EXECUTIVE BOARD MEETING

EBS/21/81

September 8, 2021

To: Members of the Executive Board

From: The Secretary

Subject: **October 2021 World Economic Outlook—Analytical Chapter 3 and Online Annex**

Board Action:	Executive Directors' **consideration** (Formal)
Tentative Board Date:	**Tuesday, September 28, 2021**
Publication:	Yes, it is intended that the full set of the World Economic Outlook documents will be released to the public at the time of World Economic Outlook press conference, tentatively scheduled for **Tuesday, October 12, 2021.** The analytical chapters will be made available to the public on the IMF website in advance of the publication of the full document.
Questions:	Mr. Natal, RES (ext. 35983) Mr. Barrett, RES (ext. 37110)
Additional Information:	The paper will be revised for publication in light of the Executive Board discussion. If Executive Directors have additional comments, they should notify Mr. Natal and Mr. Barrett by **5:30 p.m. on Friday, September 24, 2021**.

CHAPTER 3

RESEARCH AND INNOVATION: FIGHTING THE PANDEMIC AND BOOSTING LONG-TERM GROWTH

BOXES

FIGURES

CHAPTER 3

RESEARCH AND INNOVATION: FIGHTING THE PANDEMIC AND BOOSTING LONG-TERM GROWTH

How can policymakers boost long-term growth in the post-COVID global economy? This chapter looks at the role of basic research—undirected, theoretical, or experimental work. Using rich new data that draw on connections from individual innovations to scientific articles, it shows that basic research is an essential input into innovation, with wide-ranging international spillovers and long-lasting impacts. International spillovers are particularly important for emerging market and developing economies, where institutional factors—including better education and deeper financial markets—help convert innovation into economic growth, making rapid technology transfer, the free flow of ideas, and collaboration across borders key priorities. Model-based analysis reveals that advanced economies could raise long-term growth by increasing research funding, targeting basic research, and developing closer connections between public and private research. By lifting the growth potential and future tax base of the economy, these investments tend to pay for themselves within a decade. Investments in basic research may also have green benefits, as cleaner technological innovations rely on newer, more fundamental research.

Introduction

Few concepts have implications as far-reaching for economic policy as long-term growth. Growth—namely, the increase in an economy's *potential* to produce goods and services—is of central importance not only for improving living standards, but also for inequality, debt sustainability, and the cost of climate change mitigation.

Yet the past few decades have seen a long and persistent decline in long-term growth. Policymakers face an urgent and essential question: how can this trend be reversed to build a more buoyant post-pandemic global economy? Although this has so far been a mostly advanced economy phenomenon, demographic trends in China and other emerging markets make the need for an answer more urgent. With fewer active workers, aging populations will require more output per worker to maintain living standards.

Addressing this question requires an understanding of the underlying drivers of growth. The earliest explanations emphasized the role of *productivity*—the ability to create more outputs with the same inputs.[1] More recent work has emphasized the role of *innovation*—the emergence and adoption of new technologies that improve the production of goods and services—as a driver of productivity.[2] But the data present something of a challenge to this idea. Productivity growth has slowed even amid increased spending on research and development, a common proxy for innovation effort (Figure 3.1, panels 1 and 2). This apparent conflict with leading theories makes formulating policies to boost long-term growth rather difficult.

One possible answer is that the type of research matters. Innovations great and small occur not in a vacuum but draw on the stock of *basic* scientific knowledge. The invention of the cardiac pacemaker required a scientific understanding of both human anatomy and electronics. The GPS technology familiar to many smartphone users relies on Einstein's theories of relativity to

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[1] As opposed to population growth or capital accumulation; see Ramsey (1928), Solow (1956), Cass (1965), and Koopmans (1965).

[2] See the April 2018 *World Economic Outlook*; Grossman and Helpman (1991); Aghion and Howitt (1992); Mankiw, Romer, and Weil (1992); and Aghion and others (2005).

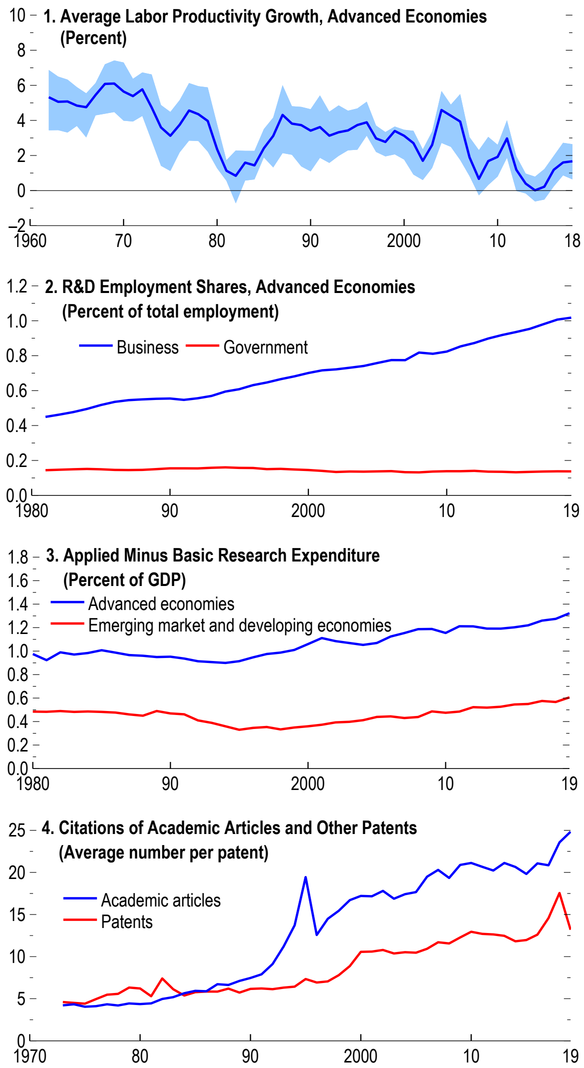
account for how time passes at different rates on fast-moving satellites and the Earth's surface. More recently, the extraordinarily rapid development of COVID-19 vaccines, based on decades of prior basic scientific research, has had the massive economic payoff of bringing forward the reopening of many economies, perhaps by years (Box 3.1). Growth in research inputs has been increasingly *applied*, even as innovation depends more on basic scientific advances (Figure 3.1, panels 3 and 4), which may help resolve part of this puzzle.

The character of basic scientific research also suggests that policies to encourage it might be particularly potent, something relevant to aspirations to build a better post-COVID economy (see Chapter 1). In contrast to applied innovation, basic research can have very broad economic applications. While this likely means that social returns from basic research are high, it also means that firms may struggle to internalize the gains from basic science, undermining private incentives. No firm could fully capture the gains from the invention of, say, the jet engine or the internet. As a result, private firms are likely to underprovide the most basic, far-reaching, and economically impactful types of research (Nelson 1959)—suggesting a role for public policy to bridge this gap.

This chapter explores whether public policy should support basic scientific research to boost growth during the exit from the global pandemic, addressing the following questions:

Figure 3.1. Measures of Research and Productivity

Productivity growth has been declining for decades despite a steady increase in research effort. The increasing importance of science, combined with a focus on more commercial research, could explain this decline.



Sources: OECD Science and Technology Indicators; Penn World Table 10.0; Reliance on Science; United States Patent and Trademark Office; and IMF staff calculations.
Note: In panel 1, labor productivity growth is reported as a three-year moving average. The shaded area denotes the 25th to 75th percentile. Sample is restricted to be balanced throughout the period. In panel 3, the figure shows the average difference in funding for applied minus basic research over time. In panel 4, average citations to academic articles and other patents are shown by year of patent application. The spike in 1995 is likely associated with a legislative change prompting an increase in patent applications (Byrne 1995).

- *What is the progression from basic science to innovation and productivity growth?* How does basic scientific knowledge diffuse internationally? And how do the economic roles of basic and more applied research differ?
- *What is the global economic benefit of scientific integration?* How might a reverse in scientific integration of major economies, such as the United States and China, affect global growth?
- *Is basic research under- or overprovided?* Can policy intervene to correct socially inefficient levels of basic research? If so, what is the appropriate policy mix? How should these policies balance

returns from public and private basic research? And what are the potential gains from such policies? Can basic scientific research help in the fight against climate change? And if so, how might those benefits manifest?

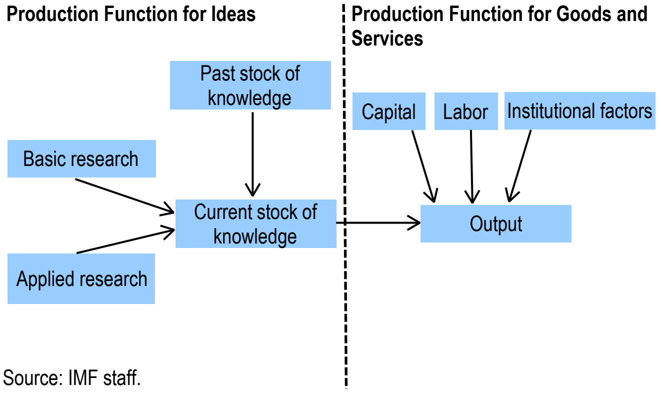
These are the chapter's main findings:

- Basic scientific research is a key driver of innovation and productivity, and basic scientific knowledge diffuses internationally farther than applied knowledge. A 10 percent increase in domestic (foreign) basic research is estimated to raise productivity by about 0.3 (0.6) percent on average. International knowledge spillovers are more important for innovation in emerging market and developing economies than in advanced economies. Easy technology transfer, collaboration, and the free flow of ideas across borders should be key priorities.
- A decoupling of basic scientific research between the United States and China could have big negative effects on global productivity, with estimated first-round declines up to 0.8 percent.
- Basic scientific research in advanced economies is underfunded. As a result, policies that fund public research and subsidize private research will have positive payoffs. A model estimated on three advanced economies suggest that subsidy rates for private research should be approximately doubled, and public research expenditure increased by about a third. Targeting support to scientific research will deliver the greatest return, but where this is not possible more public-private partnerships may be a partial substitute. While such policies pay for themselves in the long run, optimal research funding may be lower in countries with immediate fiscal constraints. Science also plays a larger role in green innovation than in dirty technological change, suggesting that policies to boost science can help tackle climate change.

Conceptual Framework

The chapter's conceptual framework draws on innovation-driven endogenous growth theory (Aghion and Howitt 1992; Akcigit and Kerr 2018; Grossman and Helpman 1991; Romer 1990), in which knowledge creation plays a central role in driving productivity growth.

Figure 3.2. Stylized Conceptual Framework



Source: IMF staff.

In its simplest form, economic output can be thought of as produced by two interlinked production functions (Figure 3.2). In the first, the production function for ideas, research inputs—both basic and applied—are combined with preexisting knowledge to produce economically-relevant innovations that add to the stock of common knowledge. The key difference between basic and applied research is that the former is undirected, theoretical, or experimental, whereas the latter is aimed at bringing products to market. In the second production function, the one for goods and services, standard macroeconomic inputs—capital and labor—are combined to produce output. The productivity of this process depends on the current stock of ideas and other country-specific institutional factors. Thus, research increases knowledge, knowledge enhances productivity, and productivity determines how much final output is generated from real inputs.

Although the analysis in the chapter adds finer details to this picture, the basic structure remains the same throughout. The empirical analysis unpacks these two production functions and estimates the direct impact and international spillovers of investing in basic science. Subsequent model-based policy analysis complements the empirical evidence by allowing for richer interactions, including between basic and applied research in general equilibrium. Given that the analysis of the more basic types of research is novel, the chapter focus is naturally on basic research. For more on applied research, readers are directed to the April 2016 *Fiscal Monitor* and the April 2018 *World Economic Outlook*.

Connecting Basic Science to Growth

This section presents an empirical investigation into the two production functions outlined in Figure 3.2, extending it to include an international dimension, distinguishing the impact not only of basic and applied research but also the extent of international spillovers. An important first step is to construct measures of the stock of foreign knowledge accessible to each country.

The Diffusion of Basic and Applied Knowledge

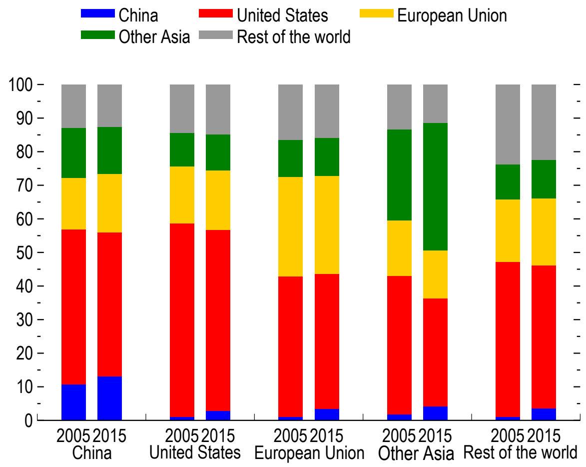
The relevance of knowledge in one country for an innovator in another may depend on a variety of factors, including proximity, language, and so forth, and might be different for basic and applied knowledge. Cross-country citations in patent applications, from the Reliance on Science database (RoS, for basic research) and from PATSTAT (for applied research) provide valuable clues about the drivers of the international transmission of knowledge.

