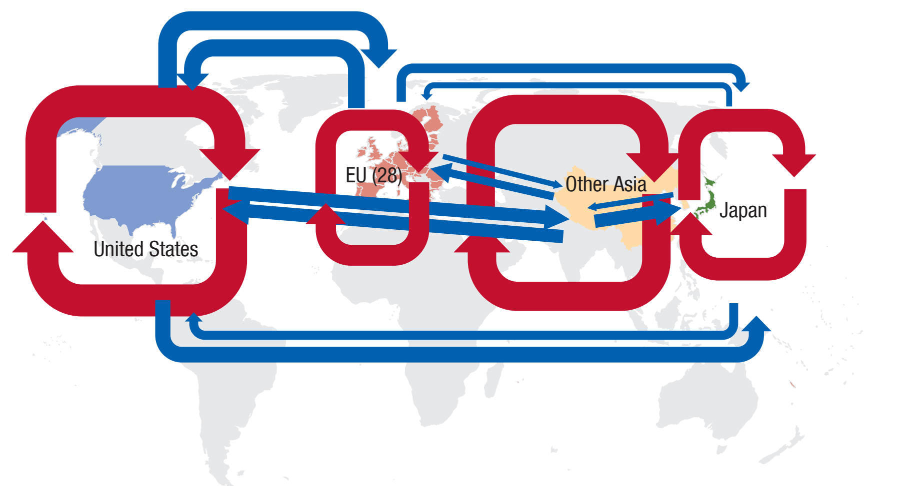
[9]Autor and others (2016) have pointed to the increased trade competition from China as a possible explanation for the decline in US firms' innovation, since it reduced profits and overall operations, including

Figure 4.6. The Evolution of Cross-Patent Citations within and across Regions

1. 1995



2. 2014

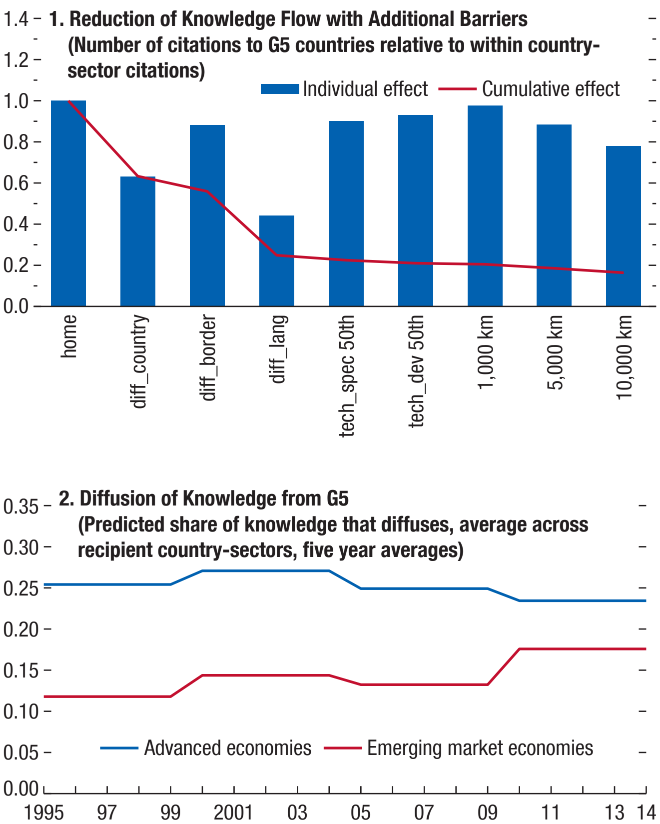


Sources: European Patent Office, PATSTAT database; and IMF staff calculations.
Note: Figure shows the evolution in citation flows between (blue) and within (red) key countries and regions. For a given year, the thickness of the arrows is proportional to the respective numbers of citations. For visibility, the increase in citations over time could not be reflected proportionally (approximate scaling factor 2014 versus 1995 is 1.5 in the figure; actual is 2.5). EU (28) = AUT, BEL, BGR, CYP, CZE, DEU, DNK, ESP, EST, FIN, FRA, GBR, GRC, HRV, HUN, IRL, ITA, LTU, LUX, LVA, MLT, NLD, POL, PRT, ROU, SVK, SVN, SWE; Other Asia = China and Korea. Data labels use International Organization for Standardization (ISO) country codes.

- *Changes in technology diffusion:* While knowledge creation at the frontier seems to have slowed for now, past ICT progress and increases in globalization have opened the potential for knowledge to travel faster and farther. Figure 4.6 shows a map of knowledge flows in which the red arrows represent cross-patent citations within a country or region, and the blue arrows point to citations across countries or regions. Similar to other measures, the map illustrates a changing international constellation. While in 1995 the United States and—to a lesser extent—Europe and Japan were dominating global patent citations, China and Korea (depicted together as "other Asia") have become increasingly more integrated into global citations. The map in Figure 4.6 also shows a general intensification of patent citations over time, captured by the increase in the size of the arrows. However,

R&D spending, of trade-exposed firms. This conclusion, however, is at odds with that of Bloom, Draca, and Van Reenen (2016), who find a positive effect of the China shock on European innovation activity, and seems less consistent with aggregate data, which show no protracted slowdown in R&D spending in the United States.

Figure 4.7. Knowledge Diffusion across Barriers over Time



Source: IMF staff calculations.
Note: G5 = France, Germany, Japan, the United Kingdom, and the United States; Panels are derived from coefficients of same-sector regression on citations to G5 countries. Tech_spec 50th denotes the 50th percentile of the variable tech_spec; and tech_dev 50th denotes the 50th percentile of the variable tech_dev. km = kilometers.

this alone does not mean that the stock of global knowledge was diffusing faster. As discussed earlier, citations are a function of the amount of innovation as well as the propensity to patent and cite other patents, which is influenced by institutional and legal differences across countries and over time. The next section derives a measure of knowledge flows that deals with these issues and is more accurate.

Determinants of Knowledge Flows

The strength of knowledge flows from the technology frontier, and how those flows have changed, can be measured in a more formal way than in the previous section. Many economists believe knowledge flows are localized, because barriers, such as geography, language, or technological differences, weaken their diffusion. These barriers can attenuate knowledge diffusion directly or indirectly, because they reduce economic transactions such as trade, FDI, and migration, which are important channels for the transfer of knowledge. This section uses a gravity model to estimate the impact of these barriers on the intensity of knowledge flows and then examines whether their effect has become less important over time (see Annex 4.2 and Peri 2005).

The focus is on international knowledge diffusion from the frontier, proxied by the G5 countries and within broadly defined industrial sectors.[10] Focusing on the G5 countries misses the changing role of emerging market economies, particularly China and Korea, but captures the bulk of the contribution to global patenting and R&D stocks for most of the sample. Korea and China are thus treated as recipients, even though, in the future, they are likely to become more important sources of global knowledge flows.[11,12]

The analysis uses country-sector rather than economy-wide data, which makes it possible to control for factors specific to each citing and cited country sector in each period. Such factors include the quantity of patenting and institutional or cultural characteristics that influence the propensity to patent or to cite other patents. The sectoral approach is also appropriate for studying knowledge diffusion because the potential for technological progress varies across industries, and the sectoral composition of a country's economic activity influences the extent of knowledge and technology diffusion. A drawback of using sector-level data is that it limits the extent to which conclusions can be drawn about the aggregate economy. Nevertheless, the average sector-level effects provide a sense of the broader effects on the economy.

A key summary of the analysis is the predicted relative frequencies of citations for each country sector (henceforth denoted $\hat{\phi}$ and used in the subsequent section). These can be interpreted as the share of knowledge that diffuses from the cited to the citing relative to what diffuses within the cited country sector (see Annex 4.2). Figure 4.7 (top panel) shows the share of knowledge diffusing from the G5 across cumulative barriers between same-sector pairs over 1995–2014. While naturally at 1 in the home country sector, this

[10]Intrasectoral spillovers are significantly stronger than spillovers across sectors, reflecting in part the broad definition of the sectors used in the analysis. Annex 4.2 provides evidence substantiating this.

[11]Annex 4.2 shows that the empirical results are robust to excluding China.

[12]In the case of China, an additional consideration is the absence of sufficiently long historical sectoral R&D data.

share declines by roughly ½ when information crosses a national border (diff_country). While the effect of contiguity (diff_border) is more moderate, a different language (diff_lang) again significantly decreases this share. Differences in technological specialization (tech_spec) and in technological development (tech_dev) also lead to a reduction in knowledge flows. Adding technological, linguistic, and geographic distances results in average shares of knowledge diffusion of 15–20 percent. Thus, knowledge flows are relatively localized.

Next, the analysis investigates how knowledge diffusion from the G5 has changed over time, based on different regressions for each five-year period. Figure 4.7 (panel 2) shows the evolution of the average degree of knowledge diffusion for advanced and emerging market economies. While emerging market economies have notably increased their access to information available at the frontier over time, this does not hold for advanced economies, which—particularly since the global financial crisis of 2008—have experienced less diffusion of knowledge, possibly related to the postcrisis slowdown in trade. The deepening integration of emerging market economies in knowledge flows is mostly driven by a change in the effect of the distance in technological development (tech_dev). In earlier periods, knowledge flows weakened with distance from the technological frontier, but this source of divergence has faded and has been replaced by a convergence trend in more recent years. These patterns remain the same even when excluding China, suggesting a broader pattern across emerging market economies.

Impact on Innovation and Productivity

The previous section focused on knowledge flows between the technology frontier and other countries. It has shown that national and linguistic borders are important, but that the combined effect of gravity has decreased for emerging market economies, increasing their access to knowledge available at the frontier.

This section examines the impact of these knowledge flows on innovation activity and productivity in recipient countries. Again, the analysis uses country-sector data instead of aggregate data. This better identifies the effects of interest, as it controls for aggregate trends that could affect domestic innovation but be mistakenly attributed to the trend in foreign knowledge flows. The sector-level effects are later aggregated to provide evidence suggestive of the impact on the broader economy.[13]

Knowledge flows are measured by weighting the G5 knowledge stock—measured by their R&D stock—with the time-varying bilateral shares of knowledge flows $\hat{\phi}$ estimated in the previous section (see Figure 4.2).[14] As discussed, the weighting method used here implicitly captures various channels of knowledge transmission, including trade, FDI, and migration. An alternative and simpler weighting method based on time-varying trade linkages at the sectoral level is also used in a robustness exercise, capturing more directly possible knowledge transmission through trade exposure with technology leaders (Annex 4.3).

The analysis then estimates how innovation (patent *flow*) or productivity in the recipient country sector (P) depends on its own R&D stock (R_c) and the weighted total R&D *stock* of the five technology leaders (R_l). Building on the work of Peri (2005); Coe, Helpman, and Hoffmaister (2009); and Acharya and Keller (2009), the approach can be summarized as

$$lnP_{i,c,t} = D_{c,t} + \gamma lnR_{i,c,t} + \mu \ln \sum_{l \neq c} \phi_{i,c,l,t} R_{i,l,t} + \varepsilon_{i,c,t}, \tag{4.1}$$

in which i denotes the industrial sector, c the country receiving spillovers, l the technology leaders (that is, the G5 countries), and t the time period. The coefficient on the weighted foreign R&D stock (μ) captures the average efficiency of use of foreign knowledge. The equation is estimated using sector-level data for a broad sample of advanced and emerging market economies from 1995 to 2014. The regression includes country-year fixed effects to control for time-varying factors that may drive innovation or productivity trends.

Impact on Innovation

The estimates suggest that knowledge flows from the G5 are important in stimulating the flow of domestic innovation, as proxied by patenting, indicating significant learning from the technological frontier (Table 4.1, column (1)). For example, on average, a 1 percent increase in the knowledge-flow-weighted

[13]In general, the sectoral approach clearly establishes the causality of the effect, but it does not capture aggregate general equilibrium effects.

[14]Using the predicted values rather than actual values helps avoid a potential endogeneity problem because they are based on highly exogenous variables and exclude the fixed effects.

Table 4.1. Impact of Foreign Knowledge on Domestic Innovation and Productivity

Dependent Variable	Patent Flow		Labor Productivity		Total Factor Productivity	
	(1)	(2)	(3)	(4)	(5)	(6)
Sample Period (1995–2014)	Baseline	Changing Diffusion	Baseline	Changing Diffusion	Baseline	Changing Diffusion
Foreign R&D Stock, weighted[1]	0.350***	0.199***	0.057***	0.040*	0.053**	0.018
	[0.055]	[0.057]	[0.020]	[0.022]	[0.021]	[0.037]
Foreign R&D Stock*2000–04		0.137***		0.039***		0.026*
		[0.031]		[0.012]		[0.014]
Foreign R&D Stock*2005–09		0.191***		0.043**		0.052**
		[0.039]		[0.018]		[0.024]
Foreign R&D Stock*2010–14		0.259***		–0.009		0.072**
		[0.048]		[0.026]		[0.030]
Own R&D Stock	0.448***	0.441***	0.118***	0.118***	0.060**	0.058*
	[0.061]	[0.060]	[0.022]	[0.022]	[0.023]	[0.030]
Observations	3,487	3,487	3,721	3,721	1,192	959
R^2	0.779	0.784	0.758	0.759	0.958	0.955
Country-Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Source: IMF staff calculations.
Note: R&D = research and development. Robust standard errors (clustered at country-sector level) in brackets.
***p < 0.01, **p < 0.05, *p < 0.1.
[1]Regression equations for labor productivity and total factor productivity use the lag value of the weighted foreign R&D stock variable.

foreign R&D stock is associated with about a 1/3 of 1 percent increase in the count of patent families by the recipient country sector. Moreover, cross-border technology diffusion seems to have intensified, as indicated by the steady and significant increase in the coefficient on the weighted foreign R&D stock between 1995 and 2014 (Table 4.1, column (2)). And while the acceleration in technology diffusion over time is visible for recipients in advanced economies, it is more pronounced for emerging market recipients (see Annex 4.3 for details).

An alternative specification using simple trade weights instead of citation weights to proxy for the use of the foreign R&D stock produces broadly consistent estimates, demonstrating the robustness of the results (Annex Table 4.3.1). These results are also robust to sensitivity checks, including the use of other quality-adjusted patent measures, or the alternative estimation method provided by dynamic ordinary least squares (OLS).[15] Measuring the stock of G5 knowledge by the weighted patent stock of technology leaders—instead of their weighted stock of R&D—to capture foreign knowledge flows confirms that G5 patents make a significant contribution to innovation in other countries. Using a similar framework, Box 4.2 presents firm-level evidence that foreign knowledge boosts the innovation capacity of firms, and highlights the role played by technology sourcing—the research carried out in the main technological leaders—to circumvent the local character of knowledge and access the knowledge of technological leaders.

Impact on Productivity

Foreign knowledge also plays a role in boosting domestic productivity (Table 4.1, columns (3) and (5)). This is true for both emerging market economies and advanced economies, though the effect is larger for emerging market economies. Separate estimations for recipients indicate that industries in emerging market economies benefit significantly more than those in advanced economies from the role of foreign knowledge flows in channeling technological transfer into higher labor productivity (Annex Table 4.3.2).

Interestingly, while the impact of foreign knowledge flows on innovation has remained strong (and even strengthened) over time, the picture is mixed for the spillover to productivity (Table 4.1, columns [4] and [6]). Indications are that the impact on total factor productivity has strengthened over the past two decades,[16] but the effect on labor productivity seems

[15]Dynamic OLS can address possible nonstationarity and cointegration of the patent and R&D series in a panel setting.

[16]The estimation sample for total factor productivity is smaller and consists mainly of advanced economies.

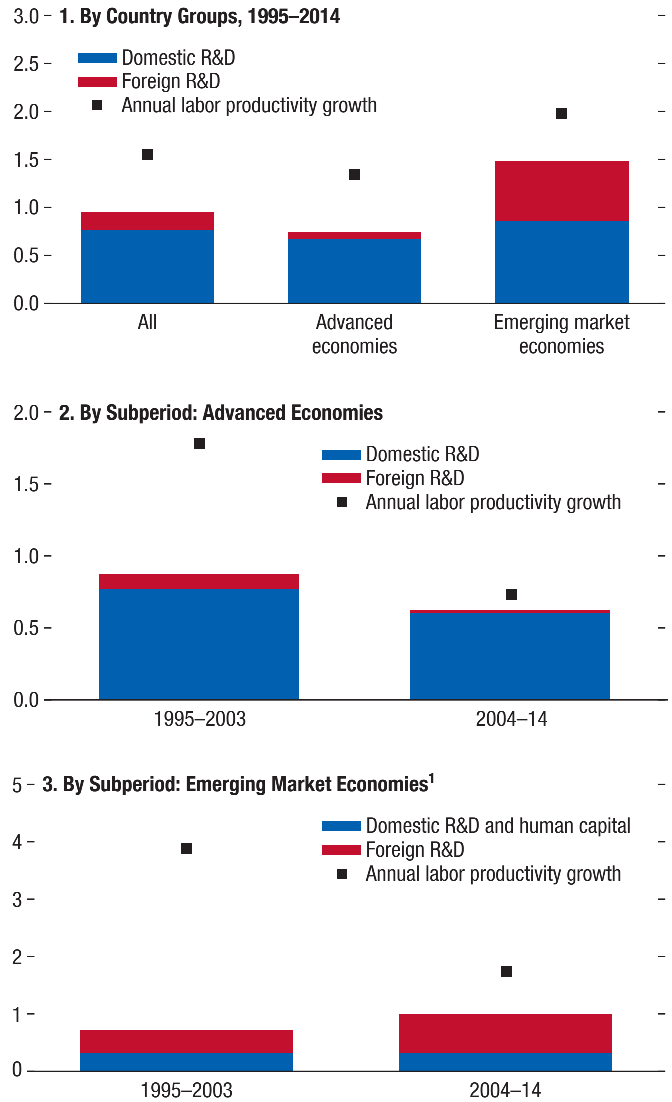
to have weakened in the postcrisis years of 2010–14.[17] This could be consistent with arguments discussed earlier—that innovations make increasingly less impact (Bloom and others 2017). Another—more benign—explanation could be that the protracted period of subdued investment following the global financial crisis reduced technology diffusion, as investment goods are an important conduit for embodied new technologies to integrate into production processes (Adler and others 2017).