The RoS database is a rich data set that tracks citations of some 38 million US and European patents to scientific articles (Marx and Fuegi 2020). By providing unique identifiers for patents issued by the US Patent and Trademark Office, RoS can identify the countries both of the patent's inventor and of the authors of cited scientific articles. PATSTAT, maintained by the European Patent Office, provides global coverage of patent applications, with 105 million records from more than 190 patenting offices. These sources illuminate two inputs to the production function for ideas, basic and applied research, and are discussed in Online Annex 3.1.

A key assumption in the empirical work is that citations to scientific articles capture dependence on basic research and citations to patents capture reliance on applied research. This draws a sharp distinction, whereas reality is more blurred; some articles may cover applied topics, and patentable work may spur major scientific breakthroughs.[3]

Figure 3.3. Geography of International Basic Knowledge Flows
(Citation share)

Most scientific citations within patent applications are to the United States, although Europe and Asia have become increasingly important.



Sources: Reliance on Science; United States Patent and Trademark Office; and IMF staff calculations.
Note: Bars correspond to the country or region of the citing patent; legend items correspond to the country or region of the cited research article.

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[3] Ahmadpoor and Jones (2017) give examples of how the two types of research mutually reinforce their role in innovation.

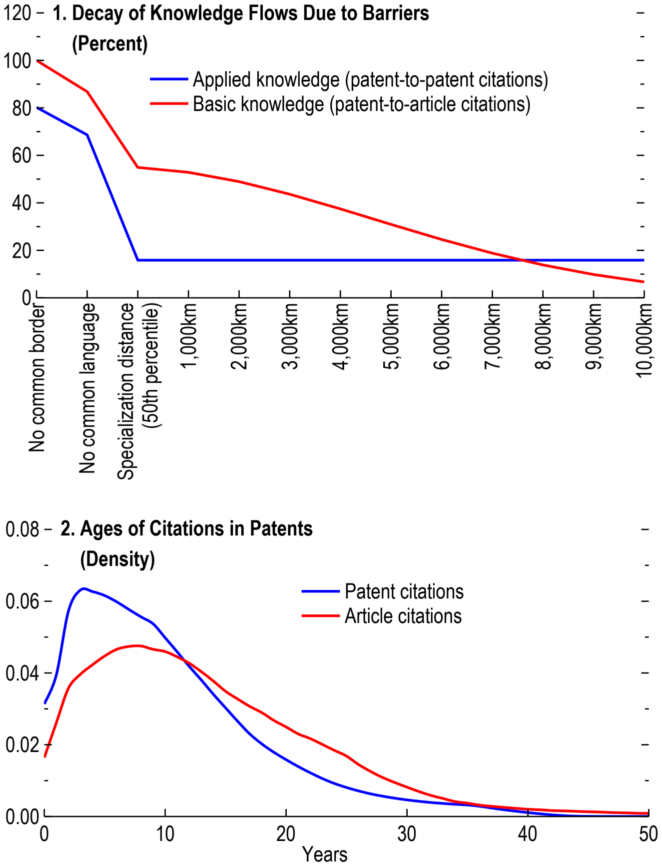
Figure 3.3 shows the main patterns of international citations of basic knowledge, using cross-border citations in the RoS. The United States is the main source of cited works—a constant in recent decades. However, citations to Chinese science have grown strongly since 2005 (albeit from a low base) as have citations across Asian countries. In general, regions tend to exhibit home bias, citing their own scientific works more than others do. This suggests that diffusion of knowledge from its source is partial—a point explored more formally in the next section.

Across Space

To harness this information, the chapter estimates a gravity-type model of international knowledge flows. The outcome variable is the number of citations from one country to another. For example, for basic research this would be the number of citations by, say, Malaysian inventors to scientific articles with Spanish authors (for applied research, the citations are to other patents). The explanatory variables are: whether the two countries share a border; whether they have a common official language; how specialization in their economies differs (scientific specialization for science citations, technological for patent citations); and geographic distance in kilometers. Citing and cited country fixed effects capture differences in the knowledge mass, intellectual property rights, and other factors that may influence a country's propensity to patent or to cite other patents. Further details are in Online Annex 3.2.

Figure 3.4. Diffusion of Basic and Applied Knowledge

Basic knowledge diffuses farther than applied and remains relevant longer.



1. Decay of Knowledge Flows Due to Barriers (Percent)

2. Ages of Citations in Patents (Density)

Sources: PATSTAT; Reliance on Science; and IMF staff calculations.
Note: In panel 1, the baseline knowledge flow equals 100 in the absence of barriers. In panel 2, the sample is restricted to patents applied for during 2010–19. Axis truncated at 50 years. Specialization distance is measured as one minus the uncentered correlation coefficient between the specialization vectors of country *i* and country *j*, where the vectors include the share of patents falling within internationally classified scientific/technological fields. km = kilometers. See Online Annexes 3.1 and 3.2 for details.

Panel 1 of Figure 3.4 shows the estimated cumulative impact of these different barriers, calculated separately for basic and applied knowledge. These show that basic knowledge diffuses more strongly than applied knowledge, with the red line staying above the blue line across most barriers. Country borders, lack of a common language, and specialization distance all present a larger impediment to the diffusion of applied knowledge. The marginal effect of geographic distance is negative for basic knowledge but insignificant for applied knowledge. Patent-to-patent citation intensity for applied knowledge is instead likely more dependent on other factors, such as tough competition. One example is the recent 5G technology race between

China, the European Union, and the United States. However, the cumulative effect differs only over very long distances. These findings are unaffected by a variety of robustness checks, including controlling for cross-country differences in scientific and technological output, as detailed in Online Annex 3.2.

This sort of exercise has a long history in the academic literature on international trade. Earlier attempts to adapt the framework to knowledge diffusion typically focused on applied knowledge flows using patent-to-patent citations.[4] The extension to basic knowledge flows using patent-to-science citations is new. Predictions of the estimated models can also be used as a measure of how relevant knowledge in one country is for research elsewhere. This point is important for the empirical analysis of the production function for ideas, which uses this measure to create country-specific aggregate foreign knowledge stocks for each country (more on this later).

Over Time

Knowledge diffuses over time as well as across space. Panel 2 of Figure 3.4 illustrates this point, showing the density of the age of scientific articles (red line) and patents (blue line) cited by different patents. As such, they approximate the influence of basic and applied knowledge over the years. Basic knowledge displays a long-lasting impact, with the density for the age of cited scientific articles reaching a peak at about eight years, versus three years for cited patents. This evidence suggests that scientific ideas can still be economically influential for long periods of time.[5]

Of course, using patent-induced knowledge flows to understand innovation drivers is subject to some caveats. Some R&D may have a direct impact on productivity without necessarily resulting in new patents, and new patent applications may be more reflective of strategic patenting practices than of authentic innovation. Yet when using only patents filed in at least two distinct national offices—a likely control for these effects—the findings are similar (Online Annex Table 3.2.3).

Knowledge Stocks and the Production Function for Ideas

The empirical production function for ideas explains how the flow of new productive ideas—as captured by patents—depends on foreign and domestic applied and basic research stocks.

Since these stocks are measures of research expenditure (that is, research inputs), they are true inputs to a production function. Domestic stocks are computed by summing past expenditures, with 10 percent annual depreciation. Construction of the foreign stocks follows Peri (2005) by calculating for each country a weighted average of the domestic research stocks in all the other countries, with the weights determined by the gravity model presented in this chapter. For example, Mexico's constructed foreign basic research stock puts weight on the United States that is proportional to the average Mexican inventor's citations to science from the United States, as predicted by the determinants of the gravity model—geography, language, and technological

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[4] The spatial diffusion of knowledge spillovers using patent data has been widely studied starting with Jaffe, Trajtenberg, and Henderson (1993). See Peri (2005) for a more recent example. While advances in communication have eased accessibility to scientific articles, there is still evidence of the localization of scientific knowledge (for example, Belenzon and Schankerman 2013), which is partly explained by national policies aiming to foster collaboration between local universities, firms, and government funding agencies (Etzkowitz and Leydesdorff 2000).

[5] A back-of-the-envelope calculation of tail decay rates reveals that in the long run basic (applied) knowledge decays at 7 (11) percent annually.

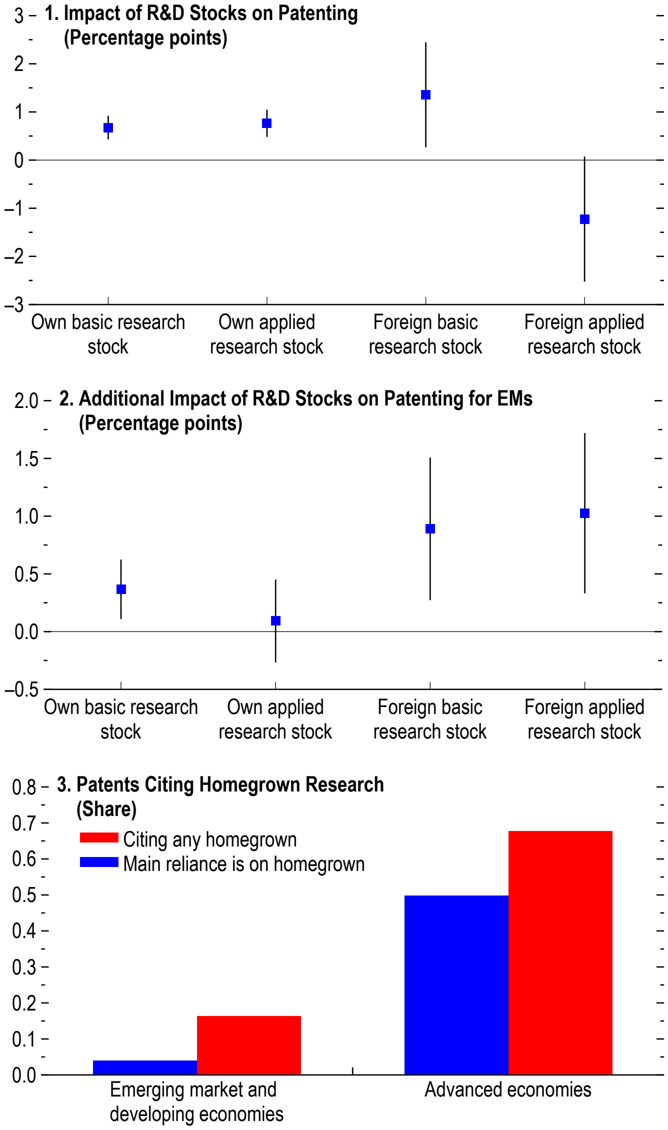
mix. In this sense, construction of the data measures how accessible foreign research stocks are to a given country.

The estimated impact of R&D stocks on innovation is plotted in panel 1 of Figure 3.5. The main estimates use dynamic ordinary least squares, which efficiently utilize the cointegration of the data.[6] The point estimates show the effect of a 1 percentage point increase in the respective research stocks on the annual flow of patents, along with 95 percent confidence bands. For "own" basic research, the impact is 0.67 percentage point, and for applied research 0.77 percentage point, each having tight confidence bands. This suggests that domestic basic and applied research each have positive effects on patenting activity and are of similar magnitudes.

Foreign basic research also has a sizable effect, leading annual patent flows to increase 1.36 percentage points. In contrast, foreign applied knowledge has a negative estimated impact on patenting activity. However, this is very imprecisely estimated. Indeed, the magnitude of imprecision prohibits any confidence about even the direction of the true effect. That said, a negative impact of foreign applied research on domestic innovation is not completely implausible, and would at least be consistent with the idea that some applied R&D leads to "business

Figure 3.5. Estimated Ideas Production Function

Basic research expenditures correlate significantly with patent creation, and spillovers from foreign research stocks are larger for emerging markets than advanced economies.



Sources: PATSTAT; Penn World Table 10.0; Reliance on Science; World Bank; and IMF staff calculations.

Note: Panel 1 shows the response of patent flows (log scale) to a 1 percentage point change in each covariate (log scale) along with the 95 percent confidence interval. Panel 2 shows the additional estimated effect of research stocks on innovation in emerging markets. See Online Annex 3.3 for details. EMs = emerging markets; R&D = research and development.

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[6] See column (7) in Table 3.3.1 in Annex 3.3.

stealing" by competitors (as opposed to the non-rival and non-excludable nature of foreign basic research; see Bloom, Schankerman, and Van Reenen 2013).[7]

Online Annex 3.3 shows the estimates of alternative specifications of the ideas production function. While the details vary, the estimates consistently reveal a strong and significant relationship between basic research and innovation, and positive spillovers from foreign research (although the relative roles of foreign basic and applied research are not always as clear). Box 3.2 extends this analysis to look at a particular type of innovation—clean technologies—and finds that basic research has larger green spillovers, suggesting that spending on basic research can play an important role in combating global climate change.

Differences in the Ideas Production Function: Advanced versus Emerging Market and Developing Economies

The estimates presented so far reflect those for an average economy in the data set. However, the estimated effects of basic and applied research stocks on innovations may differ by country. To get a sense of the size of these differences and what drives them, Figure 3.5 (panel 2) presents the estimated difference between advanced economies and emerging market and developing economies (see Table 3.3.2 in Online Annex 3.3). Two findings are apparent:

- First, access to foreign research has a larger estimated effect on innovation in emerging markets than in advanced economies. This is true for both applied and basic research. Consistent with this difference, inventors from emerging markets are also less likely to cite homegrown research (Figure 3.5, panel 3). The results suggest that foreign technology adoption is more important for emerging markets than for advanced economies, consistent with the April 2018 *World Economic Outlook*. Learning-by-doing is one possible channel; adoption of foreign technologies (e.g. through trade links, see Chuang 1998) may provide local workers the opportunity to learn new processes, forming the basis for innovation.
- Second, evidence for the role of domestic research is mixed. While the estimated effect of applied research on innovation is not significantly different across emerging markets and advanced economies, basic research seems to play a larger role in emerging markets.[8] It is possible that this reflects the larger impact of basic science in niche fields that receive less attention in advanced economies but may be relevant in emerging markets.

Overall, these results emphasize the importance of foreign knowledge for emerging market and developing economies. Although domestic basic research is more productive than for advanced economies in generating innovation, the effect is even larger for foreign research.

The Production Function for Goods and Services

Building on the estimates of the ideas production function presented earlier, this section examines the link between innovation and productivity. The analysis relies on a production

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[7] Note that foreign research stocks are an order of magnitude larger than domestic stocks, and even larger for emerging market and developing economies. This affects the interpretation of the estimated coefficients: a 1 percentage point increase in foreign research is a much larger change in the total knowledge. Further, the results in panel 1 of Figure 3.5 are robust to the exclusion of the US (as a key driver of the technological frontier) from the sample.

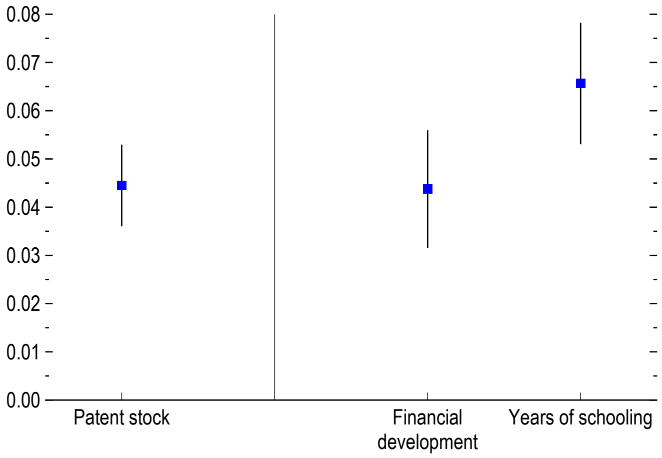
[8] Note however that the coefficient becomes insignificant (while still positive) when China is excluded from the sample (Online Annex 3.3)

function for output and estimates the long-term relationship between productivity (real output per worker) and the country-specific stock of innovation.[9] This is the empirical analogue of the production function for output in Figure 3.2.

In this setting, the stock of innovations is measured using cumulated annual flows of new patents, assuming an annual depreciation rate of 10 percent. The regression also takes in the usual factors of production, such as capital per worker and human capital, along with country and time fixed effects. Finally, the regression includes interactions between innovation and institutional factors to allow institutions to affect the transmission from innovation to productivity. Constant returns to scale are imposed, and the estimation uses data covering 138 countries during 1980–2017.[10]

Figure 3.6. Estimated Output Production Function
(Percentage points)

Innovation correlates with productivity, and more so in countries with deeper financial markets and a better-educated population.



Sources: PATSTAT; Penn World Table 10.0; Reliance on Science; World Bank; and IMF staff calculations.
Note: Patent stock shows the estimated effect of a one percent increase in the stock of patents on productivity. The other coefficients show the additional estimated effect (estimated in separate equations) of innovation on productivity from moving from the middle to the upper tercile of countries in financial development and years of schooling, respectively. See Online Annex 3.4 for details.

The estimated relationship between innovation and productivity is strong and significant (Figure 3.6). An increase in the stock of patents by 1 percent is associated with an increase in productivity per worker of 0.04 percent,[11] in line with estimates reported in Ulku (2004) and dependent on the institutional features of a country (Figure 3.6). The relationship is stronger for countries with higher financial development and more years of schooling, consistent with the idea that deeper financial markets and more educated workforces help transform innovation into productivity. Together with the findings on strong spillovers from foreign research (Figure 3.5, panel 2) these findings are relevant for emerging market and developing markets, as these results suggest that financial market and educational reforms can allow countries to better absorb the stock of foreign research.

Putting It All Together

This section combines the exercises of the previous sections to trace the path to the final impact of increases in basic research stocks on productivity.

Specifically, Figure 3.7 shows in panel 1 that the estimated effect of a 10 percent permanent increase in the stock of a country's own basic research is to increase productivity by 0.30

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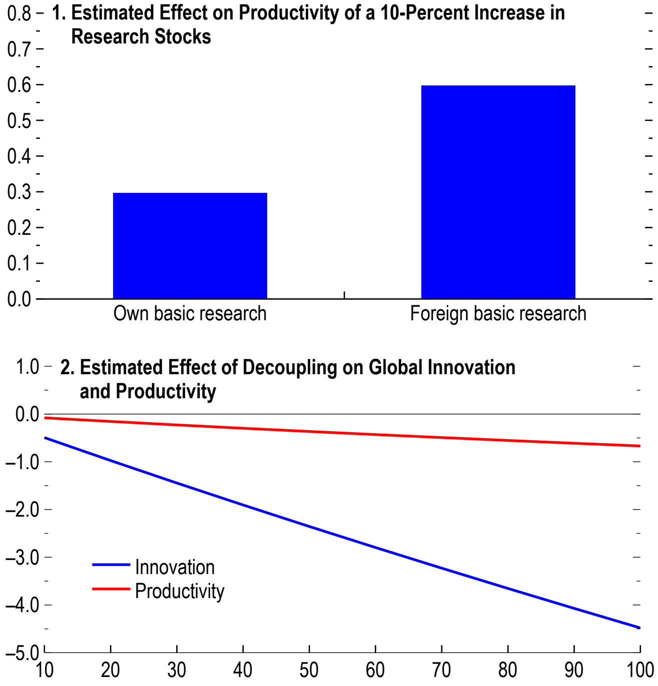
[9] See also Ulku (2004) for a similar exercise.
[10] Online Annex 3.4 reports the full econometric specification and details on the analysis.
[11] Results from alternative specifications in Online Annex 3.4 show this to be robust to averaging over multiyear intervals, which is strongly suggestive of a long-term relationship.

percent, while a similar increase in the stock of foreign basic research is estimated to have a larger impact, increasing productivity by about 0.6 percent. The impact on productivity of own applied research is estimated to be of the same order as the impact of own basic research, and international spillovers are insignificant. The differences are driven by the respective elasticities estimated from the production function for ideas (Figure 3.5).

Overall, the evidence suggests that international productivity spillovers are significant, particularly from basic research. This is in line with the earlier evidence on the extent of international spillovers in Figure 3.4, which also suggested that basic knowledge diffuses more widely and for a longer time than applied knowledge. Hence, the type of research does seem to matter for productivity growth. Quantitatively, however, large confidence bands around those estimates suggest caution in interpreting these results, especially on the impact of foreign research (Figure 3.5). In addition, the linear regression approach measures only the direct effect of basic research on innovation and productivity growth. The true effect may be even larger due to nonlinear relationships linking applied research to the stock of basic knowledge.[12]

Figure 3.7. Implications of the Empirical Findings
(Percent)

Investment in research boosts productivity, while scientific decoupling would be detrimental for global innovation and productivity.


1. Estimated Effect on Productivity of a 10-Percent Increase in Research Stocks

2. Estimated Effect of Decoupling on Global Innovation and Productivity

Source: IMF staff calculations.
Note: Panel 1 shows the estimated effect of a permanent 10-percent increase in research stocks on real GDP per worker. An estimated elasticity of 0.674/1.358 for patents with respect to own basic research/foreign basic research is used. An estimated elasticity of 0.044 for productivity with respect to the stock of patents is used. Panel 2 shows the estimated effect on global innovation (measured as flow of new patents) and productivity of a given reduction (in percent) in citations between the United States and China. See Online Annex 3.5 for details.

Policy Experiment: Scientific Decoupling Between the United States and China

In recent years, concern has been growing that rising tensions between China and the United States could lead to technological decoupling, with detrimental effects on innovation capacity and growth at the global level. This section uses the empirical framework described in this chapter to do a back-of-the-envelope calculation of the cost for global innovation of increased scientific decoupling between the two countries.

The empirical framework can be used to model scientific decoupling, implemented as a reduction in the citation intensity between the two countries. This reduces the foreign stock of basic research available to each country, which in turn decreases innovation and productivity. This is consistent with, for example, differences in technology standards inducing changes across the two countries, such that research done in one becomes less relevant for the other. Limits on knowledge flows might also arise if ongoing geopolitical tensions make it harder for researchers in the two countries to interact or work together. For instance, restriction on travel

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[12] See the policy analysis section for general equilibrium effects of policies stimulating basic research.

might prohibit the all-important personal contacts that can occur at seminars, conferences, and the like.

Figure 3.7 shows the estimated impact on global innovation as measured by the annual flow of new patents for various degrees of scientific decoupling. As a purely illustrative example, full decoupling, as modeled by citations between the two countries shrinking to zero, is estimated to reduce global patent flows by 4.4 percent and global productivity by 0.8 percent.[13]

These estimates are likely a lower bound of the impact of decoupling, for two reasons. First, they assume that only foreign stocks of basic research, innovation, and productivity for the United States and China are affected in a decoupling scenario. In reality, stocks in other countries are likely to be affected too, creating an extra dimension to the shock. Second, these estimates are partial insofar as they do not include any general equilibrium effects that could affect the impact of the initial shock on global innovation and productivity. Given the evidence presented previously on the magnitude of global basic research spillovers, these could be substantial.[14]

Policy Analysis

Earlier sections established the empirical links between basic research, innovation, and economic activity. This raises an obvious question: how can public policy best exploit these links to boost living standards? An important aspect of this empirical work is that it measures only the direct part of these links, holding all else fixed. But in reality, many indirect channels exist. For instance, policies that boost basic science spill over to increase returns to applied innovation, and changes in productivity feed back into wages, driving demand and influencing research incentives. To assess the impact of policy, a framework articulating these links is required.

The Model

Recent work by Akcigit, Hanley, and Serrano-Velarde (2021) provides a theoretical framework for answering this question. It analyzes a setting in which firms conduct two types of research: basic, which builds the stock of knowledge, and applied, which converts knowledge into products. These correspond closely to the basic and applied expenditure concepts used in the empirical analysis. The government has three policy levers: subsidies for each of the two types of research and direct funding for public basic research, such as universities and public research labs.

The key feature of this approach is that basic research is modeled as having applications in many different fields. This captures an essential aspect of basic research—that because individual firms typically operate in only a few sectors, they cannot profit fully from the range of economic applications opened up by the most fundamental and basic discoveries. As a result, private incentives for basic research are outstripped by its social benefits. Without a public policy response, this will result in inefficiently low levels of innovation and productivity.

Despite the special character of basic research, it is not the only potential target of public policy in this framework. Applied research—which is complementary to basic research, adapting

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[13] Online Annex 3.5 provides further details and a full breakdown of these effects.

[14] See Cerdeiro and others (2021) for a more structural approach to the decoupling issue.

knowledge to produce marketable products—also generates spillovers, which could also motivate public support. This is because innovations that bring a product to market can be superseded by competitors' innovations. This introduces a "quality ladder" mechanism: firms may not be able to fully internalize the social value of applied innovation, leading to underprovision of applied research as well. Whether applied or basic research is more desirable is not hard-wired into the model but is instead a function of parameters estimated from the data.