Although based on sector data alone, the effects of foreign knowledge flows on labor productivity are economically meaningful. For illustrative purposes, using the estimates in Table 4.1, one can calculate the effect of observed changes in the weighted foreign R&D stock and domestic R&D stock on the growth in domestic labor productivity in each country-sector—assuming everything else remains the same (see Annex 4.3).[18] These contributions can then be averaged over countries and sectors included in the analysis to give a sense of the magnitude of the effects. The estimates suggest that during 1995–2014, developments in domestic and foreign R&D combined would have generated about 1 percentage point average sectoral labor productivity growth a year, which is about 60 percent of the observed sectoral labor productivity growth, consistent with there being other sources of productivity improvements. The impact of knowledge flows from the G5 alone amounted to about 20 percent of the *explained* average growth in sectoral labor productivity in the sample and one-eighth of the *observed* average growth in sectoral productivity (Figure 4.8).

The effects vary for advanced economies and emerging market economies in the following ways:

- Technology diffusion boosted productivity growth in emerging markets more strongly, providing a counteracting force to the slowing innovation trends at the frontier. From 2004 to 2014, foreign knowledge accounted for about 0.7 percentage point of labor productivity growth a year, or 40 percent of observed sectoral productivity growth, compared with 0.4 percentage point annual growth during 1995–2003 (see Figure 4.8). Greater use of existing foreign knowledge by emerging market economies—combined with the stronger impact of these knowledge flows on industries in emerging market economies than on those in advanced economies—has been a significant factor in maintaining the better labor productivity performance

Figure 4.8. Contribution of Foreign Knowledge to Labor Productivity Growth
(Annual percent growth, average across country sectors)

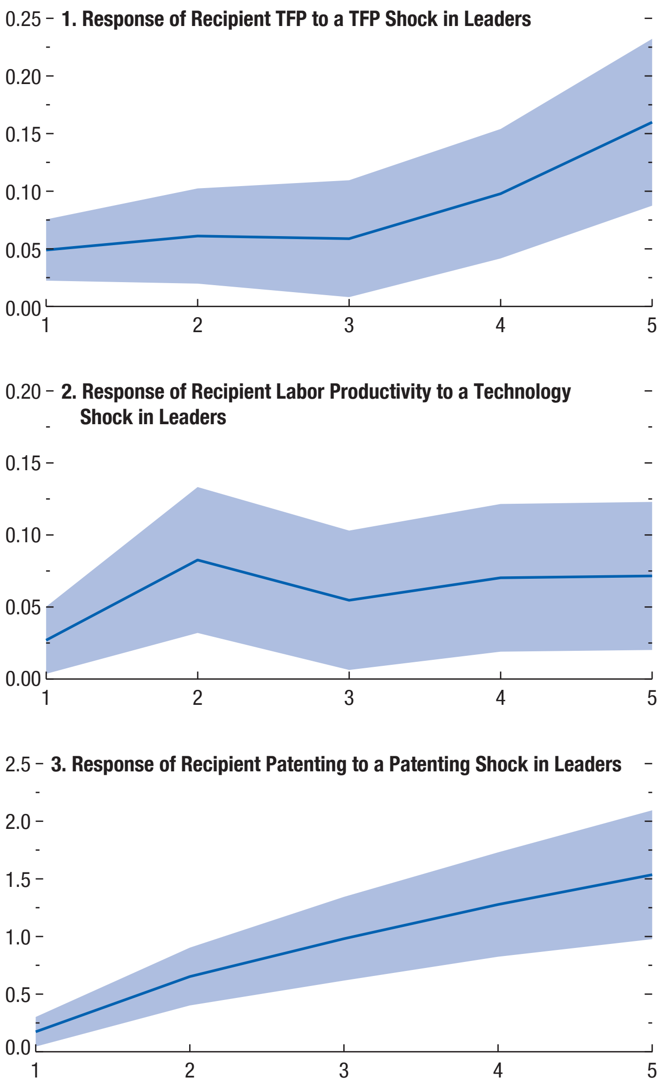


Source: IMF staff estimates.
Note: R&D = research and development.
[1]The decomposition by subperiods for emerging market economies is based on a slightly different regression specification with a less demanding data requirement, which allows for having a significantly broader sample of emerging market economies (Annex 4.3).

[17]This is consistent with OECD (2015), which, looking at a sample of firms in advanced economies, finds evidence of a rising gap in productivity growth between global frontier firms and other firms. See also Andrews, Criscuolo, and Gal (2016).

[18]To assess the impact of aggregate (country-level) variability on the coefficients estimated in equation (4.1), the regression was also run without country-time fixed effects. The estimated impact of the weighted foreign R&D stock on labor productivity was broadly unchanged.

Figure 4.9. The Dynamics of Technology Diffusion
(Percent)



Source: IMF staff estimates.
Note: TFP = total factor productivity. Blue shade denotes 90 percent confidence band. Impulse responses to a 1 percent TFP/labor productivity/patent shock estimated using local projections. *X*-axes denote years; *t* = 1 is the year of the shock.

of these economies compared with that of advanced economies. Results are robust to excluding China, which suggests that emerging market economies, more broadly, have benefited.

- In advanced economies, the contribution of foreign knowledge to labor productivity growth was much smaller, given the slowdown at the frontier and the absence of further improvements in use of foreign knowledge (this use even declined after the global financial crisis).

Estimating Short-term Dynamics

As a complementary approach to the long-term framework and robustness check, this section investigates the short-term dynamics of technology diffusion using the local projection method (see Jordà 2005). Extending the analysis in Duval and others (forthcoming), this approach focuses on the short-term impact of a productivity or innovation shock in the technology leaders on productivity or innovation in the recipient country sector (see Annex 4.4 for details and for definition of the shocks). Shocks to innovation are taken to be changes in the total patent stock of the technology leaders. Again, shocks in the leaders are weighted by the bilateral shares of knowledge that flow from the G5. The empirical specification includes country-time fixed effects to capture factors that drive the short-term dynamics of a country's productivity and innovation at the country level, such as business cycles.

The impact of technology shocks is significantly stronger in the case of innovation measures. On average, a 1 percent patent shock in the leaders would raise the patent stock in the recipient by at least 1 percent after five years (Figure 4.9). This suggests that an acceleration of innovation in technology leaders has a particularly strong effect on innovation in other countries.[19] But the effects are also significant for broad productivity measures: in response to a 1 percent total factor productivity (or labor productivity) shock in the technology leaders, total factor productivity (labor productivity) in the average recipient country sector is estimated to increase by about 0.15 (0.07) percent after five years. The results indicate that technology spillovers tend to happen relatively quickly—within a few years of the initial shock—and the size is not negligible.

Flows within the Technology Frontier

What about the G5 themselves? So far, the empirical approach has focused on the predominant pattern of knowledge and technology flows in the sample period analyzed—that is, from the frontier to other countries. However, this does not mean that flows have been going in one direction only. One way to shed light on this question is to apply the empirical approach developed above (see Equation [4.1]) to estimating knowledge and technology diffusion among

[19]This suggests that follow-on innovations respond more than proportionally to the initial innovation.

the G5. The exercise is subject to additional econometric concerns, as it is more difficult to ensure the absence of endogeneity and simultaneity bias than in the earlier exercises. With this caveat in mind, the results suggest that G5 countries themselves benefited from knowledge flows from other technology leaders, boosting their domestic innovation. Indeed, a 1 percent increase in the knowledge-flow-weighted R&D stock of "other" G5 countries is associated with about a ½ percent increase in the count of patent families in the G5 country considered—slightly larger than the ⅓ of 1 percent increase obtained in the baseline for non-G5 recipient countries (Table 4.1, column [1]). Using firm-level data to examine knowledge spillovers through technology sourcing, Box 4.2 also provides evidence that knowledge spillovers between technology leaders are strong—possibly even stronger than for nonleader recipients.

The Impact of Global Value Chains on Patenting: A Firm-Level Analysis

While the preceding sections aimed to assess the strength of international technological spillovers and their effects on productivity, this section explores one specific channel through which such transmission occurs: firms' participation in global value chains (GVCs). Firms are increasingly part of complex production networks—often centered around multinational enterprises—that process diverse goods and services inputs from other domestic and foreign firms. Potential gains to firms in emerging market economies could be economically significant, because multinational enterprises are typically at the global productivity frontier (OECD 2015). Engagement with multinational enterprises through GVCs provides opportunities for knowledge spillovers to local firms along the value chains, by pooling knowledge with domestic suppliers and encouraging new practices, specialization in productive tasks, and the use of new varieties and higher-quality foreign goods, services, and intangible inputs.

In this way, the emerging pattern of decentralized global production represents a key channel for firms in emerging markets to build innovative capacity, with potentially positive effects for the rest of the economy. However, opposing forces may be at work:

- On the one hand, innovative activity by western firms in emerging market economies has increased dramatically, albeit from relatively small levels, driven by a handful of large multinational firms (UNCTAD 2005). Griffith and Miller (2011) look at examples of how multinationals in western Europe create new knowledge using inventors located in emerging market economies.
- On the other hand, recent analysis suggests that GVC participation often implies that innovation is relocated within multinational firms to where it can be most efficiently undertaken (Stiebale 2016). A considerable increase in the postacquisition innovation of a merged entity is driven by inventors in the acquirer's country, while innovation in the country of the acquired entity tends to decline. In the case of emerging market economies, in particular, the relocation of multinational firms' innovative activities could reflect efforts to overcome inefficiencies associated with weak institutions, including weak intellectual property regimes (see Zhao 2006). Western firms respond by holding the intellectual property that results from emerging markets' innovation in the location of the parent.[20]

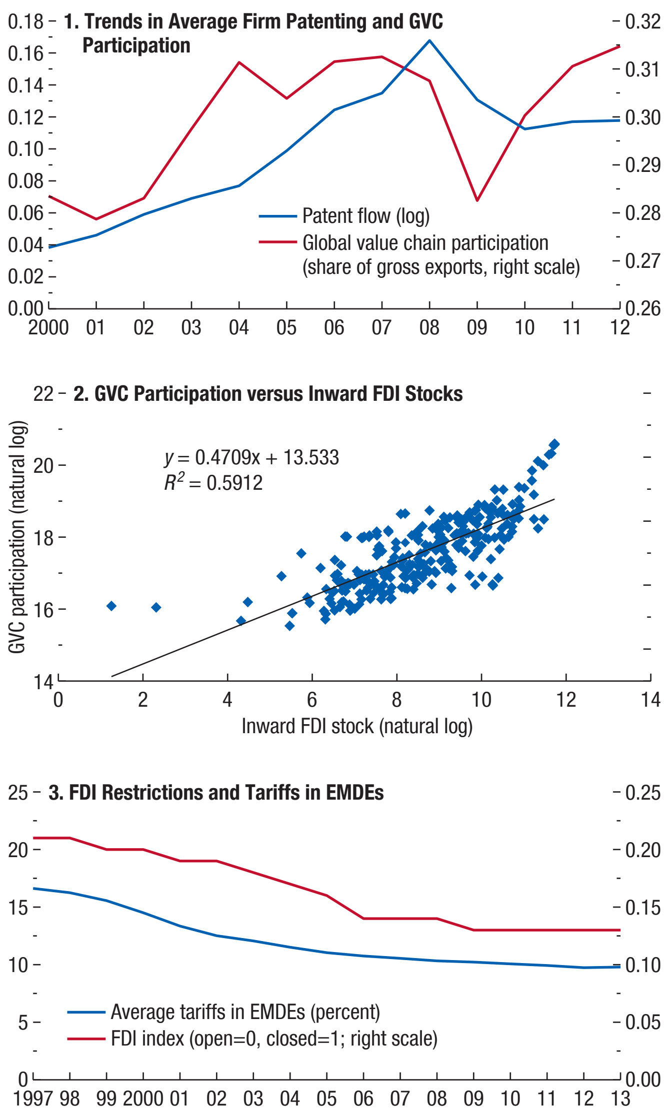
What role do GVCs play in this context? At first glance, trends in GVC participation and patenting suggest that the two appear to be related across emerging market economies (Figure 4.10, panel 1), which would suggest a positive impact. To determine whether these countries have indeed been able to capitalize on their participation in GVCs by increasing innovation, the analysis follows the firm-level framework used by Bloom, Draca, and Van Reenen (2016) (see Annex 4.5).[21] Working at the firm level makes it possible to distinguish two types of technological diffusion as a result of GVC participation: (1) a buildup of innovation capacity in the average firm—so-called within-firm effects, and (2) differentiation of this effect between firms with different rates of patenting—"between-firm" effects.[22] This between-firm

[20]Strokova (2010) documents that intellectual property regimes in emerging market economies, while improving, remain relatively weak.

[21]Firms can also benefit from participation in GVCs through technology adoption without necessarily innovating themselves (see for instance, Lopez-Garcia and Taglioni 2018, for evidence on Europe). Testing for these effects would require firm-level productivity measures, which are not broadly available for emerging market economies in this chapter's sample. The test in this section is more demanding, since it examines whether participation in GVCs has boosted emerging market firms' innovation capacity and not just their adoption of foreign technology.

[22]Due to lack of data on absorption capacity in firms or sectors, the analysis follows a direct approach by controlling for firms' initial level of innovation (as in Bloom, Draca, and Van Reenen 2016) and

Figure 4.10. Patenting and Global Value Chain Participation



Sources: EORA Multi-Region Input-Output database; External Wealth of Nations; European Patent Office, PATSTAT; Foreign Direct Investment statistics; IMF, October 2016 *World Economic Outlook*; Orbis; United Nations Conference on Trade and Development; and IMF staff calculations.
Note: EMDEs = emerging market and developing economies; FDI = foreign direct investment; GVC = global value chain.

analysis is also used to examine how GVC participation alters sectoral composition of employment across firms according to their technological intensity (measured by past patenting activity). Another advantage to working at the firm level is improved identification of the effect of GVC participation, by controlling for firm-level characteristics that may also determine innovation capacity.[23]

To ensure that the impact of GVC participation on innovation is correctly identified, the empirical strategy attempts to tackle potential reverse causality from patenting to GVC participation. While technology improvements may occur because of GVC participation, firms may be pulled into GVCs because of their high productivity, their capacity to innovate, or even through self-selection that comes from being set up with attributes that lend themselves to GVC participation. The analysis exploits the relationship between GVC participation and FDI to establish causality: it is well known that GVC participation is strongly correlated with FDI, given how both relate to the international allocation of production (see Figure 4.10, panel 2). Changes in GVC participation are therefore identified using policy instruments that affect FDI and trade—namely, an industry-level policy indicator of restrictions to FDI and changes in tariffs. These have fallen as GVC participation has increased (see Figure 4.10, panel 3), and they are found to be negatively associated with changes in GVC participation in the econometric analysis (see Annex 4.5). These instruments help correct for the potential endogeneity of GVC measures to patenting.[24]

The results show that an increase in GVC participation leads to a reallocation of innovation activity but, overall, has a positive effect on firm patenting. The effect of a change in GVC participation on firm patenting flows is significantly positive (a "within effect"), but declines with the initial level of patenting activity of the firms ("between effect") (Table 4.2, column [1]).

Once the potential endogeneity between GVC participation and patenting is controlled for, the impact of GVC participation on patenting is even stronger (Table 4.2, column [2]). This happens both within and between firms. The estimated effects imply that firms that were already patenting before the increase in GVC participation tend to see some reduction in

an indirect approach correlating the country-time fixed effects of the main regression with country-level measures of absorption capacity, such as education, quality of infrastructure, and the rule of law.

[23]The primary patent data are drawn from PATSTAT, and global input-output tables are used to construct industry-level GVC participation measures (see Annex 4.5). GVC participation is measured by the sum of (1) the domestic content in exports reused in trading partners' exports (forward linkages), and (2) the foreign value added embedded in exports (backward linkages) expressed as a share of gross exports.

[24]Standard tests confirm that the instruments satisfy the exclusion restriction.

Table 4.2. Impact of Global Value Chain Participation on Average Firm Patenting and Employment

Dependent Variable	Patent Flow (Log, five-year difference)		Employment (Log, five-year difference)
	(1)	(2)	(3)
Sample Period (2002–2012)	OLS (PATSTAT Firms)	IV (PATSTAT Firms)[1]	OLS (Matched ORBIS - PATSTAT Firms)
Initial Patent Stock (2000)	–0.07***	–0.09***	–0.02*
	[–5.703]	[–30.002]	[–1.873]
Within-firm Effects			
GVC Participation (Five-year change)	0.28***	0.98***	1.82***
	[3.133]	[7.420]	[8.002]
Between-firm Effects			
Initial Patent Stock (2000) x	–1.31***	–1.67***	0.91*
GVC Participation (Five-year change)	[–4.160]	[–4.963]	[1.943]
Observations	4,044,066	2,928,882	87,929
R^2	0.026	0.030	0.182
Country x Year Fixed Effects	Yes	Yes	Yes
Sector Fixed Effects	Yes	Yes	Yes

Source: IMF staff estimates.
[1] Instruments include foreign personnel restrictions (percent-year difference and level), screening and approval procedures (level) and tariffs (five-year difference). (See Annex 4.5 for details).
Note: IV = instrumental variable estimation; GVC = global value chain; OLS = ordinary least squares. Robust t-statistics in brackets.
***p < 0.01, **p < 0.05, *p < 0.1.

their patenting flow, possibly reflecting reallocation of some innovation activity to other parts of the GVC.[25] But more extensive GVC participation significantly increases the average patenting of firms that did not previously patent. These firms represent 75 percent of the sample—90 percent excluding China. The overall effect on patenting of the average firm is positive, with the observed 1 percent increase in GVC participation every five years explaining one-tenth of the increase in patenting in the average firm over the same period (Figure 4.11, top panel).

Turning to the broader impact on the economy, increased GVC participation leads to higher employment growth for the average firm and faster employment growth for patenting firms than experienced by nonpatenting firms (Table 4.2, column [3]).[27] The larger share of workers flowing from firms that do not innovate to high-tech firms is another way GVC participation boosts economies' technological intensity.

To gauge the role of policies in building innovation capacity in emerging market firms, Figure 4.11 (bottom panel) shows the correlation between the country-year fixed effects from the estimated patenting relationships and a number of policy factors. Policies aimed at improving the quality of education and connectivity to the world through better infrastructure are key, contributing jointly to increase growth in patenting by 2 percent over five years. Box 4.3 discusses how foreign aid can play a role in technology diffusion to low-income countries by helping build key infrastructure technologies and investing in education. Finally, the evidence presented in Figure 4.11 (panel 2) also suggests that greater adherence to the rule of law boosts firm patenting, possibly mitigating the need for multinational companies to rely on internal mechanisms, such as relocation of innovation activities from affiliates to the parent, to overcome market failures caused by poor institutions.

The Role of Greater International Competition

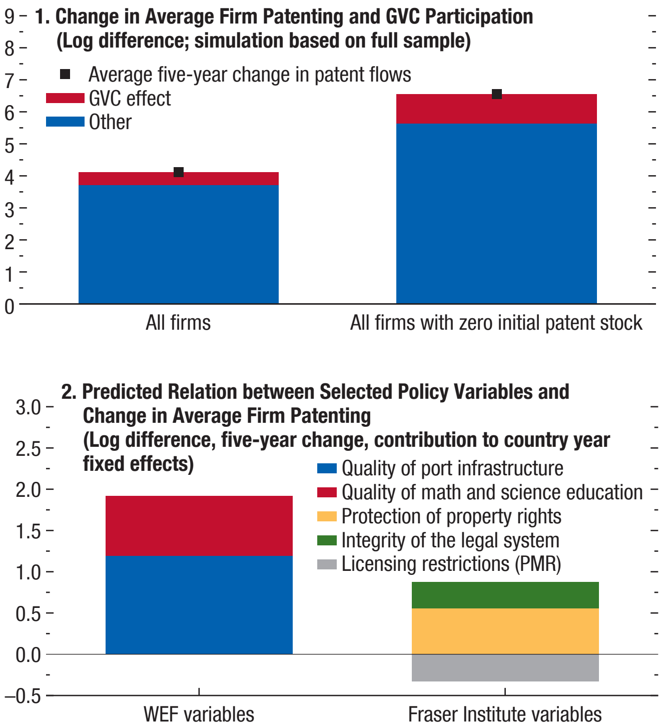
International technology diffusion is a key channel through which globalization impacts innovation, but it may not be the only one. For example, globalization could also make a difference by affecting global competition. Indeed, the evolution of global competition and global market concentration, and their impact on innovation is a much-debated issue (see Box 4.4).

[25]The latter effect is substantially weaker once patenting activity in China is excluded (see Annex 4.5). An alternative explanation could be the relocation of some innovation activity by an emerging market firm to source technology from an advanced economy (see Box 4.2).

[26]Orbis and PATSTAT data are matched to produce a data set of both patenting and nonpatenting firms.

[27]Data limitations prevent testing the effects on firm-level productivity. Performance measures, such as return on assets and return on equity, also have limitations, given that they are affected by the division of value added between labor and capital.

Figure 4.11. The Effects of Global Value Chain Participation and Policy Variables



Sources: EORA Multi-Region Input-Output database; European Patent Office, PATSTAT database; Fraser Institute, Economic Freedom of the World; World Economic Forum Global Competitiveness Report; and IMF staff calculations.
Note: Panel 1 shows result of a simulation based on the full sample. Panel 2 shows the five-year change of contribution to country year fixed effects. GVC = global value chain; PMR = product market regulation; WEF = World Economic Forum Global Competitiveness Report.

While this section does not claim to provide definitive answers, the framework used in the chapter does lend itself to exploring this issue and provides some tentative evidence of the effect of competition on innovation and the diffusion of technology.

At least two opposing forces are at work in the relationship between competition and innovation (Box 4.4). More competition and lower market concentration can depress incentives for firms to innovate because reduced market power means fewer rents from any innovation. However, at the same time, more competition and lower concentration can enhance incentives to innovate to escape competition and secure rents in the first place. And while international trade increases the size of the market over which rents can be captured by winners, it also enhances the "escape competition" effect (Akcigit and others 2017).

By some measures, the evidence suggests that international competition has increased and global concentration has declined—notwithstanding increases in domestic concentration reported in some countries (Gutierrez and Philippon 2017; Grullon, Larkin, and Michaely 2017). Trade with China has risen over the past two decades, not only in the textile industry, but also in innovation-intensive industries such as electrical and optical equipment and transport equipment (Figure 4.12). And the rise of firms from emerging market economies has transformed the international competition landscape more generally (Freund and Sidhu 2017), contributing to a reduction in global market concentration in most industries. Market concentration is usually defined at the industry level and proxied by either a concentration ratio (for example, the share of total industry sales that go to the industry's top four firms) or the Herfindahl-Hirschman Index. Data on the global concentration of patenting show a more mixed picture, though they may underestimate the extent or rise of concentration because the PATSTAT database does not include information on firms' ownership structure.

If global competition indeed has increased, has it led to more or less innovation? An extension of the sectoral framework of analysis (see equation 4.1) can be used to investigate this question (see also Coe, Helpman, and Hoffmaister 2009). In this extension, the knowledge-weighted foreign R&D stock is interacted with relevant structural factors (S), including increased trade with China and measures of global market concentration:

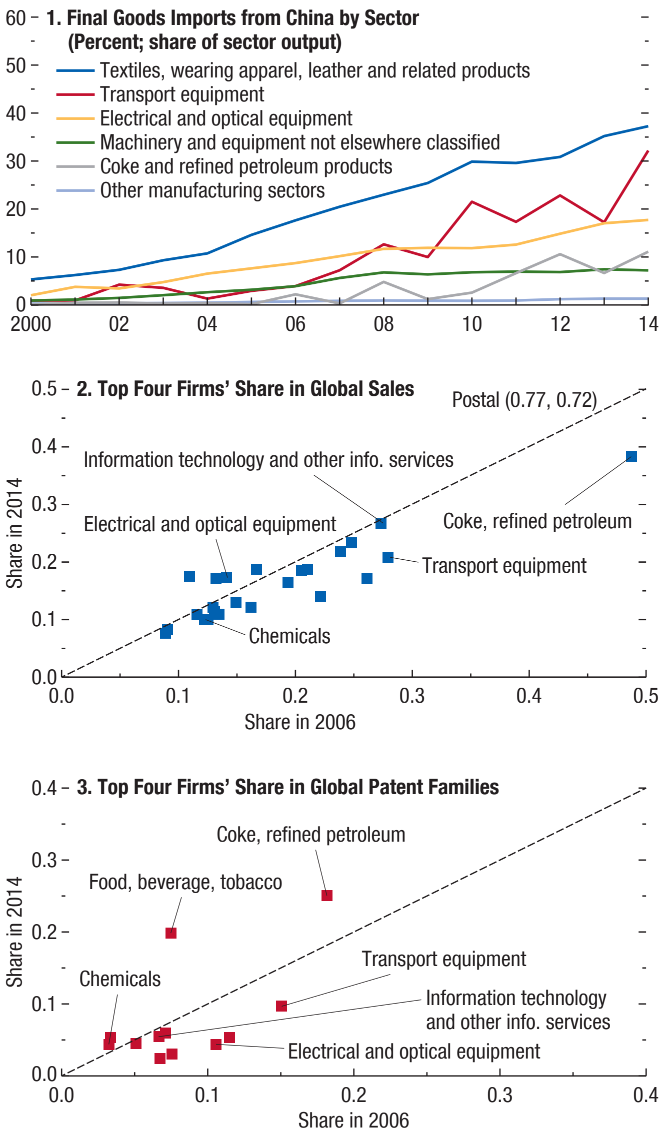
$$\begin{aligned} lnP_{i,c,t} = {} & D_{c,t} + \gamma lnR_{i,c,t} + \mu \ln \textstyle\sum_{l \neq c} \phi_{i,c,l,t} R_{i,l,t} \\ & + \delta \ln \textstyle\sum_{l \neq c} \phi_{i,c,l,t} R_{i,l,t} {}^{*} S_{i,c,t} \\ & + \theta S_{i,c,t} + \varepsilon_{i,c,t}. \end{aligned} \tag{4.2}$$

In this specification, the coefficient on the "main effect" (θ) captures the direct impact of the structural factor on innovation. The total impact of the weighted foreign knowledge stock on innovation is now given by $\mu + \delta S$, and thus the coefficient on the interaction term (δ) reflects the marginal boost to knowledge diffusion coming from the structural factor (see Annex 4.3 for details).

The results suggest that the observed increase in trade competition and decline in global market concentration may have helped strengthen technology diffusion across countries (Figure 4.13).[28]

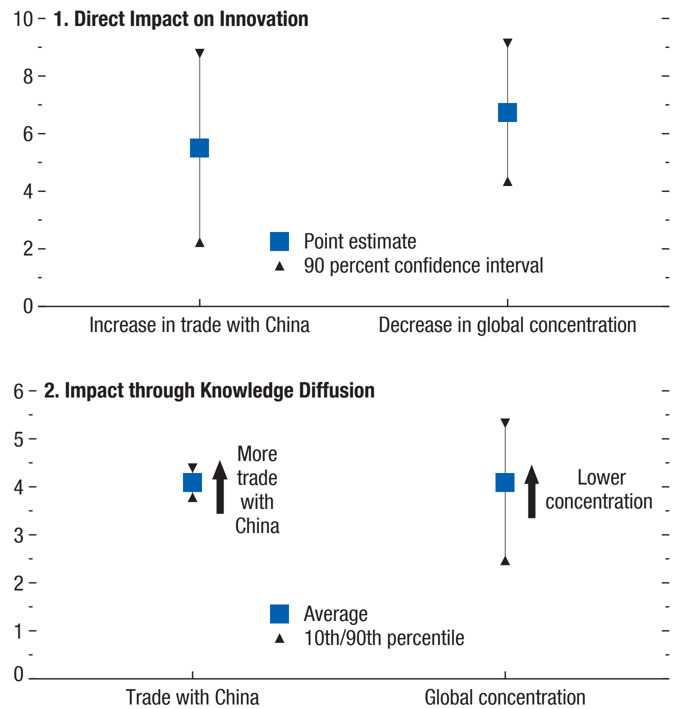
[28]While innovation and technology diffusion could affect competition and concentration, raising a risk of reverse causality, it is unlikely for measures of competition used in the present analysis. The China trade shock largely reflected exogenous policy changes, including China's entry into the World Trade Organization. If

Figure 4.12. International Competition and Global Concentration



Sources: Freund and Sidhu (2017); European Patent Office, PATSTAT database; and IMF staff calculations.

Figure 4.13. The Effect of Competition on Innovation and Technology Diffusion
(Percent)



Source: IMF staff calculations.
Note: Panel 1 shows the estimated change in the recipient's patenting activity in response to the average change in the structural factors over the sample period. Lower and upper bounds denote the 90 percent confidence interval. Panel 2 shows the estimated response of patenting activity in the recipient to a 10 percent increase in the weighted foreign research and development stock, for a range of values of structural factors.

- Increased trade with China boosts domestic innovation and technology diffusion, the latter by increasing the efficiency with which foreign knowledge is used (both the main effect and the interaction effects are positive).

anything, more innovation in a country sector would reduce import penetration from China in that sector, leading to a downward bias in the coefficient estimate. As for the measure of global market concentration, it is not likely to be influenced by individual countries' innovation, given that the G5 countries (which are treated as the technology frontier) are excluded from the sample.

- Similarly, lower global concentration—as measured by the sales share of the top four firms—stimulates both innovation and diffusion. Its impact on diffusion is nontrivial: for example, using the estimates, a 10 percent increase in the foreign R&D stock would boost domestic patenting by about 5.6 percent in a low-concentration sector, whereas the boost to innovation would be less than half of that (2.7 percent) in a high-concentration sector.

The evidence presented within the framework of analysis of this chapter, however tentative, points to a positive relationship between international competition and innovation and technology diffusion. This is broadly in line with findings reported by Bloom, Draca, and Van Reenen (2016) and Coelli, Moxnes, and Ulltveit-Moe (2016), who estimate that increased trade has a positive effect on innovation. However, the results seem to differ from those presented by Autor and others (2016), who estimate that trade with China had a negative impact on innovation among US firms. Clearly, the discussion is ongoing, and further analysis is needed to achieve a deeper understanding of the opposing forces at work. For example, the relationship among competition, concentration, and innovation or technology diffusion could differ over time, countries, and industries.

Conclusions and Policy Implications

Globalization has a positive impact on the international diffusion of knowledge and technology. While the negative side effects of globalization have been much discussed in public debates, the chapter highlights a key benefit—the contribution of globalization to the sharing of growth potential across countries. Globalization facilitates the diffusion of knowledge and technology through the international use of patents and trade. In addition—while the impact of competition on innovation is a complex issue that necessitates further investigation—there is evidence suggesting that, by enhancing international competition, globalization has increased incentives to innovate and adopt foreign technologies.

The chapter has also found that emerging market economies have made increasing use of existing foreign knowledge and technology over time. This has helped soften the impact of the slowdown in innovation at the frontier on emerging market economies and contributed to cross-country income convergence. Participation in GVCs has been one important factor behind this development, although not all firms have benefitted as multinational companies sometimes relocate innovation activities to the parent company.

Finally, the evidence suggests that knowledge does not flow only in one direction. Technology leaders have benefited from each other's research efforts and knowledge. With the growing contribution of China and Korea to the expansion of the technology frontier, one can expect positive spillovers from these countries to the traditional technology leaders. Alongside more traditional channels of gains from trade, the diffusion of knowledge and technology provides a powerful source of mutual benefits from globalization.

From a policy angle, a main conclusion of the chapter is that global interconnectedness fosters foreign knowledge flows. Policies to enhance these connections—whether through GVCs, FDI, or trade—are well known. They include relaxing excessively stringent regulations on FDI, lowering trade barriers, and building necessary infrastructure. Interconnectedness per se is not enough, though. Economists have long argued that assimilating knowledge requires absorptive capacity (for example, Cohen and Levinthal 1989). Knowledge has an important tacit component, which can be comprehended only through the acquisition of scientific and engineering know-how. Investments in R&D and human capital are essential not only to build innovation capacity but also to maximize the absorption of existing innovations (Griffith and others 2004; Coe and others 2009).

Last but not least, while the chapter has highlighted the positive growth effects from globalization, policymakers must make certain that these benefits are shared broadly across the population. This includes ensuring that innovating firms do not exploit the newly acquired technology to gain excessive control of a market to the detriment of consumers; supporting policies to facilitate adjustment (for example, by investment in education and reskilling); and adjusting the tax-benefit system to reallocate income gains in line with countries' social preferences.

Box 4.1. Patent Data and Concepts

This chapter largely relies on patent data to capture innovation and information flows; this box explains key concepts of the data and offers a quick glance at how the data are aggregated.

The database used is the Worldwide Patent Statistical Database (PATSTAT), which includes information on about 70 million patent applications from 80 countries and the relations between them.

- A patent **application** is the filing to a specific patent office that seeks intellectual property protection in the given jurisdiction. Patent applications are territorial, which implies that a separate patent needs to be filed for each country where protection is desired.
- A patent **family** groups applications that relate to the same technology. Each patent application belongs to one family, but an individual application can be a family by itself.[1]
- Patent **citations** relate patents that build upon each other. Applicants must cite prior knowledge to delimit the novelty and legal boundary of the application. Citations can themselves be an indicator of information flow.