The model is estimated for three countries: France, the United Kingdom, and the United States. Although estimating for more countries would be ideal, the data requirements needed to maintain the important distinction between basic and applied research preclude this. Still, this exercise gives some sense of the impact of country-specific factors, at least within advanced economies.

Optimal Policies

Figure 3.8 shows optimal policies and the resultant outcomes from several experiments. The first, shown in red, is the case when governments cannot subsidize applied and basic research separately and so must apply the same rate to both. This is not an unreasonable approximation of reality, as deciding which of firms' individual activities are "applied" and which are "basic" is often challenging, and so being able to target them separately may be difficult. Indeed, many data sources for such subsidies cannot make this distinction.

This exercise suggests that research in general is funded below its socially optimal level. Subsidy rates for private research should be doubled, and public research expenditure increased by around one-third. Although country-specific caveats (see "Policy Conclusions" below) might caution against a too-literal interpretation of these findings, they are at least broadly supportive of the notion that there are likely underexploited spillovers from research which can leave room for policy to make households better off. Increasing subsidies and public research expenditures as recommended would raise productivity growth in the order of about 0.2 percentage point a year. This would start to pay for itself within about a decade. If applied over the period shown in panel 1 of Figure 3.1, this would have resulted in current per capita incomes about 12 percent higher than in the data. Moreover, in an era of low real interest rates, small increases in economic growth can have very large impacts on debt sustainability.

Under this policy program, the stocks of both applied and basic knowledge increase. But because public expenditure is purely basic, the stock of basic knowledge increases by more—with an increase about several times the size of that for applied knowledge. This increase in the knowledge stock also varies across countries and is largest in the United States where higher corporate entry and exit rates mean that firms do not internalize the social benefits of research, leaving more room for policy to play a positive role. The level of wages also rises under optimal policy, with increases of between 2.5 and 3 percent, depending on the country.

Of course, assuming that no scope exists for targeting subsidies might seem somewhat restrictive, and so the results of separately subsidizing applied and basic research are also shown in Figure 3.8, in yellow. This policy clearly dominates the previous one, which implies that, where possible, governments should target subsidies aggressively toward basic research. This policy recommendation matches the earlier empirical evidence, which showed that basic research is an important determinant of productivity growth.

Although targeting has only a minor additional impact on growth, it reduces the cost of subsidies, lowering taxes and making households substantially better-off. The intuition for this is that basic research is a smaller sector than applied research. Since the subsidy is smaller and growth spillovers from basic research are larger than for applied research, this achieves a similar growth effect but with a much smaller subsidy. Lower subsidy spending can translate into lower taxes, boosting household disposable income and consumption permanently.

Exploring the Assumptions

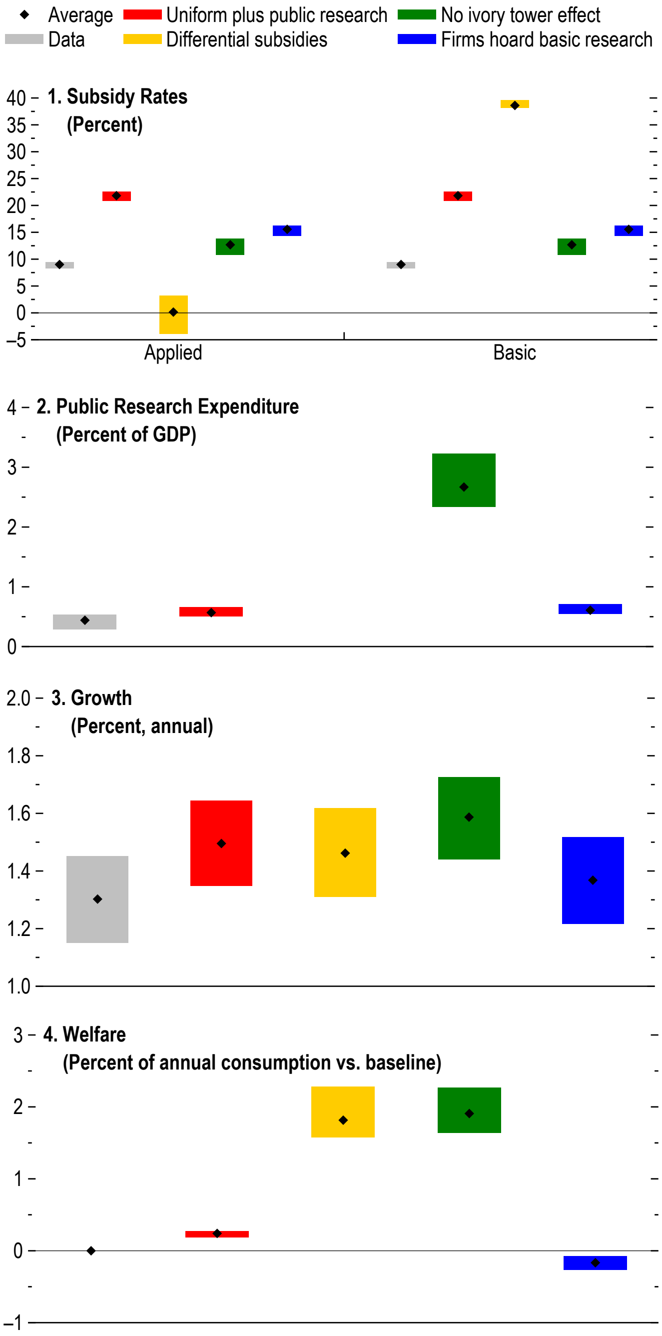
As with any model-based analysis, the results depend on the modeling assumptions. Here, two important assumptions are explored in detail.

The first is the substitutability of public and private research. In the baseline, this substitutability is imperfect; public research requires extra work to be useful for commercial innovation—the "ivory tower" effect. If this is turned off, public basic research can be commercialized more easily and can take on more of the qualities of a public-private partnership.

The most obvious effect of this experiment is that optimal research expenditure increases considerably, to about 3 percent of GDP (Figure 3.8, panel 2, in green). This is not surprising: a public sector that can deliver more commercially adaptable innovations means better use of resources. Optimal subsidies fall and growth increases by an average of another 0.1 percentage point. The policy implication is that even if discrimination between basic and applied research subsidies is not possible, governments might be able to achieve something similar by encouraging greater collaboration between public and private basic researchers.

Figure 3.8. Optimal Policy

Public and private research are underfunded; where different subsidies to basic and applied research are impossible, public-private partnerships may be a good substitute.



Sources: Organisation for Economic Co-operation and Development; and IMF staff calculations.
Note: Range shows optimal policies across the model reestimated for France, the United Kingdom, and the United States. In the differential subsidies case, public research is assumed fixed at the level in the data. See Online Annex 3.6 for details.

The second experiment investigates how sensitive these results are to assumptions about private basic research spillovers. It is conceivable that spillovers from private firms may decrease if, for example, recent technological change allows for more market power or other abilities to privatize breakthroughs. To proxy this, the blue bars in Figure 3.8 show that the spillovers from private basic research shrink by a quarter. This limits public gains from research, and so optimal public subsidy rates are increased only by half relative to the data (versus doubling in the baseline).

Policy Conclusions

The preceding experiments highlight four key policy lessons.

- First, public funding for research is too low. Gains can be made from both subsidizing more private research and doing more public research.
- Second, the ability to discriminate between different types of research is very valuable. If possible, governments could achieve similar outcomes to the baseline at roughly half the cost.
- Third, better connections between public and private researchers might be able to substitute for targeted subsidies, which can be hard to implement.
- Fourth, regarding firms' ability to protect their discoveries, if basic research spillovers decline, then the social gains from research will fall. This suggests that reducing overbearing market power or excessively broad patenting can boost productivity and growth (Box 3.3 discusses this issue more broadly).

As with any model-based analysis, tractability demands that this assessment leave out a number of other factors that could affect the policy conclusions. As such, these conclusions should be treated as a baseline, from which country-specific considerations could require some deviation.

One such issue is the absence of distorting taxation. In this setting, taxes are raised by collecting a lump sum from households. In reality, though, most tax instruments, such as labor or capital taxes, induce some sort of inefficiency. Such instruments introduce an extra cost to policy interventions. Because these costs typically increase with the size of the tax, countries with high tax distortions may find policies to support basic research to be more costly. A similar caveat applies to countries with high debt burdens or inefficient revenue collection systems. In these cases, a better source of funding might be to reprioritize expenditure or improve revenue mobilization.

Moreover, these policy conclusions are perhaps most directly relevant to advanced economies: the model lacks a channel (such as trade) for the international diffusion of knowledge, which earlier sections showed to be important in emerging market and developing economies. As such, these countries may find that policies to better adapt foreign knowledge to local conditions are a better avenue for development than investing directly in homegrown basic research (Acemoglu and others 2006). Other unmodeled factors, such as political constraints, may also hinder the kind of tax-funded innovation-boosting policies presented here.

Conclusions: Investment in Basic Science Boosts Productivity and Pays for Itself Over the Long Run

The development of COVID-19 mRNA vaccines acts as a stark reminder of the importance of science for innovation and growth. In common with other technological breakthroughs, past scientific discoveries in unrelated fields typically laid the foundation for today's technological advances, driving future productivity and economic growth (Box 3.1).

Improving growth outcomes will be essential to post-pandemic economies, helping finance higher public debt and additional post-pandemic social expenditures. It is therefore worrisome that the share of basic research has been steadily declining over the past three decades.

That the private sector underinvests in basic research is not surprising. As shown in this chapter, the benefits of basic research are diffuse and long-lasting, making it an unattractive proposition for private firms. This creates an opportunity for policy intervention. The chapter shows that doubling subsidies to private research and boosting public research expenditure by a quarter could increase annual growth per capita by a quarter of a percent. Better targeting of subsidies and closer public-private cooperation could boost this further, at lower public expense. Such investments could start to pay for themselves within a decade or so.

The chapter also shows that scientific knowledge travels far over time and distance, and that it is a key driver of innovation in both advanced economies and emerging markets. Spillovers from advanced economies to emerging markets are particularly large. Deep financial markets and better educational systems are key facilitators for cross-border technology adoption.

It is also important to ensure the free flow of ideas and scientific collaboration across borders, especially for emerging markets. The technological trajectories of China and the United States have been closely linked in the past two decades. Rising political tensions could lead to scientific decoupling, with detrimental effects on innovation capacity and global economic growth.

Beyond its impact on growth, basic science is likely to be a key contributor to a greener future. The fight against climate change requires drastic cuts in global emissions. New clean technologies will be central to this effort. Evidence presented in the chapter suggests that investment in frontier science—especially in natural sciences and engineering—could help speed the transition toward a cleaner economy.

Box 3.1. mRNA Vaccines and the Role of Basic Scientific Research

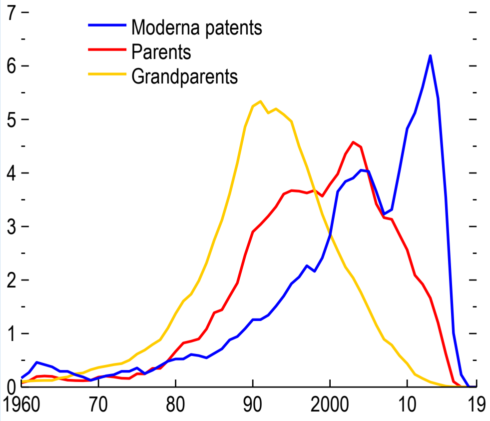
Vaccines using new mRNA technology are key to the fight against COVID-19; the most well-known are those developed by Pfizer/BioNTech and Moderna.[15] This technology uses genetic code known as messenger RNA (or mRNA) to instruct human cells to make part of the virus's protective shell. These fragments help train the body's immune system to attack the real virus. Compared with conventional approaches, mRNA technology can deliver better-performing vaccines with shorter research and production times. Their social and economic impact has been enormous, likely shortening the pandemic by years, and looks set to revolutionize medical treatments in years to come.

This technology was built on waves of prior scientific discoveries. To track these discoveries, Figure 3.1.1 shows the publication dates of scientific articles cited by five of the seven Moderna COVID vaccine patents (in blue). This distribution captures the direct dependence of vaccine development on past scientific discoveries and is concentrated around breakthroughs on the function of mRNA in the early 2010s. To measure the indirect influence of science, the yellow line shows the scientific citations of the vaccine's "parent" patents—other patents referenced in the five original vaccine patents. These peak in the early 2000s, tracking discoveries in editing genetic codes. Earlier advances in reading genetic codes drove a similar wave of citations from "grandparent" patents in the early 1990s. These waves of scientific influence illustrate how policies that help incentivize advances in basic science today influence the building blocks of future technologies and yield long-lasting economic payoffs.