While some parts of the chapter rely on patents at the micro level, for others, the data are aggregated to country and industry level so they can be matched with other variables. For this aggregation, patents are attributed to:

- The country of residence of the **first inventor:** The inventor may be different from the applicant, who owns the patent. Because the former is the creator of the new knowledge, the residence of the inventor seems more important to identify the location of innovation. The ordering of inventors in a patent application generally reflects their degree of importance. Focusing only on the first one (instead of a fractional attribution to all) simplifies the process without significantly altering the picture.
- One of 13 **industrial sectors of applicability:** The technical applicability of a patent is defined by the patent office, which maps the patent into sectors of applicability with respective weights (PATSTAT; Van Looy and Vereyen 2014). The patent is attributed to the aggregate sector with the largest weight.

Coordination on patent procedures is an early example of international collaboration. Progress in harmonizing procedures has continued since the late 19th century. Nevertheless, international comparability remains impaired by cultural and legal differences. Two examples serve as illustration:

- **Japan and the number of claims:** Until 1988, each claim (or idea) needed its own patent (Dernis and Khan 2004), a rule that inflated the number of patent applications at the Japan Patent Office. Although the number of claims per patent has increased significantly since the 1990s, the culture and fee structure have left it significantly below United States Patent and Trademark Office or European Patent Office numbers for most of the sample period (Katznelson 2008).
- **China and the incentives to patent:** Part of the reason for the recent explosion in patenting in China is a set of *Patent Promotion Policies*. Fiscal and other incentives reduce the cost of patenting or increase the payoffs not directly related to the protection of the intellectual property. Some ideas are thus patented that in other countries would not be.

The impact of such cultural and legal differences can be very significant. By the simple application count, China now patents about as many as the rest of the world combined. Using quality-adjusted measures, which weigh the patent count by proxies for their technical or economic value, often dramatically reduces this share.

Various options for quality adjustment exist.[2] As preferred measures, the chapter uses the patent family count and focuses only on international or top three families:

- An **international patent family** needs to have one application in at least two distinct patent offices. The idea is that this filter will capture many of the lower-value patents, as the reduced expected payoff would not warrant the extra cost of application, examination, and maintenance in a foreign country. In addition, the cultural influence of certain patent offices would be reduced.

[1]Different applications are connected to a "priority filing," which is the first patent filing for a technology. Under the Paris Convention of 1883, applicants have 12 months to file patents in other member countries and claim retroactive protection starting on the priority date (date of initial filing). The family definition used in this chapter (the DOCDB family) generally groups patents with the exact same priorities.

[2]See Squicciarini, Dernis, and Criscuolo (2013) for discussion of the various measures to capture the economic and technological values of patented inventions.

Box 4.1 *(continued)*

- The **top three patent families** would require an application to at least one of the top three patent offices (European Patent Office, Japan Patent Office, United States Patent and Trademark Office). Relative to the previous measure, this implies more consistency, as a very limited number of patent offices are involved. The drawback is that count measures would tend to favor inventors and applicants from Europe, Japan, and the United States.

Different measures have different strengths and weaknesses; none is fully satisfactory. It is therefore crucial to include appropriate fixed effects in the empirical analysis to capture the time-varying differences in patenting and citation culture. This chapter does that wherever possible by including country-time fixed effects.

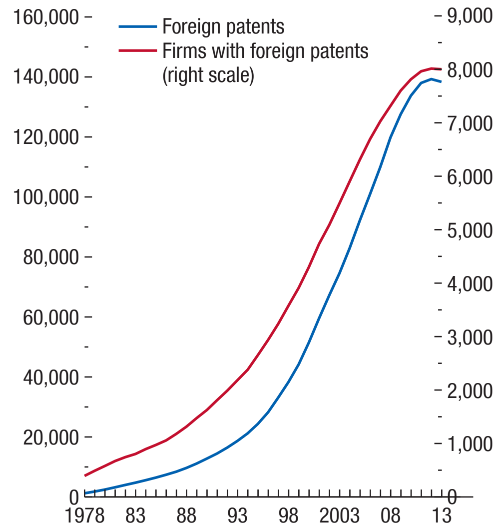
Box 4.2. International Technology Sourcing and Knowledge Spillovers

Despite the global reach of information technology, many economists believe that knowledge diffusion is largely localized (Audretsch and Feldman 1996; Jaffe, Trajtenberg, and Henderson 1993; Keller 2002). In their view, being geographically close to other inventors is important to learn from their knowledge. By performing innovation activities abroad—especially in technologically advanced economies—firms can tap into foreign knowledge more effectively and improve productivity. Data on publicly listed firms in Organisation for Economic Co-operation and Development (OECD) countries is used in this box to provide evidence on the evolution of international technology sourcing and test its role as a channel for knowledge spillovers. Data used in the analysis are from the Worldwide Patent Statistical Database (PATSTAT) maintained by the European Patent Office and the Orbis database by Bureau van Dijk.

Evolution of Global Innovation Networks

The innovation linkages are constructed using information on the source and destination countries of patents granted to publicly listed firms in OECD countries. The souce is the country of residence of patent inventors, and the destination is the headquarter country of the firm that owns the patent. Three important patterns have emerged as international innovation linkages have steadily strengthened over the past four decades. First, an increasing number of firms' innovations are carried out abroad (Figure 4.2.1). Second, the network has become increasingly multilateral: on average, the number of countries in which firms have an innovation presence has increased. Third, dominant hubs—countries where a dominant share of patents are invented—are apparent in the network. In the sample, 28 percent of all patents invented in 2013 are sourced from the United States, followed by Germany (14 percent), the United Kingdom (13 percent), and Japan (7 percent), as shown in Figure 4.2.2. Perhaps not coincidentally, these countries also have the largest aggregate knowledge among OECD countries measured by research and development (R&D) stock. The United States, Japan, and Germany are the top three, and the United Kingdom ranks sixth. The observation that the majority of foreign patents are invented in knowledge hubs is consistent with technology sourcing as a means of gaining access to foreign knowledge.

Figure 4.2.1. Innovation Intensity
(Number of firms or patents)



Sources: Chen and Dauchy (2018); and European Patent Office, PATSTAT database.

Testing for the Role of Technology Sourcing as a Channel of Knowledge Spillover

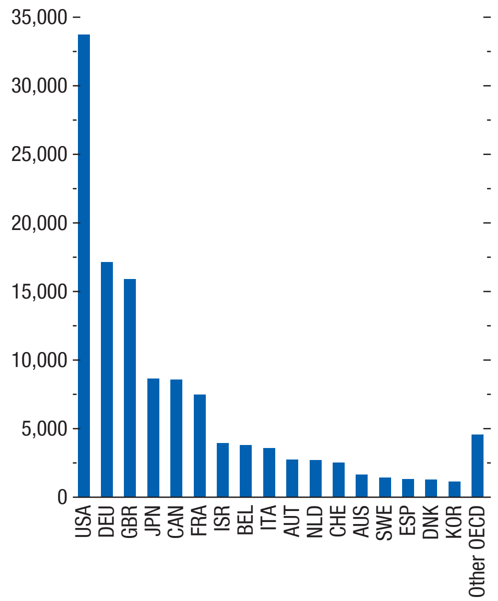
Relative to a more aggregate approach, the firm-level approach presents a number of advantages. First, it can control for home country and industry trends in innovation using fixed effects. Second, it can flexibly control for other factors that affect productivity and are correlated with the foreign innovations of firms. For example, firms with more foreign innovations may have higher productivity simply because they also have more knowledge. These firms may also be better at using foreign knowledge in general, because they have a higher "absorptive capacity."

The empirical model uses a firm-level production function augmented with firm-specific knowledge, and industry-specific domestic and foreign knowledge as well as a number of control variables (Griffith, Harrison, and Van Reenen 2006; Chen and Dauchy 2018). Knowledge is measured by R&D stocks. Technology sourcing is measured by the share of a firm's total worldwide patents whose inventor was residing in a foreign country in the pre-sample period between

The author of this box is Sophia Chen, with support from Hala Moussawi. See Chen and Dauchy (2018) for more details.

Box 4.2 *(continued)*

Figure 4.2.2. Foreign Patents by Source Country, 2013
(Number of patents)



Sources: Chen and Dauchy (2018); and European Patent Office, PATSTAT database.
Note: OECD = Organisation for Economic Co-operation and Development. Data labels use International Organization for Standardization (ISO) country codes.

1997 and 2006. It is interacted with the foreign R&D stock to test for its role as a channel of knowledge spillovers. The regression is estimated over a panel of about 12,000 publicly listed firms in OECD countries in 20 manufacturing and services industries between 2009 and 2012.

The approach distinguishes between two groups of OECD countries, based on their aggregate knowledge. This allows for details to be gathered about the overall direction and effect of international technology sourcing from more advanced and less advanced economies. The underlying assumption is that countries with more aggregate knowledge are closer to the technological frontier. The group of technology frontier countries comprises Japan, Germany, and the United States; the other group includes all other OECD countries. The results are consistent with the technology sourcing hypothesis: firms with a stronger innovation presence in technology frontier countries benefit disproportionately more from their aggregate R&D than firms that lack such presence. Besides the overall positive effect, the results show some interesting patterns in direction and size. The interaction terms between technology sourcing and aggregate R&D stocks in less advanced economies are not significant, suggesting that the spillovers from less advanced economies are weak. Moreover, spillovers from technology leader countries' aggregate R&D is strongest when the recipient countries are also technology leaders. These results are robust to alternative explanations for foreign innovation—such as profit shifting—and alternative models controlling for the absorptive capacity of firms.

The results support the idea that technology sourcing can be an effective channel of international knowledge spillovers. Optimal policy design to stimulate innovation should take into account the internationalization of innovations. For example, policies to incentivize the repatriation of foreign-based innovations may end up compromising domestic productivity growth by stifling domestic innovation. Furthermore, when evaluating the effectiveness of R&D tax policy, one should take into account the social returns from global knowledge spillovers.

Box 4.3. The Role of Foreign Aid in Improving Productivity in Low-Income Developing Countries

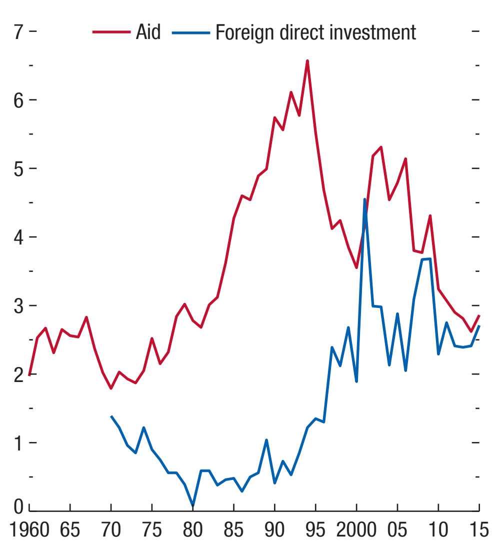
International technology transfers through such channels as trade, foreign direct investment (FDI), and technology licensing is an effective way to acquire technology and improve productivity (Hoekman, Maskus, and Saggi 2005). But low-income countries are less likely to be recipients of international technology transfers through these channels. This is because they tend to be less integrated into the world economy, they have weaker absorptive capacities, and their technology needs may differ from the technologies used in advanced economies (World Bank 2008). While there is a lot of heterogeneity across low-income countries, with countries in east and south Asia benefiting from their integration into global value chains around China, other regions still lack integration into world trade (Allard and others 2016). The evidence discussed in this box suggests that, where traditional channels of technology transfer—such as FDI and integration into world trade—are weak, foreign aid can play an important and complementary role in bridging the gap (Figure 4.3.1).

Research has shown that, at the macro level, foreign aid can help technology transfers and boost productivity in low-income countries. For instance, Walley and Cushing (2013) find that as well as trade, foreign aid in the form of technical cooperation and overseas development assistance grants are important channels through which research and development investment in G7 countries had a spillover effect on 11 sub-Saharan African countries from 1980 to 2004. Using a similar approach, Tiruneh, Wamboye, and Sergi (2017) find evidence that foreign aid is a conduit for R&D spillover effects from nine OECD member countries on labor productivity in 28 sub-Saharan African countries from 1992 to 2011.

While broad growth regression-based studies have questioned the effectiveness of aid to emerging market economies (for example, Rajan and Subramanian 2008), the new aid allocation strategies of donors are showing positive results in some cases. Foreign aid can boost technology transfers and productivity in low-income countries through various channels:

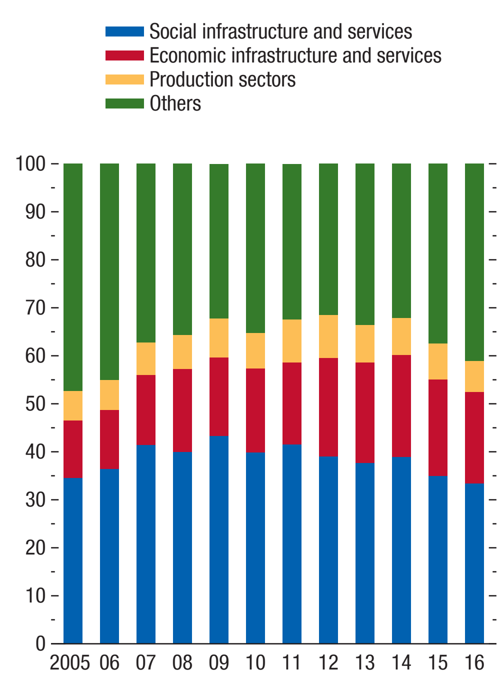
The author of this box is Pankhuri Dutt.

Figure 4.3.1. Sub-Saharan Africa: Net Foreign Direct Investment and Aid Inflows[1]
(Percent of GDP)



Sources: World Bank, World Development Indicators; and IMF staff calculations.
[1]Foreign direct investment refers to net inflows; aid refers to net official development assistance and official aid received.

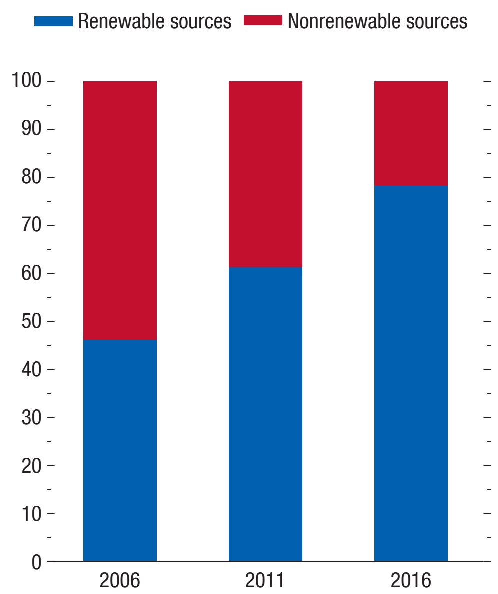
Figure 4.3.2. Official Development Assistance Commitment by Sector
(Percent)



Sources: Organisation for Economic Co-operation and Development, International Development Statistics; and IMF staff calculations.

Box 4.3 *(continued)*

Figure 4.3.3. Aid Commitment to Energy Generation
(Percent)



Sources: Organisation for Economic Co-operation and Development, Creditor Reporting System; and IMF staff calculations.

- *Aid for basic infrastructure technologies:* Over the years, official development assistance flows to economic infrastructure sectors have increased as donors recognized the importance of improving trade-related infrastructure and productive capacities of recipients, including as part of the World Trade Organization's Aid for Trade initiative beginning in 2005 (Figure 4.3.2). Many low-income countries need significant investments in basic infrastructure such as roads and electricity. Aid, along with domestic and foreign private investment, is an important source of financing for the development of this sector in these countries. Within the economic infrastructure sector, the transport and communication, energy, and banking sectors cover almost 94 percent of aid. Aid targeted at infrastructure improvements also makes the recipient country more attractive for foreign investment by reducing the cost of selling to recipient-country consumers and improving their participation in global production links. Recent empirical evidence suggests that aid in the infrastructure sector is effective in improving recipient countries' economic infrastructure endowments (see, for example, Vigil and Wagner 2012; and Donabauer, Meyer, and Nunnenkamp 2016).
- *Targeted aid for sustainable development:* Low-income countries can benefit from technological advancements that reduce the cost of technology in advanced economies. For instance, the climate change initiatives and commitments to the United Nations Sustainable Development Goals (SDGs) raised the share of aid to renewable energy projects (Figure 4.3.3), introducing new and more efficient technologies that helped reduce the energy intensity (energy use per GDP) in recipient countries (Kretschmer, Hübler, and Nunnenkamp 2013). Moreover, the evidence suggests that foreign aid combined with technical cooperation has had a substantial and significant long-term effect on the renewable energy capacity of recipients, whereas foreign aid without technical cooperation brought immediate but short-term effects (Kim 2014).
- *Building absorptive capacity:* Aid can also have a positive impact on the absorptive capacity of the recipient country when it is channeled to the health and education sectors. Donabauer, Herzer, and Nunnenkamp (2014) find that aid for education has a statistically significant and a positive effect on FDI flows in Latin American countries with lower education outcomes and labor force skills. Similarly, Selaya, and Sunesen (2012) find that aid raises the marginal productivity of private capital when it is allocated to improving the supply of complementary inputs, such as education, health, energy, and transport and communication.
- *Aid as a complement to FDI:* Foreign aid can be a complementary tool to attracting FDI, both by improving conditions for investment, but also as a signaling device. For instance, Garriga and Phillips (2014) find that foreign aid that is not geo-strategically motivated has a statistically significant and positive association with FDI inflows in postconflict recipient developing economies. They suggest that aid allocation in a postconflict country acts as a reliable and public information source that improves the credibility of the recipient government, as aid comes with a set of financial and structural covenants. Empirical evidence suggests

Box 4.3 *(continued)*

that aid is most effective in recipients with stable governments and good institutions (Burnside and Dollar 2000; Collier and Dollar 2002; Dutta, Mukherjee, and Roy 2015).

Foreign aid is not a substitute for other channels of technology transfer, rather—when used effectively—it can help lay conditions that attract foreign direct investment and foster integration into global trade and value chains. The new trend in aid allocation and utilization is blended finance. This is where development finance is used to attract private investments to fund the SDGs as a part of the "Billions to Trillions" agenda, which refers to the large gap in funding for the SDGs. China is already using all three channels of aid, trade, and FDI to invest in Africa and has become the continent's largest trading partner over the past 15 years (Busse, Erdogan, and Mühlen 2016). Africa's demographic potential makes it key to invest in the region and deepen its integration in the global production networks, both for the development of the region and for the world economy more broadly.

Box 4.4. Relationship between Competition, Concentration, and Innovation

The theoretical link between competition and innovation is complex. The early literature on endogenous growth emphasized a *Schumpeterian "rent effect,"* according to which less product market competition increases post-innovation rents for the new incumbent, thus increasing the incentives to innovate. Subsequent literature has highlighted the importance of an additional force, the *"escape competition" effect*: if competitive pressure is too low and profits are already large, a firm's incentive to exert effort on innovation to get ahead of competitors will be low. In the international context, the rent and escape competition effects have a wider interpretation. For instance, lower international barriers to trade allow innovators to extract larger rents, as the market size over which they operate is bigger. At the same time, pressure from the pool of potential competitors increases, as it is also exerted by foreign firms (Akcigit and others 2017).

The empirical literature reflects some of these conflicting forces. For instance, policies that increase product market competition have been found to spur innovation, but only up to a certain point, after which innovation decreases (Aghion and others 2005). Several recent papers have examined how innovation rates in advanced economies have been affected by the increased competitive pressure stemming from globalization and the entry of China into world trade. The effect on innovation is found to be positive in Europe and negative in the United States (Autor and others 2016; Bloom, Draca, and Van Reenen 2016). Product market competition appears to interact in important ways with the degree of intellectual property rights protection—another determinant of innovators' rents. For instance, some evidence suggests that stronger product market competition is associated with more innovation only when intellectual property rights protection is strong (Aghion, Howitt, and Prantl 2015). However, while strong protection motivates multinational companies to transfer technology across countries, it reduces innovation in other contexts (Williams 2013; Bilir 2014).

A related discussion investigates the relationship between market competition and concentration. Most of the literature focuses on product market concentration at the industry level, usually proxied by either the Herfindahl-Hirschman Index or the concentration ratio (the share of an industry's sales that goes to the top four firms in the industry). Theoretically, higher concentration could be consistent with higher competitive pressure—and possibly also greater innovation—for example, if innovative "superstar" firms were more likely to appear in more competitive markets (Autor and others 2017). However, there is empirical evidence that suggests that increased concentration in the United States is at least in part linked to reduced competition (Grullon, Larkin, and Michaely 2017; Gutierrez and Philippon 2017). A final crucial observation is that trends in concentration are sensitive to the definition of the relevant market. For instance, while concentration within some large countries is rising, global concentration appears to be falling, thanks to the increased role in international markets of firms from emerging market economies (Freund and Sidhu 2017).

The author of this box is Roberto Piazza.

Annex 4.1: Data, Sample, and Variable Definition

Annex Table 4.1.1. List of Variables, Variable Definitions, and Sources[1]

Variable	Definition	Source
Patent Flows (international)	Patent families with an application in at least two distinct patent offices	Constructed from PATSTAT
Patent Flows (top three)	Patent families with an application in at least one of top three patent offices (EPO, JPO, USPTO)	Constructed from PATSTAT
Patent Stock	Cumulated patent flows constructed using perpetual inventory method (with discount rate = 10 percent)	Constructed from PATSTAT
R&D Expenditure	Spending on research and development, in constant price PPP US dollar	OECD ANBERD database
R&D Stock	Cumulated R&D expenditure constructed using perpetual inventory method (with discount rate = 10 percent)	Constructed from OECD ANBERD data
Labor Productivity	Real value added per worker, in US dollars	Constructed from KLEMS and UNIDO data
Total Factor Productivity (TFP)	TFP adjusted for varying input utilization (see Annex 2 for details)	Constructed from KLEMS data
Trade with China	Imports of final goods from China as a share of sector gross output	WIOT
Global Concentration	Revenue share of top four firms globally	Freund and Sidhu (2017)
Aggregate R&D Stock	Cumulated gross domestic expenditure on R&D (in constant price PPP US dollar), constructed using perpetual inventory method (with discount rate = 10 percent)	Constructed from OECD data
Aggregate Human Capital	Average years of schooling	Barro-Lee dataset
Product Market Regulation	Indicator of regulation in product markets	OECD
Sector R&D Intensity	R&D spending per worker	Constructed from OECD and KLEMS data
Sector Skill Intensity	Computed as 1 - share of production worker	Bureau of Labor Statistics, Occupational Employment Statistics
Sector Turnover	Business churn rate	OECD
Technological Specialization	Uncentered bilateral correlation between two country-sectors' vectors of patent applications in the 23 IPC subsection	Constructed based on PATSTAT
Technological Distance	Absolute ln-difference between two country-sectors in the ratio of R&D (in constant PPP terms) per number of person engaged	Constructed from OECD and KLEMS data
Different Country	Dummy for an international country pair	Mayer and Zignago (2011)
Different Border	Dummy for a country pair sharing no common border	Mayer and Zignago (2011)
Different Language	Dummy for a country pair sharing no common official language	Mayer and Zignago (2011)
International Distance	Distance between the capital cities of two countries, zero for the same country pair	Mayer and Zignago (2011)
Bilateral Citations	Sum of citations between two country-industry pairs	Constructed based on PATSTAT
Global Value Chain (GVC)		Eora multi-region input-output database and World input-output database (2000–12)
Firm Employment Growth	Five-year difference of the logarithm of employee count per firm	Bureau van Dijk Orbis (2000–12)
FDI Regulatory Restrictiveness Index	Index summarizing regulation restrictions on FDI; range from 0 (open) to 1 (closed).	OECD FDI database (2000–12)
Tariffs		UNCTAD TRAINS (2000–12)
IPR, Education, Infrastructure Quality	Index, ranging from 1 (lowest) to 7 (best)	World Economic Forum (2000–12)
PMR, Institutions	Index, ranging from 1 (lowest) to 10 (best)	Fraser (2000–12)

[1]"Notes on CEPII's distances measures: The GeoDist Database," CEPII Working Paper 2011–25.

Note: EPO = European Patent Office; IPC = International Patent Classification; JPO = Japan Patent Office; OECD = Organisation for Economic Co-operation and Development; PMR = product market regulation; PPP = purchasing power parity; R&D = research and development; UNIDO = United Nations Industrial Development organisation; USPTO = United States Patent and Trademark Office; WIOT = World Input–Output Tables.

Annex Table 4.1.2. List of Sectors in Estimation Samples[1]

ISIC4 Code	Sector Description
10–12	Food products, beverages, and tobacco
13–15	Textiles, wearing apparel, leather, and related products
16–18	Wood and paper products, printing, and reproduction of recorded media
19	Coke and refined petroleum products
20–21	Chemicals and chemical products
22–23	Rubber and plastics products, and other non-metallic mineral products
24–25	Basic metals and fabricated metal products, except machinery and equipment
26–27	Electrical and optical equipment
28	Machinery and equipment, not elsewhere classified
29–30	Transport equipment
31–33	Other manufacturing, repair and installation of machinery and equipment
F	Construction
62–63	Information technology and other information services

[1]The construction and Information technology services sectors are only included in the first-stage sample.

Annex Table 4.1.3. List of Countries in Estimation Samples[1]

Regression	Advanced Economies	Emerging Market Economies
Gravity model of knowledge diffusion sample (with technological distance based on research and development)	Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Ireland, Israel, Italy, Japan, Korea, Netherlands, New Zealand, Norway, Portugal, Singapore, Spain, Sweden, Switzerland, United Kingdom, United States	China, Czech Republic, Estonia, Hungary, Mexico, Poland, Slovenia, Slovakia, Turkey
Alternative gravity model of knowledge diffusion sample (with technological distance based on value added)	Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Ireland, Israel, Italy, Japan, Korea, Netherlands, New Zealand, Norway, Portugal, Singapore, Spain, Sweden, Switzerland, United Kingdom, United States	Argentina Brazil, Bulgaria, Chile, China, Colombia, Czech Republic, Estonia, Hungary, India, Indonesia, Malaysia, Mexico, Poland, Russia, Slovakia, Slovenia, South Africa, Thailand, Turkey, Uruguay, Vietnam
Patent and labor productivity sample	Australia, Austria, Belgium, Canada, Denmark, Finland, Ireland, Israel, Italy, Korea, Netherlands, New Zealand, Norway, Portugal, Singapore, Spain, Sweden, Switzerland	China, Czech Republic, Estonia, Hungary, Mexico, Poland, Slovakia, Slovenia, Turkey
Patent and labor productivity sample, expanded emerging market economy sample		Argentina, Bulgaria, Brazil, Chile, China, Colombia, Czech Republic, Estonia, Hungary, India, Malaysia, Mexico, Poland, Russia, Slovakia, Slovenia, South Africa, Turkey, Uruguay
Total factor productivity sample	Austria, Denmark, Finland, Italy, Netherlands, Spain, Sweden	Czech Republic, Slovakia
Patent and global value chain sample, emerging market firm level		Brazil, China, India, Indonesia, Mexico, Philippines, Poland, Russia, South Africa, Thailand, Turkey

[1]The classification of countries into advanced economies and emerging economies is as of the beginning of the sample period, that is, around 1995. Israel, Korea, and Singapore all became advanced economies around 1997 and thus are classified as advanced economies in the sample.

Annex 4.2. Determinants of Knowledge Flows: Additional Results

This annex provides details and robustness tests of the baseline results presented in the chapter's "Determinants of Knowledge Flows" section.

Baseline Results

As discussed in the chapter, a gravity model helps investigate the determinants of knowledge flows. It follows Peri (2005) and models the citations made in the patents of a given country sector to patents from the technology frontier as a function of a set of geographic, linguistic, and technological variables. Dummy variables indicate whether citations involve two distinct sectors (diff_sector) or countries (diff_country) and whether the countries share a common border (diff_border) or an official language (diff_lang). The regression also includes a measure of the distance between countries' capital cities (dist_int) and differences in technological specialization (tech_spec) and technological development (tech_dev). While technological development captures the difference in technological intensity (measured as the log difference either in research and development [R&D] or value added per worker), technological specialization captures compositional differences in the types of technology used.[29] Defining ϕ as the citations, the model can be written as follows:

$$\begin{aligned}\phi_{i,n;j,m} = \exp\Big[&a + \rho_{i,n} + \vartheta_{j,m} + b_1(\mathit{diff\_sector})\\ &+ b_2(\mathit{diff\_country}) + b_3(\mathit{diff\_border})\\ &+ b_4(\mathit{diff\_lang}) + b_5(\mathit{dist\_int}) + b_6(\mathit{tech\_spec})\\ &+ b_7(\mathit{tech\_dev}) + \varepsilon_{i,n;j,m}\Big], \qquad (4.3)\end{aligned}$$

in which i and n denote the citing country and sector, and j and m the cited country and sector. It includes country-sector fixed effects for both the citing and cited country sector to control for differences in the amount of innovation, and institutional or cultural factors that might influence the propensity to patent and cite other patents. The model is estimated using the Pseudo-Poisson-Maximum Likelihood estimator, a natural choice for a gravity-type model with significant data heteroscedasticity, many zero entries, and a large number of dummies (Santos Silva and Tenreyro 2006, 2011).

A key summary of the analysis is the predicted relative frequencies of citations for each country sector (denoted $\hat{\phi}$). The predicted values exclude the fixed effects. Given the exponential function and that all variables are zero for the same country sector, the predicted value will be equal to 1 within, and generally a fraction thereof across, different country sectors (see Peri 2005 for more details). These can be interpreted as the share of knowledge that diffuses from the cited to the citing relative to what diffuses within the cited country sector.

The baseline estimation focuses on same-sector pairs and restricts the cited countries to members of the G5 (France, Germany, Japan, United Kingdom, United States). The model is estimated for two samples (see Annex 4.1):

- The first sample uses the log difference of R&D per worker to measure the distance in technological development between citing and cited country sector. In this case, the sample of citing countries includes 23 advanced economies and 9 emerging market economies, reflecting in part the limited availability of sectoral R&D data for emerging market economies.
- To expand coverage of emerging market economies, the chapter follows Peri (2005) in considering an alternative measure of distance in technological development: the log difference of real value added per worker between citing and cited country sector. This expands the sample to 22 emerging market economies.

Annex Table 4.2.1 shows the baseline results presented in the chapter, based on the R&D measure of distance in technological development. Column (1) shows the results for the model estimated as a cross section during 1995–2014; columns (2) to (5) show the results for the model estimated over each five-year subperiod.

In an alternative specification, the difference in technological development is defined based on value added per worker instead of R&D spending. While the effects of geographic variables are generally comparable to those obtained using R&D spending, somewhat more positive (or at least less negative) effects of differences in technological specialization and develop-

[29] The difference in technological specialization is based on compositional differences in patent application. Similar to Peri (2005), for each country sector, a vector is produced for which the cells are the proportions of all patent applications that relate to each of the 23 International Patent Classification subsections. The variable is then defined as 1 minus the uncentered correlation between the two country industries' proportion vectors.

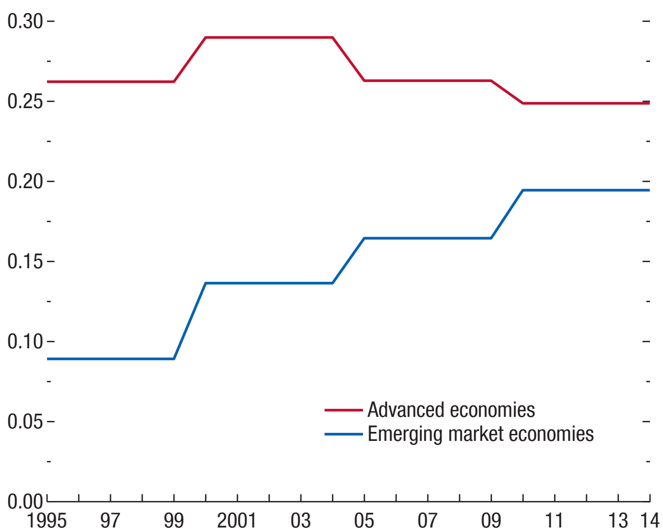
Annex Table 4.2.1. Gravity Model of Knowledge Diffusion: Baseline Results for Different Time Periods

	(1) 1995–2014	(2) 1995–99	(3) 2000–04	(4) 2005–09	(5) 2010–14
diff_country	−0.457*** [−3.69]	−0.595*** [−7.45]	−0.407*** [−5.18]	−0.370*** [−3.78]	−0.726*** [−4.52]
diff_border	−0.124 [−0.93]	−0.333*** [−4.89]	0.0117 [0.12]	0.117 [1.09]	−0.435* [−2.53]
diff_lang	−0.810*** [−11.96]	−0.539*** [−10.42]	−0.708*** [−11.70]	−0.940*** [−12.61]	−0.815*** [−7.66]
dist_int	−0.02493 [−1.51]	0.017* [1.96]	−0.036** [−3.02]	−0.050*** [−4.51]	0.004 [0.20]
tech_spec	−2.214*** [−3.30]	−3.779*** [−8.32]	−2.971*** [−5.96]	−2.411*** [−4.52]	−2.786*** [−4.03]
tech_dev_R&D	−0.0655 [−0.68]	−0.143*** [−3.89]	−0.169*** [−3.63]	−0.169*** [−3.32]	0.185 [1.48]
Citing-Country-Industry Fixed Effect	Yes	Yes	Yes	Yes	Yes
Cited-Country-Industry Fixed Effect	Yes	Yes	Yes	Yes	Yes
Observations	1,759	1,139	1,263	1,710	1,654

Note: Result from same-sector regression with cited countries limited to the G5 (France, Germany, Japan, United Kingdom, United States) for each sector. Robust t-statistics (clustered at citing country-industry level) are in brackets.
***p < 0.001, **p < 0.01, *p < 0.05.

Annex Figure 4.2.1. Diffusion of Knowledge from G5 with Expanded Emerging Market Economy Sample

(Predicted share of knowledge that diffuses, average across recipient country-sectors)



Source: IMF staff calculations.
Note: The figure shows the average share of knowledge from G5 that diffuses, based on a same sector regression with the difference in technological development based on value added per worker and using interactions to estimate separate coefficients for emerging markets and advanced economies. G5 includes France, Germany, Japan, United Kingdom, United States.

ment are found in emerging market economies. The size and evolution of the predicted use of information is, however, very similar to the baseline used (Annex Figure 4.2.1).