Developing mRNA vaccines relied on a broad base of scientific knowledge. On average, the Moderna vaccine patents are in the same technological category as only 55 percent of their parent patents, a number that falls further as citation chains lengthen (Figure 3.1.2). This

Figure 3.1.1. mRNA Technology Was Built on Waves of Previous Scientific Discoveries

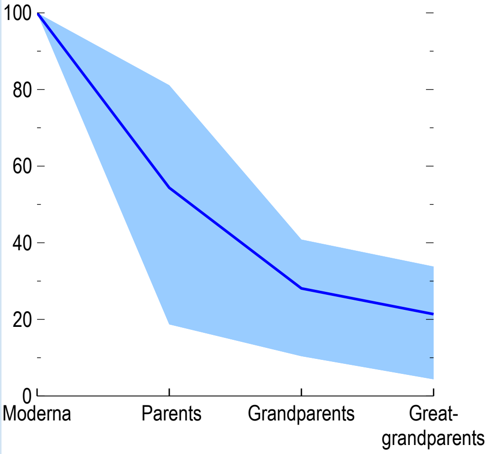
(Percent of citations)



Sources: Moderna; Reliance on Science; United States Patent and Trademark Office; and IMF staff calculations.
Note: The *y*-axis shows the scientific citations by Moderna's mRNA patents and their ancestors. Parent patents are those cited by Moderna's mRNA vaccine patents. Grandparents are those cited by parent patents.

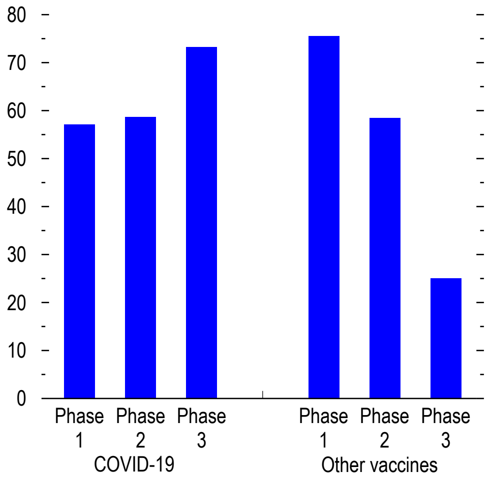
Figure 3.1.2. mRNA Vaccines Relied on Broad Base of Scientific Knowledge

(Percent)



Sources: Moderna; United States Patent and Trademark Office; and IMF staff calculations.
Note: The *y*-axis shows the fraction of patents in the same technological categories as the seven Moderna vaccine patents. The blue line is the averaged percentage for each ancestor. The shaded area shows the range of each ancestor of citation across the seven Moderna vaccine patents. Total number of categories is 7,523 based on the International Patent Classification. Parent patents are those cited by Moderna's mRNA vaccine patents. Grandparents are those cited by parent patents. Great-grandparents are those cited by grandparent patents.

Figure 3.1.3. Unprecedented Public Support for COVID-19 Vaccine Clinical Trials
(Percent)

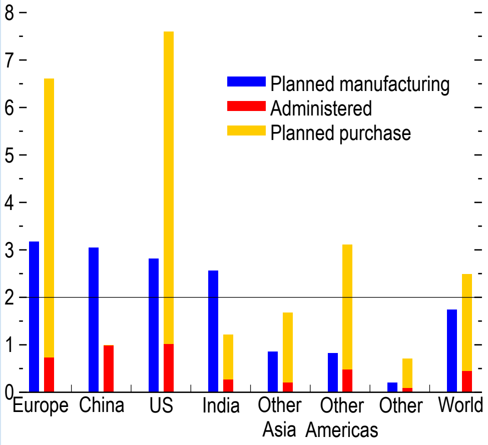


Sources: US National Library of Medicine; and IMF staff calculations.
Note: The *y*-axis shows the fraction of clinical trials with no private support. The three bars on the left show the clinical trial data for the COVID-19 vaccine. Support may include activities related to funding, design, implementation, data analysis, or reporting. Funder type is defined as private if support comes only from organizations in industry. Phases are based on the US Food and Drug Administration definition.

shows how wide-ranging basic science contributed to mRNA vaccines, indicating that policies to develop a broad scientific base can pay off in many and unexpected ways. The development of COVID vaccines was encouraged by unprecedented public support. This included regulatory forbearance (emergency use authorization of COVID vaccines), at-risk up-front investment and subsidies for vaccine production (Operation Warp Speed), help in scaling up manufacturing (Indian government grants to vaccine producers), joint licensing agreements with local producers (India, South Africa), and advance public purchase commitments (Israel, United Kingdom, United States). A distinguishing feature of public support for a COVID vaccine was its continuation throughout the development process. Typically, public funding is most generous for early trials, falling as products near market. For COVID vaccines, public and academic funding for clinical trials stayed high even at the latest stages of development (Figure 3.1.3). This highlights how support throughout the production process can incentivize research by forward-looking firms.

Global distribution of vaccines remains a challenge. Although reliable data are hard to come by, global supply seems sufficient. World production of COVID vaccines is likely to hit almost two doses per capita by the end of 2021—slightly less than demand. Although supply disruptions and capacity constraints can hamper delivery of vaccines, even planned purchases are unevenly distributed, with outsize demand in the United States and Europe. So fair distribution of vaccines will require adjustment of planned allocations, irrespective of where they are produced.

Figure 3.1.4. Global Distribution of Vaccines Remains a Key Policy Challenge
(Doses per capita)



Sources: Duke Global Health Innovation Center; Our World in Data; and IMF staff calculations.
Note: Blue bars show the planned doses of manufactured vaccines by region by the end of 2021, which also includes doses in contracts under discussion. Red bars show the number of administered vaccines by region. Yellow bars show the differences between the number of planned purchase of vaccines by the end of 2021 and the number administered. Other Americas = Americas excluding the United States; Other Asia = Asia excluding China and India.

The authors of this box are Philip Barrett and Xiaohui Sun.

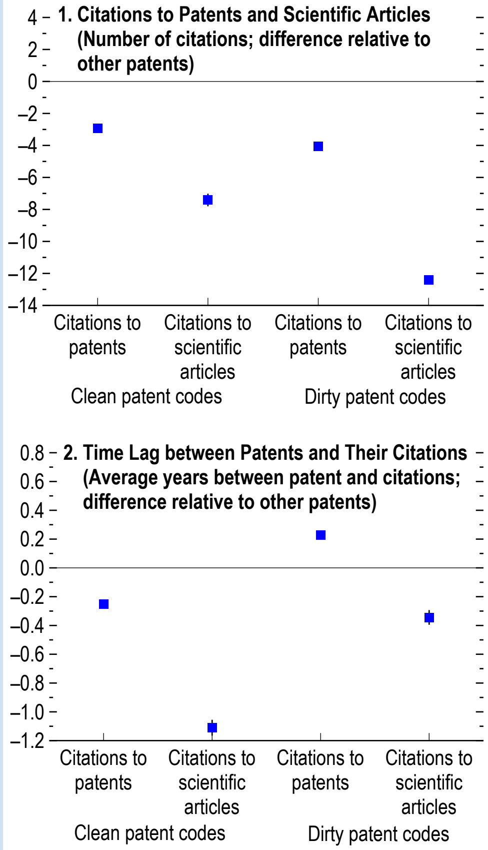
[15] While the reliance of the Moderna vaccine on just a few patents makes it easy to trace through the links from basic research, the main conclusions likely hold for other vaccines. This applies both to those using new immunization technologies (such as Johnson & Johnson and Oxford/AstraZeneca) and more traditional approaches (such as Sinopharm);they all require scientific knowledge that was once new.

Box 3.2. Clean Tech and the Role of Basic Scientific Research

Avoiding catastrophic climate change requires a rapid reduction in emissions of greenhouse gases. This will be possible only if global energy consumption transitions to predominantly clean (zero carbon emissions) energy sources. Technological advances to drive down the cost of clean energy are a key part of any strategy to minimize the economic impact of that switch. This box shows how investment in basic research is especially important to foster innovation in clean technologies and thus spur emission reductions.

This question is addressed using the patent-level Reliance on Science data set. This includes detailed information on the industrial category of its constituent patents, which is used to classify the technology covered in each patent as a clean or a dirty innovation (following Dechezleprêtre, Muckley, and Neelakantan 2020). Clean innovations include renewable energy technology and electric vehicles; dirty innovations cover gas turbines, furnaces, and the like. Comparing the properties of clean and dirty innovations against all other patents (as a benchmark) can help uncover the relationship between scientific research and the direction of technical change.[16]

Figure 3.2.1. Clean Innovation Relies Relatively More on Basic and Newer Research



Sources: Reliance on Science; United States Patent and Trademark Office; and IMF staff calculations.
Note: Panel 1 (panel 2) shows coefficients from regression of citations (citation lag) on dummies for patent type, year, and country of inventor. Error bars represent 95 percent confidence intervals. Because the sample is very large, confidence intervals are sometimes so small as to be narrower than the width of the marker for the point estimate.

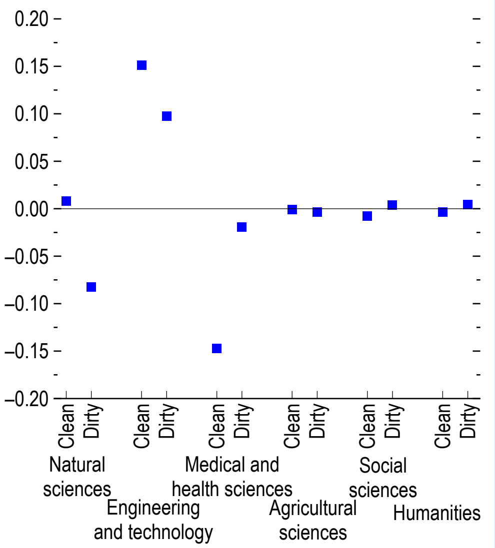
The first dimension for comparing clean and dirty patents is their relative citations to prior patents and scientific articles. This contains information on how different types of innovation depend on applied and basic knowledge stocks. Figure 3.2.1 summarizes the results of this exercise. The first panel shows that both clean and dirty innovations cite less prior research than other sorts of innovation. Clean innovations cite more research than dirty innovations, but mainly within scientific articles. With a sample of several million patents, these differences are very precisely estimated.

The second panel compares the age of the research used by clean and dirty innovation, which can be thought of as a proxy for distance to the technological frontier. Clean innovations cite newer patents and scientific articles than both dirty innovations and other types of innovations.

The authors of this box are Philip Barrett and Niels-Jakob Hansen

Figure 3.2.2. Clean Innovation in Particular Cites Engineering and Technology

(Fraction of citations; difference relative to other patents)



Sources: Reliance on Science; United States Patent and Trademark Office; and IMF staff calculations.
Note: Figure shows coefficients from regression of research field dummies on dummies for patent type. Error bars represent 95 percent confidence intervals. Because the sample is very large, confidence intervals are sometimes so small as to be narrower than the width of the marker for the point estimate.

However, the difference is largest for scientific articles, which are on average 0.8 year newer than those cited by dirty innovation. In other words, clean breakthroughs rely more on scientific research closer to the frontier than dirty innovation.

Figure 3.2.2 shows the fraction of scientific research in different fields, relative to other patents. It shows that clean innovation is particularly likely to rely on research in engineering and technology and unlikely to rely on medical research. Interestingly, dirty innovations cite the natural sciences much less frequently than clean ones do. Unsurprisingly, neither clean nor dirty innovation seems to depend much on research in agriculture, social science, or the humanities.

Overall, the evidence presented here suggests that clean innovations depend more than dirty ones on frontier science, particularly natural sciences and engineering. Accordingly, basic research investment in these fields is likely to have a positive impact in the fight against climate change. That said, public promotion of basic research in these fields will be only part of the solution. Other factors, such as incentives to bring new clean technologies to market, as well as addressing stranded assets associated with dirty fuels, will also be important.

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[16] This comparison is done via regression, allowing for results that account for third factors that might otherwise influence this relationship. This includes the year that the patent is issued and the country of the inventor.

Box 3.3. Intellectual Property, Competition, and Innovation

Intellectual property rights are among several public policy tools to foster private innovation. Innovation requires costly and risky up-front investments in R&D. Would-be innovating firms may undertake them only with some guarantee that their ideas can be protected from potential imitators, at least for some time. These rights are designed to do just that. By granting temporary monopoly power to inventors, intellectual property rights make it profitable to invest in R&D and incentivize a continuous flow of innovation. Strong intellectual property rights also complement growth-enhancing pro-competition policies, such as reduced market entry barriers and tougher antitrust frameworks (Aghion, Howitt, and Prantl 2015). Competition is generally good for innovation, but when too strong it can weaken firms' prospective monopoly rents and therefore their incentive to innovate (April 2019 *World Economic Outlook*; IMF 2021), unless these future rents are well protected by patent laws.