Robustness

This section shows that the baseline results are robust to different choices of the estimation sample and other regression specifications. Three main alternatives are considered:

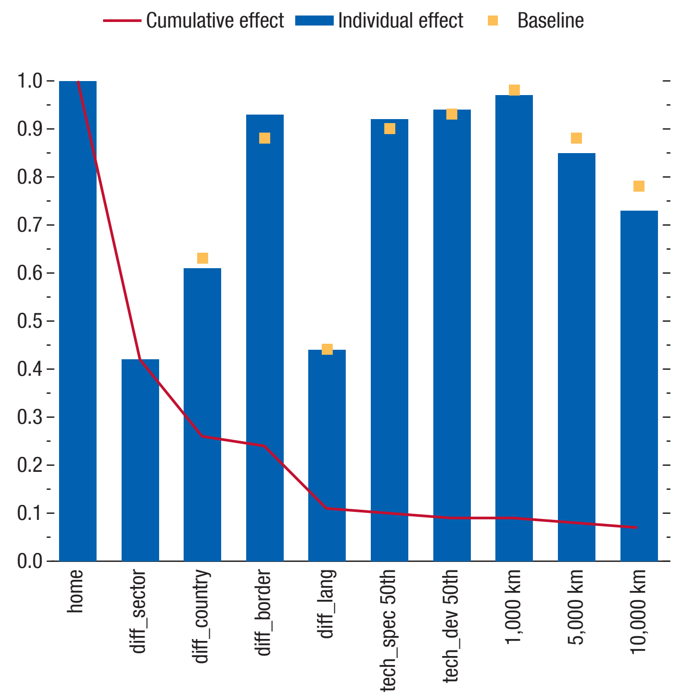
- *Inclusion of cross-sectoral citations:* The sample is expanded to include cross-sectoral patent citations by including, in the gravity equation, a dummy *diff_sector* for the case in which the citing and cited sectors differ. Annex Figure 4.2.2 presents the regression result for the share of knowledge that flows from a given country sector ($\hat{\phi}$). As can be expected, crossing a sectoral barrier entails a significant reduction in knowledge diffusion. Accordingly, the average $\hat{\phi}$ now converges to levels just below 10 percent, roughly half compared with the same-sector setup. The detailed regression results are shown in Annex Table 4.2.2.
- *Inclusion of all countries as source:* In this specification all countries in the sample, and not just the

G5, are included as potential sources of knowledge (for example, all countries are on both the citing and the cited side). The differences with the baseline estimation are small (as shown in Annex Figure 4.2.3), with the effect that most barriers are slightly larger than in the baseline, consistent with the finding that information from nonleaders tends to diffuse less (see Peri 2005).

- *Excluding China from the baseline regression:* This specification is the same as in the baseline, but China is excluded from the estimation sample. As shown in Annex Figure 4.2.4, the importance of the national border is reduced, but this is partly compensated for by the increased importance of technology barriers. Moreover, a shift is observed between sharing a border (getting weaker) and international distance (getting stronger). Overall, point estimates and the average $\hat{\phi}$'s are comparable, suggesting that the inclusion of China, though important, is not a key driver of the results.

Annex Figure 4.2.2. Reduction of Knowledge Flow with Additional Barriers: Including Cross-Sectoral Citations

(Share of information that diffuses across cumulative and individual barriers)



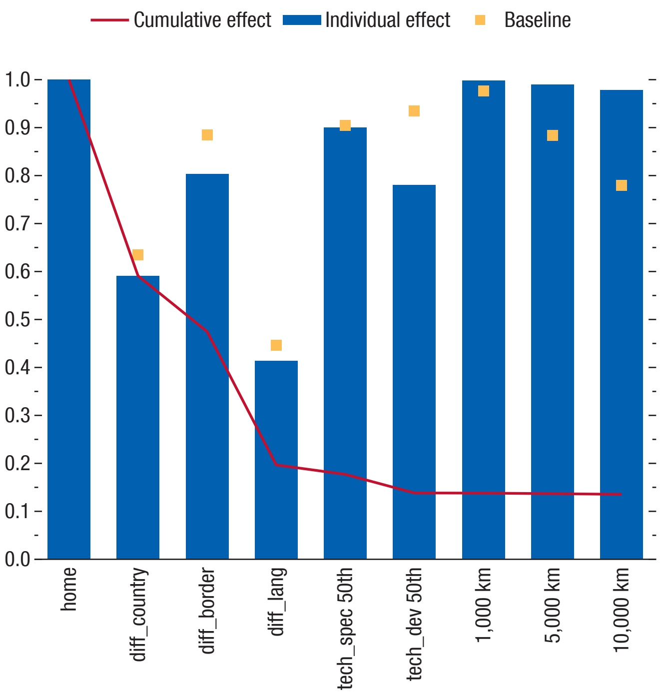
Source: IMF staff calculations.
Note: Square reflects baseline from Figure 4.7 for comparison. km = kilometers.

Annex Table 4.2.2. Gravity Model of Knowledge Diffusion: Including Cross-Sectoral Pairs

	(1)	(2)	(3)	(4)	(5)
	1995–2014	1995–99	2000–04	2005–09	2010–14
diff_sector	−0.866***	−0.908***	−0.875***	−0.818***	−0.972***
	[−5.15]	[−4.14]	[−3.87]	[−5.50]	[−5.82]
diff_country	−0.490***	−0.672***	−0.496***	−0.466***	−0.560***
	[−5.50]	[−8.59]	[−6.21]	[−5.21]	[−6.21]
diff_border	−0.0735	−0.309***	−0.00757	0.114	−0.292*
	[−0.67]	[−4.16]	[−0.09]	[1.16]	[−1.97]
diff_lang	−0.810***	−0.542***	−0.687***	−0.899***	−0.956***
	[−12.90]	[−12.20]	[−12.19]	[−12.50]	[−12.20]
dist_int	−31.84*	12.03	−35.65***	−54.48***	−7.275
	[−2.25]	[1.38]	[−3.41]	[−5.34]	[−0.38]
tech_spec	−1.926***	−2.086***	−1.887***	−1.906***	−1.886***
	[−9.70]	[−7.97]	[−6.62]	[−9.87]	[−9.62]
tech_dev_R&D	−0.0610	−0.0997***	−0.0866***	−0.0660*	−0.0291
	[−1.70]	[−5.75]	[−3.38]	[−2.30]	[−0.65]
Citing-Country-Industry Fixed Effect	Yes	Yes	Yes	Yes	Yes
Cited-Country-Industry Fixed Effect	Yes	Yes	Yes	Yes	Yes
Observations	22,726	14,337	15,930	22,162	21,502

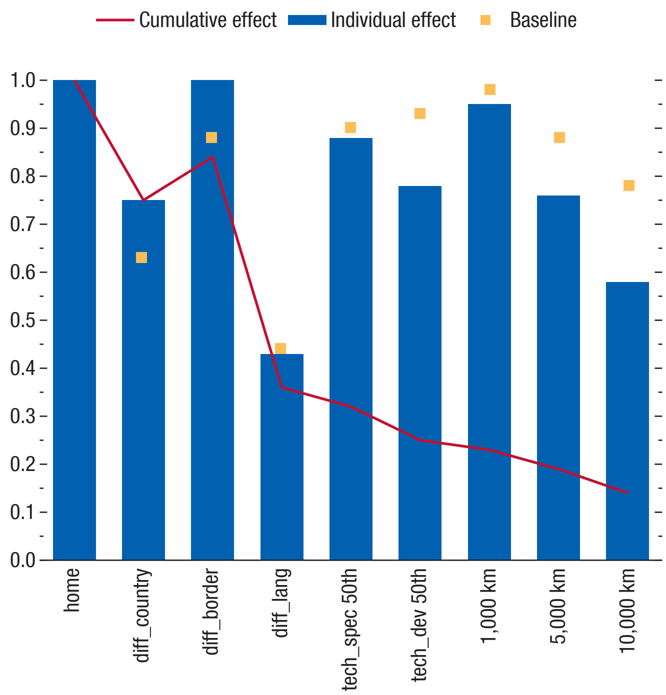
Note: Result from same-sector regression as well as cross-sectoral pairs and cited countries limited to the G–5 (France, Germany, Japan, United Kingdom, United States) for each sector. Robust t-statistics (clustered at citing country-industry level) are in brackets.
***p < 0.001, **p < 0.01, *p < 0.05.

Annex Figure 4.2.3. Reduction of Knowledge Flow with Additional Barriers: Unrestricted Cited Sample
(Share of information that diffuses across cumulative and individual barriers)



Source: IMF staff calculations.
Note: Square reflects baseline from Figure 4.7 for comparison. km = kilometers.

Annex Figure 4.2.4. Reduction of Knowledge Flow with Additional Barriers: Excluding China from Baseline
(Share of information that diffuses across cumulative and individual barriers)



Source: IMF staff calculations.
Note: Square reflects baseline from Figure 4.7 for comparison. km = kilometers.

Annex 4.3. Impact of Foreign Knowledge on Domestic Innovation and Productivity: Additional Results for Panel Estimation of Long-Term Relationships

This annex presents additional discussion and robustness tests of the panel estimation results presented in the sections "Impact on Innovation and Productivity" and "The Role of Greater International Competition."

Impact on Innovation and Productivity: Additional Robustness

The chapter estimated the long-term relationship between the stock of foreign research and development (R&D) and domestic innovation (measured by patent flow) or productivity using a panel data set at the country-sector-year level. Various robustness exercises were conducted for both the impact on innovation (Annex Table 4.3.1) and on productivity (Annex Table 4.3.2). The results are summarized below.

- *Advanced economies versus emerging market economies:* Splitting the estimation sample into advanced economies and emerging market recipients shows that foreign knowledge matters for both groups of countries in boosting innovation—measured by patenting—and productivity (Annex Tables 4.3.1 and 4.3.2, columns [1] and [2]). Foreign R&D seems to play a comparatively more important role for innovation in emerging market economies, while for advanced economies domestic R&D efforts matter more. Compared with advanced economies, emerging market recipients also enjoy a stronger productivity boost for a given change in the foreign stock of knowledge. Focusing on the dynamics of knowledge diffusion, the impact of foreign knowledge flows on domestic innovation appears to have increased more strongly over time in emerging market economies (Annex Tables 4.3.1 and 4.3.2, columns [3] and [4]).
- *Dynamics of knowledge diffusion:* The increase over time in the coefficient on foreign R&D in the innovation equation is robust to restricting the sample to be roughly balanced (that is, keeping only country sectors with a long period) to

Annex Table 4.3.1. Impact of Foreign Knowledge on Domestic Innovation: Robustness

Variables	(1) AE Recipients	(2) EM Recipients	(3) Changing Diffusion-AE	(4) Changing Diffusion-EM	(5) EM Recipients-Broad	(6) Dynamic OLS	(7) Top Three Patent Families	(8) Trade Weight	(9) Sector-Year Fixed Effect
Foreign R&D Stock, Weighted	0.353***	0.342***	0.232***	0.115	0.240***	0.298***	0.359***	0.240***	0.508***
	[0.070]	[0.088]	[0.078]	[0.085]	[0.078]	[0.070]	[0.057]	[0.033]	[0.113]
Foreign R&D Stock*2000–04			0.125***	0.239***					
			[0.034]	[0.064]					
Foreign R&D Stock*2005–09			0.184***	0.280***					
			[0.044]	[0.076]					
Foreign R&D Stock*2010–14			0.249***	0.353***					
			[0.056]	[0.083]					
Own R&D Stock	0.477***	0.361***	0.440***	0.346***		0.410***	0.464***	0.468***	0.724***
	[0.077]	[0.089]	[0.091]	[0.107]		[0.042]	[0.064]	[0.066]	[0.039]
Aggregate R&D Stock*					0.130***				
Sector R&D Intensity					[0.042]				
Human Capital*					0.139*				
Sector Skill Intensity					[0.073]				
Observations	2,345	1,142	2,132	940	2,115	1,605	3,468	3,021	3,487
R^2	0.750	0.707	0.747	0.723	0.646	0.323	0.790	0.794	0.758
Country-Year Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No
Sector-Year Fixed Effect	No	No	No	No	No	No	No	No	Yes

Source: IMF staff calculations.
Note: AE = advanced economy; EM =emerging market; OLS = ordinary least squares.
Robust standard errors (clustered at country-sector level) in brackets.
***p < 0.01, **p < 0.05, *p < 0.1.

Annex Table 4.3.2. Impact of Foreign Knowledge on Domestic Labor Productivity: Robustness

Variables	(1) AE Recipients	(2) EM Recipients	(3) Changing Diffusion-AE	(4) Changing Diffusion-EM	(5) EM Recipients-Broad	(6) Dynamic OLS
Foreign R&D Stock,	0.039**	0.080**	0.021	0.074	0.073**	0.065**
Weighted (Lagged)	[0.017]	[0.040]	[0.020]	[0.046]	[0.031]	[0.032]
Foreign R&D Stock*2000–04			0.027**	0.060***		
			[0.011]	[0.021]		
Foreign R&D Stock*2005–09			0.050***	0.062**		
			[0.018]	[0.029]		
Foreign R&D Stock*2010–14			–0.006	–0.034		
			[0.033]	[0.055]		
Own R&D Stock (Lagged)	0.133***	0.103***	0.123***	0.108***		0.133***
	[0.022]	[0.037]	[0.025]	[0.038]		[0.023]
Aggregate R&D Stock*					0.039*	
Sector R&D Intensity					[0.022]	
Human Capital*					0.035	
Sector Skill Intensity					[0.064]	
Observations	1,968	1,753	1,751	1,511	2,248	1,785
R^2	0.619	0.693	0.633	0.725	0.992	0.067
Country-Year Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes

Source: IMF staff calculations.
Note: AE = advanced economy; EM = emerging market; OLS = ordinary least squares.
Robust standard errors (clustered at country-sector level) in brackets.
***p < 0.01, **p < 0.05, *p < 0.1.

avoid sample composition effects. In addition, period-by-period estimation, which allows all coefficients to vary over time, yields similar results. The subperiod coefficients on the foreign R&D stock are all statistically significant.

- *Expanded emerging market sample:* Given that the availability of sector-level R&D data limits the sample to a small number of emerging market economies, an alternative specification is estimated for a larger number of emerging market economies, in which the domestic-sector-level R&D stock is replaced by the domestic aggregate R&D stock interacted with a sector's R&D intensity.[30] The specification also controls for a measure of human capital (that is, aggregate years of schooling interacted with a sector's skill intensity).[31] The results regarding the economic significance of the foreign R&D stock also hold for this larger sample (Annex Tables 4.3.1 and 4.3.2, column [5]).
- *Dynamic ordinary least squares (DOLS):* Given that the R&D stock and patent/labor productivity series are possibly nonstationary and cointegrated, the baseline specification is reestimated using DOLS (see Kao and Chiang 2001). The procedure essentially involves adding several lags and leads of the change in the regressors and requires a strongly balanced sample. The number of lags chosen is two, and the number of leads is one. The baseline results hold for both the innovation and labor productivity specifications, with a slightly larger coefficient on the foreign R&D stock (Annex Tables 4.3.1 and 4.3.2, column [6]). For the total factor productivity specification, the balanced-sample requirement significantly reduces the degrees of freedom, and thus the dynamic OLS estimation was not performed.
- *Alternative patent measure:* While the baseline uses international patent families, the results are very similar using patent families with at least one application at one of the top three patent offices, which is another measure of quality-adjusted patent counts (Annex Table 4.3.1, column [7]).
- *Alternative weighting method:* The baseline results are robust to using the (time-varying) bilateral trade links between country sectors in place of the predicted share of knowledge flow ($\hat{\phi}$) based on cross-patent citations. For each receiving country sector, the trade weights are constructed as imports of goods from the originating country sector as a share of gross output (Annex Table 4.3.1, column [8]).
- *Fixed effects:* While the baseline specifications use country-year fixed effects, in line with Peri (2005), the results are robust to using sector-year fixed effects instead, which can capture sector-specific developments that are common across countries.[32] The coefficients on both foreign and domestic R&D become significantly larger under the specification with sector-year fixed effects (Annex Table 4.3.1, column [9]).
- *Calculation of contributions:* To calculate the contribution of foreign knowledge to productivity, the estimated coefficient on foreign R&D is applied to the average annual change in the variable over the relevant period. The contributions by country groups are obtained from separate regression estimates for advanced economies and emerging market recipients, and those by subperiods are obtained from the regression specification in which the coefficient on foreign R&D stock is allowed to vary over time. Only "long panels" (country sectors with ample coverage over time) are included in the calculation of contributions to make sure that changes in sample composition do not affect the results.

The Role of Greater International Competition: Results and Robustness

Within the same framework used to estimate the impact of foreign knowledge on domestic innovation, the impact of competition and market concentration on domestic innovation and the strength of technology diffusion are also estimated. Annex Table 4.3.3 presents these estimates for measures that affect the extent of competition: trade with China, global market concentration, and product market regulation.

- *Trade with China* is measured as imports of final goods from China as a share of the receiving country sector's gross output, calculated from the World Input-Output Tables. This variable increases domestic innovation directly, but also indirectly, by increasing technology diffusion (Annex Table 4.3.3, column [1]). Alternative measures using final goods trade from the

[30]The correlation between sector-level R&D stock and this interacted variable is about 0.49 (calculated over country sectors for which both are available). The sector's R&D intensity used in the interaction term to create sectoral variation is based on US data.

[31]The sector's skill intensity is based on US data.

[32]The inclusion of both country-year and sector fixed effects removes most of the variation in the data, and thus the results are not discussed here.