However, there is a limit to how strong intellectual property rights should be. If overly protective they can cement leading firms' position and weaken their incentive to innovate, discouraging lagging firms from doing so as well (Akcigit and Ates 2021). This is particularly likely if patents excessively reward incremental innovations or if market leaders use them as barriers to competition. "Patent thickets"—overly complicated legal setups that require a firm to seek agreements with many parties to use a technology— are an example (Shapiro 2001).

In summary, intellectual property rights should be neither too weak nor too strong, and they should reward disruptive innovations far more than those that are incremental. Yet, even when well calibrated, intellectual property rights confer temporary monopoly power and so delay the widespread dissemination of innovation to competitors and the general public. This could at times run counter to society's broader goals. In a pandemic, for example, any delay in widespread vaccine production has enormous human and economic costs. Therefore, during a public emergency, and when the use of a targeted innovation is clearly identified, governments should consider alternative, less distortive approaches. Tax credits for specific R&D, direct government support, and innovation prizes, in particular, have been proposed in such situations (Kremer and Williams 2010; Maskin 2020). These policies better align society's goals with private incentives when the targeted innovation (for example, a new vaccine) and success criteria (such as effectiveness and safety) are well identified.

By covering costs and risks *up-front*, Operation Warp Speed generated the necessary incentives for pharmaceutical companies to develop effective vaccines in record time. Intellectual property rights also likely helped stimulate the development of vaccines, but at the risk of slowing global production in the near future. In response, a proposal—supported by China, Russia, and the United States—to temporarily waive these rights for vaccines is currently under discussion at the World Trade Organization. In future pandemics, alternative policy support, such as well-designed innovation prizes, could be considered, which would stimulate vaccine development just as powerfully while *also* facilitating rapid vaccine dissemination.

The authors of this box are Romain Duval and Jean-Marc Natal

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CHAPTER 3

RESEARCH AND INNOVATION: FIGHTING THE PANDEMIC AND BOOSTING LONG-TERM GROWTH

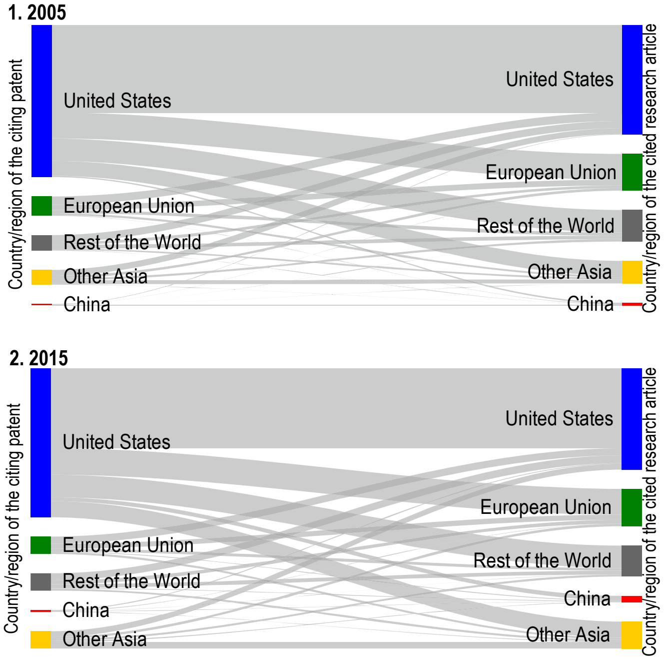
Online Annex

Annex 3.1 Data Sources, Sample Coverage, and Variable Definitions

Data sources used in the chapter are listed in Annex Table 3.1.1.

The Reliance on Science (RoS) database, used for patent-to-(scientific)article citations, covers US and European patents. PATSTAT, which is used for patent-to-patent citations, provides global coverage from more than 190 patenting offices. The RoS is further matched to the USPTO database to obtain the country of residence of the inventor. This restricts the sample to patent-to-article citations in patents applied for in the USPTO; however, it still includes inventors from all over the world. To verify how representative the subsample is of cross-country citations, the critical element in our analysis of international spillovers, we compared patent-to-patent citations from the RoS-USPTO sample to patent-to-patent citations from the global universe of patents in PATSTAT. The correlation coefficient ranged from 0.97 to 0.98 using different citation lag windows (2, 4, 6, 8 and 10 years).

Annex Figure 3.1.1. The Geography of International Basic Knowledge Flows
(Citation share)



Sources: Reliance on Science; United States Patent and Trademark Office; and IMF staff calculations.
Note: The shaded area corresponds to the number of citations, where the left hand side represents 100% of the citing patents and the right hand side represents 100% of the cited articles.

Each patent is assigned to a country based on the location of residence of the inventor. For patents with several inventors (or several countries for the same inventor), the main country is determined based on the largest share of countries. For patents with an equal split between countries, the patent is not assigned to any country. 2% of patents found in Reliance on Science and USPTO are not assigned to a country.

Each scientific article is assigned a country based on the academic affiliation of the author. Academic affiliation, provided by Reliance on Science, includes an institution name or geographic information that is matched to a country for 90% of unique affiliations.[1] For articles with several countries, the main country is determined based on the largest share of countries. Articles with an equal split between countries are not assigned to any country. This holds for

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[1] For the remaining 10 percent the used algorithm was not able to match affiliations to country.

1% of all articles. The flow of citations between patents and scientific articles is illustrated in Annex Figure 3.1.1.

Similarity in technological specialization between country pairs is calculated following Peri (2005). The calculation is based on patent classification into 131 technological categories as defined by the International Patent Classification codes. For each country, the vector of shares of patents falling into each category is used to calculate the uncentered correlation coefficient between the vectors of country i and country j. The resulting measure ranges from 0 (no overlap in technological classes) to 1 (complete overlap in technological classes). Technological distance is then defined as (1 – technological similarity). Similarity in scientific specialization and distance in scientific specialization are calculated analogously using the Reliance on Science database and the OECD classification of scientific fields (37 fields) for academic articles.

Technological development of each country is defined as the natural logarithm of the 5-year (2015-2019) average R&D expenditure per employed person. For each country pair, the difference between the technological development of the two countries was then calculated. R&D expenditure was taken from OECD Main Science and Technology Indicators; total employment was taken from Penn World Table 10.0.

Scientific development of each country is defined as the natural logarithm of the 5-year (2015-2019) average scientific article production per person employed in R&D. For each country pair, the difference between the scientific development of the two countries was then calculated. Scientific article production was calculated from Reliance on Science citations; number of R&D personnel was taken from OECD Main Science and Technology Indicators.

Patents are classified into clean energy technologies, dirty energy technologies, and emerging technologies based on USPTO's Cooperative Patent Classification (CPC) codes following Dechezleprêtre, Muckley, Neelakantan (2021).

The research expenditure on R&D is obtained from the OECD Main Science and Technology Indicators database, which is detailed by the type of expenditure. Following the OECD (2015) Frascati Manual, the data is collected following precise definitions for basic research, applied research and experimental development. Experimental development is combined with applied research into one category, and the data capture total expenditure (public and private) on R&D.

All regression results are produced using STATA 16.1.

Annex Table 3.1.1. Data Sources

Source	Indicators
PATSTAT Global 2020 Spring Edition	Patents flows; patent stock; patent-to-patent citations; International Patent Classification codes
Reliance on Science database; Marx and Fuegi (2020, 2020b)	Patent-to-article citations; OECD classification codes of scientific fields; year cited article was published; author affiliation
United States Patent and Trademark Office	Location of inventor; Cooperative Patent Classification codes; year patent application was filed
CEPII, GEO Dist; Mayer and Zignago (2011)	Common border dummy; common official language dummy; distance between countries' capital cities
World Bank, World Development Indicators; National Science Foundation, Science and Engineering Indicators	Scientific and technical journal articles (count)
OECD Product Market Regulation Statistics database	Indicator of regulation in product markets
OECD Science and Technology Indicators database	Basic R&D expenditure; basic R&D stock; non-basic R&D expenditure; non-basic R&D stock; total business enterprise R&D personnel; government total R&D personnel; higher education total R&D personnel; total employment
Penn World Table 10.0; Feenstra, Inklaar, and Timmer (2015)	Output-side real GDP at chained PPPs (in mil. 2017US$); number of persons engaged (in millions); average annual hours worked by persons engaged; TFP at constant national prices (2017=1); capital stock at current PPPs (in mil. 2017US$)
Barro-Lee Educational Attainment Dataset	Average years of schooling
Worldwide Governance Indicators	Control of corruption; government effectiveness; political stability and absence of violence/terrorism; rule of law; regulatory quality; voice and accountability (percentile rank)
World Economic Forum	Intellectual property protection; quality of overall infrastructure; quality of the education system
PRS Group, The International Country Risk Guide (ICRG)	Contract viability/expropriation
International Monetary Fund, Financial Development Index database	Financial development index
World Bank, Doing Business database	Ease of doing business score

Source: IMF staff compilation.