Annex Table 4.3.3. Impact of Competition on Innovation

Variables	(1)	(2)	(3)	(4)
Foreign R&D Stock	0.337***	0.413***	0.335***	0.405***
	[0.054]	[0.046]	[0.045]	[0.075]
Own R&D Stock	0.494***	0.435***	0.447***	0.478***
	[0.063]	[0.055]	[0.061]	[0.059]
China Trade	2.465***			2.086***
	[0.777]			[0.758]
Foreign R&D Stock*China Trade	1.474***			1.236***
	[0.442]			[0.394]
Global Concentration		-4.021***		-4.059***
		[0.923]		[0.879]
Foreign R&D Stock*Global Concentration		-2.121***		-2.27***
		[0.559]		[0.565]
PMR*Firm Turnover			-0.021***	0.02
			[0.007]	[0.019]
Foreign R&D Stock*(PMR*Firm Turnover)			-0.01***	0.004
			[0.003]	[0.008]
Observations	2,281	1,559	2,533	1,175
R^2	0.801	0.819	0.789	0.832
Country-Year Fixed Effect	Yes	Yes	Yes	Yes

Source: IMF staff calculations.
Note: PMR = product market regulation; R&D = research and development.
Robust standard errors (clustered at country-sector level) in brackets.
***p < 0.01, **p < 0.05, *p < 0.1.

Organisation for Economic Co-operation (OECD) Structural Analysis Database or total goods trade from the COMTRADE Database yield similar estimates. Interestingly, measures of imports of inputs from China do not seem to matter for innovation, suggesting that the effect comes from the competition channel, which is better captured by trade in final goods.

- *Global market concentration* is measured for each sector as the global market share of the four largest firms based on sales. It is calculated from the firm-level Orbis data set made available by Freund and Sidhu (2017), following their methodology, which uses the largest 650 firms globally by revenue in each sector. Only data for 2006 and 2014 are available, and values for the years in between are interpolated for use in the regression. Global concentration has a negative impact on domestic innovation, directly and through lower technology diffusion (Annex Table 4.3.3, column (2)). Alternative measures such as the Herfindahl Index or patent-based concentration measures calculated from PATSTAT data bring similar results.[33] Results are also robust to including an interaction term between foreign R&D and time dummies, which would control for the possible presence of a global trend in technology diffusion. This ensures that changes in global concentration (at the sector level) are not just picking up this global trend.
- *Domestic competition* is proxied by the OECD indicator of product market regulation (interpolated between available years). As the indicator is only available at the country level, a difference-in-difference approach is used, in which product market regulation is interacted with the sectoral turnover rate for the United States (proxied by the average business churn rate collected from the OECD). The assumption underlying this strategy is that sectors with higher turnover are more likely to be affected by regulation that restricts firm entry and exit. The coefficients on both the main and interaction terms are statistically significant in themselves, but become insignificant when all competition variables enter the regression simultaneously (Annex Table 4.3.3, columns [3] and [4]). Alternative measures of domestic concentration based on patent data produce similar results, although their reverse causality risk may be higher.
- *Additional variables:* In addition to the baseline regressors presented in Annex Table 4.3.3, education and intellectual property rights protection were also considered as alternative independent variables. These measures seemed to matter for innovation and technology diffusion when included individually, but their significance was not robust to controlling for other policies and structural factors. The results are thus omitted.

[33]However, the patent-based measures may underestimate the extent of concentration because the PATSTAT database does not have information on firms' ownership structure.

Annex 4.4. Methodology for Local Projection Method Estimation

This annex presents the estimation framework for the local projection method analysis used in the section "Impact on Innovation and Productivity" and explains the identification of productivity shocks used in this framework.

Estimation Framework

To examine the short-term dynamics of technology diffusion, the impulse response of productivity and innovation to a technology shock in leader countries is estimated using the following equation, one for each time horizon h ($h = 1, \ldots, 5$):

$$dlnY_{i,c,t+h} = \alpha_h \omega_{i,c,l,t} dln\, Y_{i,l,t} + \beta_h X_{i,c,t-1} + \theta_{ct} + \varepsilon_{i,c,t}, \quad (4.4)$$

in which i denotes the sector, c the country receiving the spillovers, l the technological leader, and t the time period. $dlnY_{i,c,t+h} = lnY_{i,c,t+h} - lnY_{i,c,t-1}$ is the change in Y in the recipient between period $t - 1$ and $t + h$ and $dln\, Y_{i,l,t} = lnY_{i,l,t} - lnY_{i,l,t-1}$ is the shock in the leader, in which the variable under investigation, Y, could be either total factor productivity, labor productivity, or the patent stock of a country sector. Similarly to the long-term approach, the shock is weighted using bilateral country-sector weights ($\omega_{i,c,l,t}$) reflecting the strength of linkages between the receiving and the originating country sectors. $X_{i,c,t-1}$ is a vector of controls, including two lags of the shock in the leaders and two lags of the growth rate of domestic total factor productivity.[34] Finally, θ_{ct} denotes the country-year fixed effects, capturing time-varying factors driving productivity and innovation trends at the country level, such as the business cycle. The impulse response to a technology shock in the leader countries is constructed from a sequence of parameter estimates $\{\alpha_h\}_{h=1}^{5}$ and the associated standard errors (see Jordà 2005).

Identification of Labor Productivity Shocks

Shocks to labor productivity are identified using a structural vector autoregression with long-term restrictions as in Galí (1999). The estimation is performed using the *vars* package in *R*.

[34]Including the leads of the shock, as in Teulings and Zubanov (2014), to correct for possible misspecification does not change the results materially.

The specification considered corresponds to the differencing of both productivity and hours. More precisely, a vector autoregression (VAR) of the following form is first estimated,

$$y_t = A_1 y_{t-1} + \ldots + A_p y_{t-p} + u_t, \quad (4.5)$$

in which $y_t = \begin{bmatrix} \Delta x_t \\ \Delta n_t \end{bmatrix}$, with Δx_t the change in log labor productivity (measured as gross value added per hour) and Δn_t the change in log hours. The lag order p is selected according to an Akaike information criterion, which, for annual data, in virtually all cases returns a value $p = 1$.

The identification of structural innovations is achieved by setting restrictions on the impact matrix B defined implicitly by

$$u_t = B\epsilon_t, \quad (4.6)$$

in which $\epsilon_t = \begin{bmatrix} \epsilon_t^z \\ \epsilon_t^m \end{bmatrix}$ is the vector of structural innovations with covariance equal to the identity matrix. The restrictions on B are placed so that a nontechnological innovation, represented by a shock ϵ_t^m, has no long-term effect on x_t. By premultiplying the estimated vector of reduced form shocks $\hat{u}_t$ for B^{-1}, the above equation can be used to calculate the vector of estimated structural innovations $\hat{\epsilon}_t$.

Finally, the series of technological shocks $\hat{e}_t^z$ is retrieved as the sequence of technological impacts on labor productivity:

$$\hat{e}_t^z = B(1,1)\,\hat{\epsilon}_t^z. \quad (4.7)$$

The data for the estimation are obtained by merging the ISIC 3 and ISIC 4 versions of the KLEMS data set for the G5 countries (France, Germany, Japan, United Kingdom, United States). Due to data availability, only the manufacturing and construction sectors are considered. For the various country-sector pairs, the available data are annual and span about 1970–2015 (only shocks for 1995–2015 are used in the local projection estimation).

Identification of Total Factor Productivity Shocks

The measure of total factor productivity (TFP) that enters the local projection estimation (both as shocks in the leaders and as TFP in the recipients) are changes in utilization-adjusted TFP, which is TFP adjusted for varying input utilization, nonconstant returns and imperfect competition following Basu, Fernald, and Kimball (2006) to obtain a measure of "purified" technology shocks. The adjustment involves estimating a production function at the sector level. In particular, for sector i, which belongs to a group k (k = durable manufacturing, nondurable manufacturing, or nonmanufacturing):

$$dy_i = \gamma^k dx_i + \beta^k dh_i + dz_i, \tag{4.8}$$

in which dy_i is the growth rate of real gross output; $dx_i = sk_i dk_i + sl_i dl_i + sm_i dm_i$ is the growth rate of the composite input (consisting of capital, labor, and materials), with sk, sl, and sm denoting the share of each input in gross output; dh_i is the growth rate of hours worked (measured as the first difference in detrended log hours)—a proxy for unobserved input utilization; and dz_i is the residual/adjusted TFP or a measure of industry technology shocks.

The parameters γ and β are assumed to be the same for all sectors within a group.[35] Given the potential correlation between input growth (dx_i and dh_i) and technology shocks in the residual, input growth is instrumented using oil prices, growth in real government defense spending (for the United States), or changes in the cyclically adjusted fiscal balance (for other advanced economies in the sample) and a measure of monetary shocks.[36]

The exercise is conducted for 24 manufacturing and services sectors in 17 advanced economies[37] over 1995–2015 (the sample period for the United States goes back to 1970). Sector-level data on gross output, labor, capital, and intermediate input are taken from the KLEMS database.

Annex 4.5. Impact of Global Value Chains on Firm-Level Patenting: Methodology and Robustness

This annex presents the estimation framework for the firm-level analysis presented in the section "The Impact of Global Value Chains on Patenting: A Firm-level Analysis." It also discusses robustness of the results, the instrumentation strategy, and the examination of the effect of institutional variables on firm-level innovation.

Estimation Framework

The country-sector-firm level analysis in the section on global value chains and patenting follows the framework developed by Autor and others (2016) and Bloom, Draca, and Van Reenen (2016). To assess whether changes in global value chain (GVC) participation at the sectoral level are related to firms' technological change—measured by the change in the patent flow—and growth prospects, measured by the change in employment, the following equation is estimated:

$$\begin{aligned}\Delta^5 X_{ijkt} = {} & \delta^X P^s_{ijk,2000} + \alpha^X \Delta^5 GVC_{jkt} \\ & + \gamma^X\left(P^s_{ijk,2000} * \Delta^5 GVC_{jkt}\right) \\ & + f^X_{kt} + s^X_j + \varepsilon^X_{ijkt},\end{aligned} \tag{4.9}$$

in which the subscript i denotes firms, j denotes sectors, k denotes countries, and t periods.

$X = \{P^f, N\}$, in which N is the logarithm of employment, and P^f and P^s denote the logarithm of a *transformed* count of patent flows and stocks, respectively.[38] $P^s_{ijk,2000}$, a firm's patent stock at the beginning of the sample, is a measure of the firm's initial technological intensity. GVC_{jkt} is the standard measure of participation in global value chains in a given country sector and year, computed as the sum of (1) the domestic content in exports reused in trading partners' exports (forward linkages) and (2) the foreign value added embedded in exports (backward linkages) expressed as a share of gross exports. f^X_{kt} is a full set of country dummies interacted with year dummies (country-year fixed effects), which are used to capture country-specific factors that support the capacity to innovate, such as education levels and infrastructure and macroeconomic shocks. s^X_j are sector fixed effects, which control for systematic differences in patenting and employment trends across industries. Δ^5 denotes

[35]This is a more restrictive assumption than in Basu, Fernald, and Kimball (2006), which allows the returns-to-scale parameter (γ) to differ across all sectors. This assumption allows for better performance of the instruments.

[36]For the United States, monetary shocks—identified in a vector autoregression as in Burnside (1996)—are obtained from Basu, Fernald, and Kimball (2006). For other advanced economies in the sample, monetary shocks are estimated as the forecast error of the policy rates, defined as the difference between the actual policy rates and the rate expected by analysts as of October of the same year using forecasts from Consensus Economics. This approach follows Furceri, Loungani, and Zdzienicka 2016.

[37]Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Ireland, Italy, Japan, Korea, Netherlands, Spain, Sweden, United Kingdom, United States.

[38]To account for the zeros in patent counts when taking logarithms, the estimation follows Bloom, Draca, and Van Reenen (2016) and uses the following transformation: $P^d = ln\left(1 + pat^d\right)$, in which $d = \{f, s\}$ and pat is the untransformed patent count. Furthermore, data limitations prevent the construction of firm-level total factor productivity and labor productivity measures. Other firm performance measures, such as return on assets and return on equity, were considered, but concerns about how these measures are affected by the division of value added between labor and capital ultimately excluded them from the analysis.

five-year differences, and the errors $\left(\varepsilon^{X}_{ijkt}\right)$ are assumed to be heteroscedastic.

The data cover 2000–12 for eight manufacturing sectors across 11 emerging market and developing economies: Brazil, China, India, Indonesia, Mexico, Philippines, Poland, Russia, South Africa, Thailand, and Turkey.[39,40] The primary data are drawn from PATSTAT, which provides comprehensive coverage of all patenting firms. Global input-output tables are used to construct industry-level GVC participation measures. To examine the employment effect, the PATSTAT data set is merged with Orbis to produce a data set of both patenting and nonpatenting firms. This allows employment data to be obtained and the reallocation of employment between nonpatenting and patenting firms to be examined.[41]

This framework allows for analysis of two types of effects:

- A *"within-firm" (intensive margin) effect*, captured by coefficient α^X: It measures how changes in GVC participation relate to firms' average performance in terms of technology upgrading or employment growth. As discussed in the text, the results indicate that $\alpha^X > 0$, suggesting that increasing GVC participation increases firm performance.
- *A "between-firm" (extensive margin) effect*, captured by coefficient γ^X: The latter captures whether, after 2000, the buildup of innovation or job creation associated with increased GVC participation is disproportionately larger for lower-tech firms $(\gamma^X < 0)$ or higher-tech firms $(\gamma^X > 0)$. The results indicate that technological advances have been relatively larger in initially lower-tech firms $(\gamma^P < 0)$, whereas job growth has been relatively higher in higher-tech firms $(\gamma^N > 0)$.

The results are robust to a number of tests (Annex Table 4.5.1), including (1) clustering errors at the country-industry level; (2) using alternative GVC measures—backward linkages, forward linkages, lagged measures, and participation only with regard to advanced economies; (3) using alternative methods of adjusting patent counts for their quality—such as forward citation or family-size weights or focusing only on granted patents; (4) estimating over a different time period—the years after the global financial crisis were excluded to ensure the results were not driven by the shock of the crisis; and (5) excluding from the sample either China or the electrical and machinery equipment sector—each accounting for a large share of the sample.

Instrumentation

In the patenting equation, changes in GVC participation are likely to be correlated with the unobserved shocks $\left(\varepsilon^{XP}_{ijkt}\right)$, due to the possibility of reverse causality, innovative firms may be more likely to be pulled into GVCs because of their high productivity and capacity to innovate, or self-selection—firms may be geared toward GVC participation. Therefore, the use of instrumental variables—the restrictiveness of foreign direct investment (FDI) regulations, as well as changes in FDI restrictions and tariffs—are considered to address potential endogeneity.[42] The first-stage regression of the model can be written as

$$\Delta^5 G_{jkt} = \theta Z^n_{kt} + f^G_{kt} + s^G_j + \varepsilon^G_{ijkt}, \tag{4.10}$$

in which $\Delta^5 G_{jkt} = \left\{\Delta^5 GVC_{jkt}, P^s_{ijk,2000} * \Delta^5 GVC_{jkt}\right\}$ and Z^n_{kt} is the vector of instruments. As expected, all the coefficients in θ have a negative sign, suggesting that with stricter restrictions on FDI or higher tariffs, integration into GVCs is expected to be lower in the subsequent five years. Standard tests indicate that the set of instruments satisfies the exclusion restriction that the error term be uncorrelated with sectoral-level changes in tariffs and FDI restrictions, and the degree of restrictiveness of the latter.[43]

[39]The Czech Republic and the Slovak Republic were originally included in the sample, but they have been dropped because they do not have any patenting activity in PATSTAT. Although Poland is currently considered an advanced economy, it is still included in the sample because it was not considered a high-income country at the start of the sample period.

[40]Food and beverages, textiles and wearing apparel, wood and paper, petroleum-chemicals and nonmetallic mineral products, metal products, electrical and machinery, transport equipment and other manufacturing.

[41]Initially, the relationship between GVC participation and innovative capacity is tested only for patenting firms in the sample. While the sample of patenting firms is much smaller, the results qualitatively confirm those obtained using the full sample of patenting firms from the original exercise using the PATSTAT data set.

[42]The Durbin-Wu-Hausmann endogeneity test indicates that changes in GVC participation variables—the variable itself and the interaction term—are indeed endogenous. The components of the FDI restrictions used in the estimation correspond to screening and approval procedures and restrictions on foreign personnel. The chosen instruments can only be matched with five of the eight sectors in the primary data set, but rerunning the ordinary least squares regression on the subsample for which the instrumental variables estimation is carried out leaves the results broadly unaffected.

[43]In general, tariffs and FDI restrictions could be correlated with innovation through channels other than GVCs, such as knowledge flows more broadly or changes in the degree of competition. However, the tests confirm the strength and validity of the instruments, likely reflecting the difference in aggregation levels between GVC measures and instruments (sectoral) and patenting (firm level), making the former more exogenous.

Annex Table 4.5.1. Impact of Global Value Chain Participation on Firm-Level Innovation: Robustness

Dependent Variable	Patent Flow (log, five-year difference)							
	Baseline (Robust Errors)	Clustered Errors	GVC Forward	GVC Backward	Family-size Weighted Patents	Granted Patents	Excluding China	Excluding Electrical and Machinery
Sample Period (2002–12)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Initial Patent Stock (2000)	–0.07***	–0.07***	–0.08***	–0.07***	–0.08***	–0.06***	–0.05***	–0.05***
	[–91.317]	[–5.703]	[–111.620]	[–90.896]	[–90.624]	[–82.359]	[–48.643]	[–50.686]
Within-Firm Effects								
GVC Participation (five-year change)	0.28***	0.28***	0.19***	0.44***	0.28***	0.11***	0.14***	0.55***
	[16.494]	[3.133]	[9.273]	[13.756]	[14.356]	[7.269]	[4.656]	[28.131]
Between-Firm Effects								
Initial Patent Stock (2000) x GVC Participation (five-year change)	–1.31***	–1.31***	–1.03***	–1.42***	–1.36***	–0.94***	–0.08*	–1.49***
	[–44.878]	[–4.160]	[–21.249]	[–41.980]	[–42.087]	[–36.306]	[–1.889]	[–37.928]
Observations	4,044,066	4,044,066	4,044,066	4,044,066	4,044,066	4,044,066	792,584	1,684,033
R^2	0.026	0.026	0.025	0.026	0.025	0.022	0.025	0.024
Country x year Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No

Source: IMF staff calculations.
Note: Robust t-statistics in brackets.
***p < 0.01, **p < 0.05, *p < 0.1.

Correlation between Country-Year Fixed Effects and Policy Variables

Finally, the extent to which country-specific factors—estimated using country-year fixed effects in equation (4.9) for the patenting variable -timates for the country- ailan$\left(\hat{f}^P_{kt}\right)$—capture absorption capacity factors at the country level is tested by estimating

$$\hat{f}^P_{kt} = \omega_0 + \omega_m I^m_{kt} + \mu_{kt}, \tag{4.11}$$

in which I^m_{kt} is a vector containing $m$institutional variables, including a firm's perceptions of the quality of infrastructure and education, the strength of the property rights system, and competition and the rule of law.

Annex Table 4.5.2 shows the correlation between these institutional variables and the country-year fixed

Annex Table 4.5.2. Relationship between County-Year Fixed Effects and Selected Policy Variables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Interconnectedness								
Quality of Port Infrastructure	0.01080*			0.01189*				
Education	[1.754]			[1.932]				
Quality of Primary Education		0.01308**						
		[2.590]						
Quality of Math and Science Education			0.00668*	0.00733**				
Rule of Law			[1.875]	[2.328]				
Protection of Property Rights					0.00407*			0.00553**
					[1.955]			[2.200]
Integrity of the Legal System						0.00301*		0.00320**
Product Market Regulation						[1.906]		[2.044]
Licensing Restrictions							–0.00346**	–0.00329**
							[–2.391]	[–2.118]
Constant	0.01610	0.01068	0.02919**	–0.01562	0.02631**	0.03068***	0.07200***	0.02333
	[0.701]	[0.698]	[2.428]	[–0.752]	[2.256]	[3.248]	[7.609]	[1.122]
Observations	70	60	70	70	110	110	90	90
R^2	0.042	0.089	0.044	0.095	0.031	0.023	0.060	0.128

Source: IMF staff calculations.
Note: Robust t-statistics in brackets.
***p < 0.01, **p < 0.05, *p < 0.1.

effects from the estimated patenting relationships. As illustrated in the chapter, the results suggest that the country-year fixed effects in patenting are positively correlated with firms' perceptions of the quality of infrastructure and education, the strength of the property rights system, competition, and rule of law.

References

Acharya, Ram C., and Wolfgang Keller. 2009. "Technology Transfer through Imports." *Canadian Journal of Economics/Revue canadienne d'économique* 42 (4): 1411–48.

Adler, Gustavo, Romain Duval, Davide Furceri, Sinem Kiliç Çelik, Ksenia Koloskova, and Marcos Poplawski-Ribeiro. 2017. "Gone with the Headwinds: Global Productivity." *IMF Staff Discussion Note 17/04*, International Monetary Fund, Washington, DC.

Aghion, Philippe, Nick Bloom, Richard Blundell, Rachel Griffith, and Peter Howitt. 2005. "Competition and Innovation: An Inverted-U Relationship." *Quarterly Journal of Economics* 120 (2): 701–28.

Aghion, Philippe, Peter Howitt, and Susanne Prantl. 2015. "Patent Rights, Product Market Reforms, and Innovation." *Journal of Economic Growth* 20 (3): 223–62.

Akcigit, Ufuk, Sina Ates, and Giammario Impullitti. 2017. "Innovation and Trade Policy in a Globalized World." Unpublished.

Allard, Céline, Jorge I. Canales Kriljenko, Jesus R. Gonzalez-Garcia, Emmanouil Kitsios, Juan P. Trevino, and Wenjie Chen. 2016. "Trade Integration and Global Value Chains in Sub-Saharan Africa: In Pursuit of the Missing Link." IMF African Departmental Paper 16/02, International Monetary Fund, Washington, DC.

Andrews, Dan, Chiara Criscuolo, and Peter Gal. 2016. "The Global Productivity Slowdown, Technology Divergence, and Public Policy: A Firm-Level Perspective." Background Paper for OECD Global Forum on Productivity.

Audretsch, David B., and Maryann P. Feldman. 1996. "R&D Spillovers and the Geography of Innovation and Production." *The American Economic Review* 86 (3): 630–40.

Autor, David, David Dorn, Gordon H. Hanson, Gary Pisano, and Pian Shu. 2016. "Foreign Competition and Domestic Innovation: Evidence from US Patents." NBER Working Paper 22879, National Bureau of Economic Research, Cambridge, MA.

Autor David, David Dorn, Lawrence F. Katz, Christina Patterson, and John Van Reenen. 2017. "The Fall of the Labor Share and the Rise of Superstar Firms." NBER Working Paper 23396, National Bureau of Economic Research, Cambridge, MA.

Basu, Susanto, John Fernald, and Miles Kimball. 2006. "Are Technology Improvements Contractionary?" *The American Economic Review* 96 (5): 1418–48.

Bilir, L. Kamran B. 2014. "Patent Laws, Product Life-Cycle Lengths, and Multination Activity." *The American Economic Review* 104: 1979–2013.

Bloom, Nicholas, Mirko Draca, and John Van Reenen. 2016. "Trade Induced Technical Change? The Impact of Chinese Imports on Innovation, IT and Productivity." *Review of Economic Studies* 83(1): 87–117.

Bloom, Nicholas, Charles I. Jones, John Van Reenen, and Michael Webb. 2017. "Are Ideas Getting Harder to Find?" NBER Working Paper 23782, National Bureau of Economic Research, Cambridge, MA.

Branstetter, Lee. 2001. "Are Knowledge Spillovers International or Intranational in Scope? Microeconomic Evidence from the US and Japan." *Journal of International Economics* 53: 53–79.

Brynjolfsson, Erik, Daniel Rock, and Chad Syverson, C. 2017. "Artificial Intelligence and the Modern Productivity Paradox: A Clash of Expectations and Statistics." In *Economics of Artificial Intelligence*. Chicago: University of Chicago Press.

Burnside, Craig. 1996. "Production Function Regressions, Returns to Scale, and Externalities." *Journal of Monetary Economics* 37 (2): 177–201.

———, and David Dollar. 2000. "Aid, Policies, and Growth." *The American Economic Review* 90 (4): 847–68.

Busse, Erdogan C., and H. Mühlen. 2016. "China's Impact on Africa—The Role of Trade, FDI and Aid." *KYKLOS* 69 (2): 228–62.

Chen, Sophia, and Estelle Dauchy. 2018. "International Technology Sourcing and Knowledge Spillovers: Evidence from OECD Countries." IMF Working Paper 18/51, International Monetary Fund, Washington, DC.

Coe, David T., Elhanan Helpman, and Alexander W. Hoffmaister. 2009. "International R&D Spillovers and Institutions." *European Economic Review* 53 (7): 723–41.

Coelli, Federica, Andreas Moxnes, and Karen Helene Ulltveit-Moe. 2016. "Better, Faster, Stronger: Global Innovation and Trade Liberalization." NBER Working Paper 22647, National Bureau of Economic Research, Cambridge, MA.

Cohen, Wesley M., and Daniel A. Levinthal. 1989. "Innovation and Learning: The Two Faces of R&D." *Economic Journal* 99 (397): 569–96.

Collier, Paul, and David Dollar. 2002. "Aid Allocation and Poverty Reduction." *European Economic Review* 46: 1475–500.

Dernis, Hélène, and Mosahid Khan. 2004. "Triadic Patent Families Methodology." OECD Science, Technology and Industry Working Papers 2004/02, Organisation for Economic Co-operation and Development, Paris.

Donaubauer, Julian, Birigt Meyer, and Peter Nunnenkamp. 2016. "Aid, Infrastructure and FDI: Assessing the Transmission Channel with a New Index of Infrastructure." *World Development* 78: 230–45.

Donaubauer, Julian, Dierk Herzer, and Peter Nunnenkamp. 2014. "Does Aid for Education Attract Foreign Investors? An Empirical Analysis." *European Journal of Development Research* 26:597–613.

Dutta, Nabamita, Deepraj Mukherjee, and Sanjukta Roy. 2015. "Re-Examining the Relationship between Domestic Investment and Foreign Aid: Does Political Stability Matter?" *International Review of Applied Economics* 29 (3): 259–86.

Duval, Romain, Davide Furceri, Sinem Kiliç Çelik, and Marcos Poplawski-Ribeiro. Forthcoming. "Productivity Spillovers in Advanced Economies."

Eaton, Jonathan, and Samuel Kortum. 2002. "Technology, Geography and Trade", *Econometrica* (70): 1741–779.

Freund, Caroline, and Dario Sidhu D. 2017. "Global Competition and the Rise of China." PIIE Working Paper 17-3.

Furceri, Davide, Prakash Loungani, and Aleksandra Zdzienicka. 2016. "The Effects of Monetary Policy Shocks on Inequality." IMF Working Paper 16/245, International Monetary Fund, Washington, DC.

Galí, Jordi. 1999. "Technology, Employment, and the Business Cycle: Do Technology Shocks Explain Aggregate Fluctuations?" *The American Economic Review* 89 (1): 249–71.

Garriga, Ana Carolina, and Brian J. Phillips. 2014. "Foreign Aid as Signal to Investors: Predicting FDI in Postconflict Countries." *Journal of Conflict Resolution* 58 (2): 280–306.

Gordon, Robert J. 2012. "Is US Economic Growth Over? Faltering Innovation Confronts the Six Headwinds." NBER Working Paper 18315, National Bureau of Economic Research, Cambridge, MA.

Griffith, Rachel, Rupert Harrison, and John Van Reenen. 2006. "How Special Is the Special Relationship? Using the Impact of US R&D Spillovers on UK Firms as a Test of Technology Sourcing." *The American Economic Review* 96 (5): 1859–75.

Griffith, Rachel, and Helen Miller. 2011. "Innovation in China: The rise of Chinese Inventors in the Production of Knowledge." IFS Working Paper W11/15, Institute for Fiscal Studies, London.

Griffith, Rachel, Stephen Redding, and John Van Reenen. 2004. "Mapping the Two Faces of R&D: Productivity Growth in a Panel of OECD Industries." *Review of Economics and Statistics* 86 (4): 883–95.

Grossman, Gene M., and Elhanan Helpman. 1991. *Innovation in the World Economy.* Cambridge, MA: MIT Press.

Grullon, Gustavo, Yelena Larkin, and Roni Michaely. 2017. "Are US Industries Becoming More Concentrated?" Unpublished Working Paper.

Gutiérrez, Germán, and Thomas Philippon. 2017. "Declining Competition and Investment in the US." NBER Working Paper 23583, National Bureau of Economic Research, Cambridge, MA.

Hoekman, Bernard M., Keith E. Maskus, and Kamal Saggi. 2005. "Transfer of Technology to Developing Countries: Unilateral and Multilateral Policy Options." *World Development* 33 (10): 1587–602.

Jaffe, Adam B., Manuel Trajtenberg, and Rebecca Henderson. 1993. "Geographic Localization of Knowledge Spillovers as Evidenced by Patent Citations." *Quarterly Journal of Economics* 108 (3): 577–98.

Jordà, Òscar. 2005. "Estimation and Inference of Impulse Responses Local Projections." *The American Economic Review* 95 (1): 161–82.

Kao, Chihwa, and Min-Hsien Chiang. 2001. "On the Estimation and Inference of a Cointegrated Regression in Panel Data." In *Nonstationary Panels, Panel Cointegration, and Dynamic Panels (Advances in Econometrics, Volume 15)*, edited by Badi H. Baltagi, Thomas B. Fomby, and R. Carter Hill. Emerald Group Publishing Limited.

Katznelson, Ron D. (2008). "Bad Science in Search of Bad Patents." *Federal Circuit Bar Journal* 17 (1).

Keller, W. 2004. "International Technology Diffusion." *Journal of Economic Literature* 42:752–82

Keller, Wolfgang. 2010, "International Trade, Foreign Direct Investment, and Technology Spillovers." In *Handbook of the Economics of Innovation* (2): 793–829. Amsterdam: Elsevier.

Keller, Wolfgang. 2002. "Geographic Localization of International Technology Diffusion." *The American Economic Review* 92 (1): 120–42.

Kim, Jung Eun. 2014. "Expanding the Usage of Renewable Energy Through Innovation and Technology Transfer." Dissertations ALL, Paper 57.

Kretschmer, Betinna, Michael Hübler, and Peter Nunnenkamp. 2013. "Does Foreign Aid Reduce Energy and Carbon Intensities of Developing Economies?" *Journal of International Development* 25: 67–91.

Lopez-Garcia, Paloma, and Daria Taglioni. 2018. "Knowledge Transfers from International Openness in Trade and Investment: The European Case." In *Critical Connections: Why ECA's Regional and Global Network of Interconnections Matter for Inclusive Growth and Stability*, edited by David M. Gould. Washington, DC: World Bank.

MacGarvie, Megan. 2006. "Do Firms Learn from International Trade?" *Review of Economics and Statistics* 88 (1): 46–60.

Madsen, Jakob B. 2007. "Evidence for the OECD Countries." *Journal of International Economics* 72: 464–80.

Organisation for Economic Co-operation and Development (OECD). 2009. OECD Patent Statistics Manual. OECD Publishing, Paris.

——. 2015. *The Future of Productivity*. OECD Publishing, Paris.

Peri, Giovanni. 2005, "Determinants of Knowledge Flows and Their Effect on Innovation." *Review of Economics and Statistics* 87 (2): 308–22.

Rajan, Raghuram G., and Arvind Subramanian. 2008. "Aid and Growth: What Does the Cross-Country Evidence Really Show?" *Review of Economics and Statistics* 90 (4): 643–65.

Santos Silva, João, and Silvana Tenreyro. 2006. "The Log of Gravity." *Review of Economics and Statistics* 88 (4): 641–58.

Santos Silva, J.M C., and Silvana Tenreyro. 2011. "Further Simulation Evidence on the Performance of the Poisson Pseudo-Maximum Likelihood Estimator." *Economics Letters* 112 (2): 220–22.

Selaya, Pablo, and Eva Rytter Sunensen. 2012. "Does Foreign Aid Increase Foreign Direct Investment?" *World Development* 40 (11): 2155–176.

Squicciarini, M., H. Dernis and C. Criscuolo. 2013. "Measuring Patent Quality: Indicators of Technological and Economic Value." In *OECD Science, Technology and Industry Working Papers* 2013/03, OECD Publishing, Paris, http://dx.doi.org/10.1787/5k4522wkw1r8-en.

Stiebale, Joel. 2016. "Cross-Border M&As and Innovative Activity of Acquiring and Target Firms." *Journal of International Economics* 99:1–15.

Strokova, Victoria. 2010. "International Property Rights Index: 2010 Report." United Nations Conference on Trade and Development, New York.

Teulings, Coen N., and Nikolay Zubanov. 2014. "Is Economic Recovery a Myth? Robust Estimation of Impulse Responses." *Journal of Applied Econometrics* 29 (3): 497–514.

Tiruneh, Esubalew Alehegn, Evelyn Wamboye, and Bruno S. Sergi. 2017. "Does Productivity in Africa Benefit from Advanced Countries' R&D?" *Technology Analysis & Strategic Management* 29 (7): 804–16.

Van Looy, Bart, Caro Vereyen, and Ulrich Schmoch 2015. "Patent Statistics: Concordance IPC V8—NACE Rev. 2 (version 2.0)." Eurostat Working Paper, Luxembourg.

Vigil, Mariana, and Laurent Wagner. 2012. "Does Aid for Trade Enhance Export Performance? Investigating the Infrastructure Channel." *World Economy* 35 (7): 838–68.

Walley, Bernard, and Matthew Cushing. 2013. "Development Aid and Foreign R&D Spillovers in Sub-Saharan Africa." *International Journal of Applied Economics* 10 (2): 10–31.

Williams, Heidi L. 2013. "Intellectual Property Rights and Innovation: Evidence from the Human Genome." *Journal of Political Economy* 121 (1): 1–27.

World Bank (WB). 2008. "Global Economic Prospects: Technology Diffusion in the Developing World." Washington, DC.

United Nations Conference on Trade and Development (UNCTAD). 2005. "World Investment Report 2005: Transnational Corporations and the Internationalization of R&D." New York.

Zhao, Minyuan. 2006. "Conducting R&D in Countries with Weak Intellectual Property Rights Protection." *Management Science* 52: 1185–199.