Annex Table 3.1.2. Economies Included in the Analysis

Figure / Exercise	List of Economies
Figure 3.1 (panel 1)	Australia; Austria; Belgium; Canada; Denmark; Finland; France; Germany; Greece; Hong Kong SAR; Ireland; Italy; Japan; Korea; Norway; Portugal; Singapore; Spain; Sweden; Switzerland; United Kingdom; United States
Figure 3.1 (panel 2)	Australia; Austria; Belgium; Canada; Denmark; Finland; France; Germany; Greece; Hong Kong SAR; Ireland; Italy; Japan; Korea; Norway; Portugal; Singapore; Spain; Sweden; Switzerland; United Kingdom; United States
Figure 3.1 (panel 3)	Argentina; Australia; Austria; Belgium; Chile; China; Czech Republic; Denmark; Estonia; France; Germany; Greece; Hungary; Iceland; Ireland; Israel; Italy ; Japan; Korea; Latvia; Lithuania; Luxembourg; Mexico; Netherlands; New Zealand; Norway; Poland; Portugal; Romania; Russia; Singapore; Slovak Republic; Slovenia; South Africa; Spain; Sweden; Switzerland; Taiwan Province of China; United Kingdom; United States
Figure 3.1 (panel 4)	Albania; Algeria; Antigua and Barbuda; Argentina; Armenia; Australia; Austria; Azerbaijan; Bahamas, The; Bahrain; Bangladesh; Barbados; Belarus; Belgium; Belize; Bolivia; Brazil; Brunei Darussalam; Bulgaria; Burkina Faso; Cameroon; Canada; Chile; China; Colombia; Costa Rica; Croatia; Cyprus; Czech Republic; Denmark; Dominican Republic; Ecuador; Egypt; El Salvador; Estonia; Eswatini; Fiji; Finland; France; Gabon; Georgia; Germany; Ghana; Greece; Grenada; Guatemala; Guinea; Honduras; Hong Kong SAR; Hungary; Iceland; India; Indonesia; Iran; Iraq; Ireland; Israel; Italy; Jamaica; Japan; Jordan; Kazakhstan; Kenya; Korea; Kuwait; Kyrgyz Republic; Latvia; Lebanon; Lithuania; Luxembourg; Macao SAR; Malaysia; Malta; Marshall Islands; Mauritius; Mexico; Moldova; Mongolia; Morocco; Nepal; Netherlands; New Zealand; Nicaragua; Niger; Nigeria; North Macedonia; Norway; Oman; Pakistan; Panama; Papua New Guinea; Paraguay; Peru; Philippines; Poland; Portugal; Puerto Rico; Qatar; Romania; Russia; Saudi Arabia; Serbia; Seychelles; Sierra Leone; Singapore; Slovak Republic; Slovenia; South Africa; Spain; Sri Lanka; St. Kitts and Nevis; Suriname; Sweden; Switzerland; Syria; Taiwan Province of China; Tanzania; Thailand; Trinidad and Tobago; Tunisia; Turkey; Uganda; Ukraine; United Arab emirates; United Kingdom; United States; Uruguay; Uzbekistan; Venezuela; Vietnam; Yemen; Zimbabwe
Figure 3.3	Albania; Algeria; Angola; Antigua and Barbuda; Argentina; Armenia; Australia; Austria; Azerbaijan; Bahrain; Bangladesh; Barbados; Belarus; Belgium; Benin; Bolivia; Bosnia and Herzegovina; Botswana; Brazil; Brunei Darussalam; Bulgaria; Cambodia; Cameroon; Canada; Central African Republic; Chad; Chile; China; Colombia; Costa Rica; Croatia; Cyprus; Czech Republic; Côte d'Ivoire; Denmark; Dominica; Dominican Republic; Ecuador; Egypt; El Salvador; Estonia; Ethiopia; Fiji; Finland; France; Gambia, The; Georgia; Germany; Ghana; Greece; Grenada; Guatemala; Guinea; Haiti; Hong Kong SAR; Hungary; Iceland; India; Indonesia; Iran; Iraq; Ireland; Israel; Italy; Jamaica; Japan; Jordan; Kazakhstan; Kenya; Korea; Kuwait; Lao P.D.R.; Latvia; Lebanon; Liberia; Libya; Lithuania; Luxembourg; Macao SAR; Malawi; Malaysia; Mali; Malta; Mauritius; Mexico; Micronesia; Moldova; Mongolia; Montenegro, Rep. of; Morocco; Mozambique; Myanmar; Namibia; Nepal; Netherlands; New Zealand; Nicaragua; Niger; Nigeria; North Macedonia; Norway; Oman; Pakistan; Panama; Papua New Guinea; Paraguay; Peru; Philippines; Poland; Portugal; Puerto Rico; Qatar; Romania; Russia; Saudi Arabia; Senegal; Serbia; Singapore; Slovak Republic; Slovenia; South Africa; Spain; Sri Lanka; Sudan; Sweden; Switzerland; Syria; Taiwan Province of China; Tajikistan; Tanzania; Thailand; Trinidad and Tobago; Tunisia; Turkey; Uganda; Ukraine; United Arab Emirates; United Kingdom; United States; Uruguay; Uzbekistan; Venezuela; Vietnam; West Bank and Gaza; Yemen; Zambia; Zimbabwe
Figure 3.4 (Panel 1)	Afghanistan; Albania; Algeria; Angola; Antigua and Barbuda; Argentina; Armenia; Aruba; Australia; Austria; Azerbaijan; The Bahamas; Bahrain; Bangladesh; Barbados; Belarus; Belgium; Belize; Benin; Bhutan; Bolivia; Bosnia and Herzegovina; Botswana; Brazil; Brunei; Darussalam; Bulgaria; Burkina Faso; Burundi; Cabo Verde; Cambodia; Cameroon; Canada; Central African Republic; Chad; Chile; China; Colombia; Republic of Congo; Costa Rica; Croatia; Cyprus; Czech Republic; Côte d'Ivoire; Denmark Djibouti; Dominica; Dominican Republic; Ecuador; Egypt; El Salvador; Eritrea; Estonia; Eswatini; Ethiopia; Fiji; Finland; France; Gabon; The Gambia; Georgia; Germany; Ghana; Greece; Grenada; Guatemala; Guinea; Guyana; Haiti; Honduras; Hong Kong SAR; Hungary; Iceland; India; Indonesia; Iran; Iraq; Ireland; Israel; Italy; Jamaica; Japan; Jordan; Kazakhstan; Kenya; Korea; Kuwait; Kyrgyz Republic; Lao P.D.R.; Latvia; Lebanon; Lesotho; Liberia; Libya; Lithuania; Luxembourg; Macao SAR; Madagascar; Malawi; Malaysia; Maldives; Mali; Malta; Marshall Islands; Mauritania; Mauritius; Mexico; Micronesia; Moldova; Mongolia; Morocco; Mozambique; Myanmar; Namibia; Nauru; Nepal; Netherlands; New Zealand; Nicaragua; Niger; Nigeria; North Macedonia; Norway; Oman; Pakistan; Palau; Panama; Papua New Guinea; Paraguay; Peru; Philippines; Poland; Portugal; Puerto Rico; Qatar; Romania; Russia; Rwanda; Samoa; San Marino; Saudi Arabia; Senegal; Seychelles; Sierra Leone; Singapore; Slovak Republic; Slovenia; Solomon Islands; Somalia; South Africa; Spain; Sri Lanka; St. Kitts and Nevis; Sudan; Suriname; Sweden; Switzerland; Syria; São Tomé and Príncipe; Taiwan Province of China; Tajikistan; Tanzania; Thailand; Togo; Tonga; Trinidad and Tobago; Tunisia; Turkey; Turkmenistan; Tuvalu; Uganda; Ukraine; United Arab Emirates; United Kingdom; United States; Uruguay; Uzbekistan; Vanuatu; Venezuela; Vietnam; Yemen; Zambia; Zimbabwe
Figure 3.5 (Panels 1 and 2)	Argentina; Australia; Austria; Belgium; Chile; China; Czech Republic; Denmark; Estonia; France; Germany; Greece; Hungary; Iceland; Ireland; Israel; Italy; Japan; Korea; Latvia; Lithuania; Luxembourg; Mexico; Netherlands; New Zealand; Norway; Poland; Portugal; Romania; Russia; Singapore; Slovak Republic; Slovenia; South Africa; Spain; Sweden; Switzerland; Taiwan Province of China; United Kingdom; United States
Figure 3.6	Albania; Algeria; Angola; Argentina; Armenia; Australia; Austria; Bahrain; Bangladesh; Barbados; Belgium; Belize; Benin; Bolivia; Brazil; Brunei Darussalam; Bulgaria; Burkina Faso; Burundi; Cambodia; Cameroon; Canada; Central African Republic; Chile; China; Colombia; Congo, Democratic Republic of the; Costa Rica; Croatia; Cyprus; Czech Republic; Côte d'Ivoire; Denmark; Dominican Republic; Ecuador; Egypt; El Salvador; Estonia; Eswatini; Ethiopia; Fiji; Finland; France; Gabon; Gambia, The; Germany; Ghana; Greece; Guatemala; Haiti; Honduras; Hong Kong SAR; Hungary; Iceland; India; Indonesia; Iran; Iraq; Ireland; Israel; Italy; Jamaica; Japan; Jordan; Kazakhstan; Kenya; Korea; Kuwait; Kyrgyz Republic; Lao P.D.R.; Latvia; Lesotho; Liberia; Lithuania; Luxembourg; Macao SAR; Madagascar; Malawi; Malaysia; Mali; Malta; Mauritania; Mauritius; Mexico; Moldova; Mongolia; Morocco; Myanmar; Namibia; Nepal; Netherlands; New Zealand; Nicaragua; Niger; Nigeria; Norway; Pakistan; Panama; Paraguay; Peru; Philippines; Poland; Portugal; Qatar; Romania; Russia; Saudi Arabia; Senegal; Serbia; Sierra Leone; Singapore; Slovak Republic; Slovenia; South Africa; Spain; Sri Lanka; Sudan; Sweden; Switzerland; Syria; Taiwan Province of China; Tajikistan; Tanzania; Thailand; Togo; Trinidad and Tobago; Tunisia; Turkey; Uganda; Ukraine; United Arab Emirates; United Kingdom; United States; Uruguay; Venezuela; Vietnam; Yemen; Zimbabwe

Source: IMF staff compilation.

Annex 3.2. The Diffusion of Basic and Applied Knowledge

This annex provides details and further robustness tests of the baseline results presented in the chapter's "The diffusion of basic and applied knowledge" subsection.

Gravity Model

The spatial diffusion of knowledge using patent data has been widely studied since Jaffe, Trajtenberg and Henderson (1993).[1] However, this literature has focused mostly on applied knowledge flows using patent-to-patent citations. The chapter extends this literature by studying *both* applied and basic knowledge spillovers. It does so by estimating a gravity-type model of international knowledge flows similar to Peri (2005) but for basic and applied knowledge flows distinctly.[2] In the model, bilateral country-to-country patent citations are regressed on measures of geographic and linguistic barriers, as well as scientific and technological distance.

Peri's (2005) model implies the following Poisson regression:

$$c_{ij} = \exp\{\alpha + \theta_i + \theta_j + \delta_1(diff\_bord) + \delta_2(diff\_lang) + \delta_3(spec\_dist) + \delta_4(geog\_dist) + e_{ij}\} \tag{3.1}$$

where c_{ij} is the bilateral citation count with country i citing country j. The model is fitted to patent-to-article citations to capture the determinants of basic knowledge flows, and to patent-to-patent citations to capture applied knowledge flows, where the citations are taken over a fixed 10-year window. The specific regressors are dummy variables taking the value 1 if *i* and *j* do not have a common border (*diff_bord*) or a common official language (*diff_lang*), a measure of specialization distance (*spec_dist*), and finally geographic distance in thousand kilometers (*geog_dist*).[3] The regressions include citing and cited country fixed effects to control for differences in the number of patent applications across countries as well as other factors that may influence a country's propensity to patent or to cite other patents. The model is estimated using the Pseudo-Poisson-Maximum Likelihood estimator, which is robust to the presence of significant heteroscedasticity in the data and the large number of dummies. It also allows for the inclusion of zero values for the dependent variable (Santos Silva and Tenreyro, 2006).

The baseline estimation, reported in column (1) of Annex Table 3.2.1, includes all countries for which bilateral citations are available in RoS (patent-to-article citations) and PATSTAT (patent-to-patent citations). The baseline results show that basic knowledge diffuses more strongly relative to applied knowledge: national borders only impede diffusion of applied knowledge (negative and significant coefficient); common language affects both types of flows, but has a marginally larger negative impact on applied knowledge diffusion; specialization distance matters more for applied knowledge than for basic knowledge pointing to the more generic nature of scientific discoveries and its potential application in diverse fields across countries. Note that the geographic distance variable is statistically significant for basic knowledge diffusion but not for applied knowledge. This is potentially explained by the legal requirement to cite earlier patents

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[1] Jaffe, Trajtenberg and Henderson (1993) relied on the case-control matching method, which is more suited to micro-level analysis.

[2] See IMF (2018) for a recent application to applied knowledge spillovers.

[3] For the specialization distance variable, we use scientific specialization for patent-to-article citations and technological specialization for patent-to-patent citations; see Annex 3.1 for details on the construction of these variables.

when developing new marketable technologies – irrespective of the geographical distance – coupled with evidence of China and Korea becoming formidable competitors to the US and the EU in certain technology classes (e.g. 5G technology). Columns (2) and (3) confirm that these findings are unaffected by changing the length of the lag window for citations using 6 years and 2 years, respectively.

Annex Table 3.2.1. Gravity Model of Basic and Applied Knowledge Diffusion: Baseline Specification with Different Lag Lengths for Citation Window

	(1)		(2)		(3)	
	Patent-to-Article Citations (10Y)	Patent-to-Patent Citations (10Y)	Patent-to-Article Citations (6Y)	Patent-to-Patent Citations (6Y)	Patent-to-Article Citations (2Y)	Patent-to-Patent Citations (2Y)
No Common Border	0.147	-0.220***	0.130	-0.243***	0.065	-0.243***
	(0.102)	(0.056)	(0.097)	(0.058)	(0.071)	(0.063)
No Common Language	-0.141***	-0.156**	-0.132***	-0.162**	-0.099***	-0.172**
	(0.045)	(0.063)	(0.043)	(0.069)	(0.032)	(0.082)
Scientific Distance	-1.656***		-1.777***		-1.854***	
	(0.453)		(0.491)		(0.418)	
Technological Distance		-3.053***		-3.091***		-3.086***
		(0.232)		(0.241)		(0.270)
Geographic Distance (1,000 km)	-0.038***	-0.010	-0.038***	-0.008	-0.032***	-0.007
	(0.013)	(0.007)	(0.012)	(0.007)	(0.008)	(0.008)
Constant	11.083***	13.971***	10.588***	13.545***	9.438***	12.382***
	(0.046)	(0.040)	(0.045)	(0.039)	(0.047)	(0.040)
Number of Observations	19,506	30,104	18,552	29,589	16,359	26,252
Citing-Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Cited-Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Source: IMF staff calculations.

Note: Robust standard errors (clustered by citing country) are reported in parentheses. 10Y = 10 years; 6Y = 6 years; 2Y = 2 years; km = kilometers. ***, **, and * indicate statistical significance at 1, 5, and 10 percent, respectively.

Controlling for productivity Differentials

In column (1) of Table 3.2.2, we include the productivity differential between country *i* and country *j* as an additional regressor in equation (3.1) while maintaining the distinction between basic and applied knowledge flows. This allows us to investigate whether countries with lower productivity tend to cite countries with higher productivity more often. The productivity differential measure is intended to proxy for the relative distance between countries in relation to the technological frontier. The productivity differential is measured as the (log) difference between output per worker averaged over the years 2015-2019. The results for the baseline variables are in line with the estimates in Table 3.2.1 with basic knowledge diffusing more strongly across most barriers. The output productivity differential shows a negative sign for patent-to-article citations indicating that countries cite science produced in countries with lower productivity less often. On the other hand, the coefficient for patent-to-patent citations is positive and significant indicating the opposite impact. This can again be rationalized by large competitive pressures from emerging markets in patenting activity, and legal requirements for advanced economies to cite patents from emerging economies competitors.

Annex Table 3.2.2. Gravity Model of Basic and Applied Knowledge Diffusion: Specifications Including the Difference in Levels of Output, Scientific and Technological Productivity (Top 5)

	(1)		(2)		(3)	
	Patent-to-Article Citations	Patent-to-Patent Citations	Patent-to-Article Citations	Patent-to-Patent Citations	Patent-to-Article Citations	Patent-to-Patent Citations
No Common Border	0.146	-0.221***	-0.007	-0.209***	-0.001	-0.346***
	(0.102)	(0.056)	(0.025)	(0.061)	(0.036)	(0.054)
No Common Language	-0.140***	-0.156**	-0.121***	-0.157**	-0.088***	-0.085**
	(0.045)	(0.063)	(0.028)	(0.068)	(0.019)	(0.041)
Scientific Distance	-1.682***		-2.048***		-1.248***	
	(0.450)		(0.518)		(0.267)	
Technological Distance		-3.054***		-3.023***		-2.996***
		(0.232)		(0.242)		(0.121)
Geographic Distance (1,000 km)	-0.038***	-0.010	-0.062***	-0.011	-0.015***	0.009
	(0.013)	(0.007)	(0.011)	(0.007)	(0.005)	(0.006)
Differences in Output Productivity	-2.074***	1.561***			-2.138***	1.588***
	(0.073)	(0.035)			(0.070)	(0.019)
Differences in Scientific Productivity			-0.769***			
			(0.055)			
Differences in Technological Productivity				1.319***		
				(0.002)		
Constant	-9.874***	-7.618***	-0.299	9.873***	-10.168***	-7.751***
	(0.286)	(0.830)	(0.226)	(0.047)	(0.258)	(0.797)
Number of Observations	17,669	24,806	1,560	1,892	17,139	24,026
Citing-Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Cited-Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Source: IMF staff calculations.

Note: Robust standard errors (clustered by citing country) are reported in parentheses. km = kilometers. ***, **, and * indicate statistical significance at 1, 5, and 10 percent, respectively.

The productivity differential measure does not distinguish between the flows of basic and applied knowledge. Therefore, for robustness, we also include flow-specific measures of differences in scientific and technological productivity, respectively. To measure relative scientific (technological) productivity between country pairs, we use the log difference between scientific articles (patents) produced per total R&D personnel averaged over the years 2015-2019. Due to lack of data on R&D personnel in many countries, most notably the US, the sample is reduced to less than 2,000 observations (about a tenth of the original sample). This also allows to check the robustness of the results to the exclusion of the US. Estimates are reported in column (2). The coefficient stability in terms of magnitude and statistical significance is noteworthy, perhaps with the exception of scientific distance and geographic distance, which appear to have a stronger effect on basic knowledge flows under this specification. Interestingly, using these alternative productivity measures does not alter the main findings: differences in scientific (technological) productivity have a negative (positive) impact on the frequency of citations. In column (3), we use the same specification as column (1) but exclude China and Korea, two emerging markets that recently joined the ranks of the world's top innovators. The results in column (3) confirm that neither country is driving the results obtained in earlier specifications. Two differences are worth highlighting here: having no common border has a stronger impact on applied knowledge diffusion; geographic distance matters less for basic knowledge diffusion.

Using International Patent Families

The previous results used patent counts based on the "Top 5" definition, which included patents from the top 5 patenting offices (China, EU, Japan, Korea and US). In Table 3.2.3, we report robustness checks using the "international patent family" definition, which only counts patents that have been applied for in at least two distinct patenting offices. This restricts the count to patents with presumably higher commercial value to justify the higher cost to the inventors of applying in more than one patenting office. The column specifications are similar to those of Table 3.2.2. The results are largely consistent with those for the "Top 5". The only noteworthy difference is that geographic distance now seems to matter for applied knowledge diffusion in columns (2) and (3), while the impact of this same barrier on basic knowledge diffusion is smaller under this patent count.

Annex Table 3.2.3. Gravity Model of Basic and Applied Knowledge Diffusion: Specifications Including the Difference in Levels of Output, Scientific and Technological Productivity (International Patent Families)

	(1)		(2)		(3)	
	Patent-to-Article Citations	Patent-to-Patent Citations	Patent-to-Article Citations	Patent-to-Patent Citations	Patent-to-Article Citations	Patent-to-Patent Citations
No Common Border	0.023	-0.148***	-0.041	-0.134***	-0.046*	-0.253***
	(0.048)	(0.038)	(0.025)	(0.042)	(0.026)	(0.047)
No Common Language	-0.094***	-0.150***	-0.089***	-0.156**	-0.082***	-0.090**
	(0.023)	(0.058)	(0.032)	(0.063)	(0.023)	(0.038)
Scientific Distance	-1.436***		-3.000***		-0.883***	
	(0.441)		(0.746)		(0.289)	
Technological Distance		-2.978***		-3.011***		-2.927***
		(0.237)		(0.252)		(0.100)
Geographic Distance (1,000 km)	-0.019***	-0.016**	-0.040***	-0.015**	-0.009**	0.004
	(0.006)	(0.007)	(0.007)	(0.007)	(0.004)	(0.005)
Differences in Output Productivity	-1.578***	1.366***			-1.635***	1.392***
	(0.079)	(0.038)			(0.071)	(0.018)
Differences in Scientific Productivity			-1.210***			
			(0.053)			
Differences in Technological Productivity				1.253***		
				(0.003)		
Constant	0.826***	-7.239***	-4.058***	9.609***	-12.650***	-7.352***
	(0.048)	(0.738)	(0.509)	(0.046)	(0.285)	(0.665)
Number of Observations	11,622	23,559	1,560	1,892	11,186	22,949
Citing-Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Cited-Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Source: IMF staff calculations.

Note: Robust standard errors (clustered by citing country) are reported in parentheses. km = kilometers. ***, **, and * indicate statistical significance at 1, 5, and 10 percent, respectively.

In addition to learning about the determinants of cross-border knowledge flows for basic and applied knowledge, the gravity model also gives the weights necessary to construct the foreign research stocks accessible to each country for the estimation of the ideas production function. Specifically, the frequency of bilateral citations between countries is taken into account in the construction of the foreign research stocks as it influences the intensity of international knowledge spillovers. This is described further in Online Annex 3.3.

Annex 3.3 Production Functions for Ideas

This Annex describes the methodology used to analyze the impact of own and foreign research inputs on innovation.

Specification

The empirical specification of the ideas production function yields the following regression:

$$ln(p_{i,t}) = \beta_1 ln(b_{i,t}) + \beta_2 ln(r_{i,t}) + \gamma_1 ln\left(\sum_{j \neq i} w_{ij}^{(b)} b_{j,t}\right) + \gamma_2 ln\left(\sum_{j \neq i} w_{ij}^{(r)} r_{j,t}\right) + \varepsilon_{i,t}, \tag{3.2}$$

where $p_{i,t}$ is the flow of new patent applications by an inventor resident in country i in year t, $b_{i,t}$ is the cumulative basic research stock by country i, and $r_{i,t}$ is the stock of applied research expenditure. The third and fourth terms in brackets are, respectively, the foreign basic and applied research stocks. The bilateral weights, $w_{ij}^{(b)}$ and $w_{ij}^{(r)}$, determine how accessible the foreign research stocks are to country i, and are derived from the gravity model discussed above. In particular, $w_{ij}^{(b)}$ ($w_{ij}^{(r)}$) are the fitted values, excluding the citing and cited country fixed effects, from the gravity Poisson regression using patent-to-article (patent-to-patent) citations. The research stocks are built from the annual R&D expenditure data for each country using the perpetual inventory method and assuming 10 percent depreciation (Peri 2005, IMF 2018).

Robustness

Table 3.3.1 shows the estimates of alternative specifications of the ideas production function. The estimates reveal a strong and significant relationship between basic research and innovation, a finding that is robust across all specifications. Column (1) reports panel OLS estimates with fixed effects and shows that the coefficient on the own basic research stock is positive and highly significant. To control for potential endogeneity of research stocks, column (2) estimates the same equation lagging each regressor by 1-year. Results are comparable. Columns (3) and (4) explore robustness to the assumed depreciation rate in the construction of the research stocks Column (3) assumes 5% depreciation for both basic and applied stocks, while column (4) assumes 5% depreciation for the basic stocks and 10% for the applied stocks. The positive and significant impact of own basic research persists, while the coefficient on foreign applied research increases in magnitude and now shows statistical significance. Column (5) applies the regression using non-overlapping 5-year averages of the observations to mitigate potential year-to-year volatility due to business cycle effects. The results yet again confirm the positive impact of own basic research. Panel unit root and cointegration tests reveal strong evidence of non-stationarity and cointegration among the variables. The dynamic OLS estimates are super consistent, and hence are robust to biases due to omitted variables and simultaneity. Columns (6) and (7) report specifications similar to column (1) but estimated using dynamic OLS, which efficiently utilizes the cointegration property of the data. Again, the relationship between basic research and innovation is positive and highly significant. The contribution of own applied research also appears positive and significant as is the contribution of foreign basic research.

Annex Table 3.3.1. Ideas Production Function: Alternative Specifications and Estimation Methods

	Panel OLS					Dynamic OLS	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Log(Own BASIC Research Stock)	0.633***	0.570**	0.662***	0.554***	0.728***	0.514***	0.674***
	(0.226)	(0.217)	(0.216)	(0.196)	(0.265)	(0.103)	(0.126)
Log(Own APPLIED Research Stock)	0.275	0.222	0.180	0.352	0.256	0.674***	0.765***
	(0.246)	(0.241)	(0.239)	(0.257)	(0.244)	(0.113)	(0.144)
Log(Foreign BASIC Research Stock)	-0.106	-0.375	-0.974	-1.026	-0.741	0.559	1.358**
	(1.394)	(1.372)	(1.019)	(1.212)	(1.537)	(0.449)	(0.557)
Log(Foreign APPLIED Research Stock)	1.031	1.426	1.954**	1.944*	1.855	-0.055	-1.225*
	(1.382)	(1.385)	(0.832)	(1.019)	(1.541)	(0.513)	(0.663)
Constant	-2.655	-3.486	-4.546**	-3.395*	-4.831*		
	(2.275)	(2.444)	(1.749)	(1.924)	(2.502)		
Number of Observations	1,430	1,390	1,430	1,430	264	1,310	1,154
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Source: IMF staff calculations.

Note: Robust standard errors are reported in parentheses. Specification (1) is the baseline specification; specification (2) uses the first lag of the right-hand-side variables; specification (3) uses the research stocks with 5% depreciation in the construction of all the research stock; specification (4) uses the research stocks with 5% depreciation for the basic stocks and 10% depreciation for the applied stocks; specification (5) uses non-overlapping 5-year averages over the period 1980–2014; specification (6) is estimated using dynamic ordinary least squares (DOLS) with 1 lead and 1 lag; specification (7) is estimated using DOLS with 2 leads and 2 lags. Panel unit root tests (Levin, Lin and Chu 2002; Im, Pesaran and Shin 2003; Hadri 2000) and panel cointegration tests (Pedroni 2004; Westerlund 2007), not reported for brevity, confirm evidence of nonstationarity and cointegration in the data. Log = natural logarithm. ***, **, and * indicate statistical significance at 1, 5, and 10 percent, respectively.

Further Results for EMDEs

Table 3.3.2 shows the additional impact of the research stocks for EMDEs using an interaction dummy. The results in column (1) suggest that own basic research contributes more to innovation in EMDEs than in AEs; however, this result holds only if China is included in the sample. It may be reflective of the focus on some niche fields in which emerging markets are building specialized knowledge. Column (2) shows that the impact of own applied research is roughly the same across the two country groups.

Annex Table 3.3.2. Ideas Production Function: Further Results for EMDEs

	Panel OLS			
	(1)	(2)	(3)	(4)
Log(Own BASIC Research Stock)	0.528**	0.618***	0.641***	0.644***
	(0.225)	(0.222)	(0.196)	(0.197)
Log(Own APPLIED Research Stock)	0.267	0.260	0.409*	0.416*
	(0.250)	(0.255)	(0.231)	(0.227)
Log(Foreign BASIC Research Stock)	-0.328	-0.151	-0.721	-0.514
	(1.456)	(1.450)	(1.370)	(1.409)
Log(Foreign APPLIED Research Stock)	1.340	1.103	1.318	1.070
	(1.557)	(1.494)	(1.518)	(1.523)
Log(Own BASIC Research Stock) × EMDE	0.367***			
	(0.131)			
Log(Own APPLIED Research Stock) × EMDE		0.093		
		(0.183)		
Log(Foreign BASIC Research Stock) × EMDE			0.890***	
			(0.315)	
Log(Foreign APPLIED Research Stock) × EMDE				1.026***
				(0.354)
Constant	-3.468	-2.896	-2.603	-2.572
	(2.922)	(2.681)	(2.842)	(2.815)
Number of Observations	1,430	1,430	1,430	1,430
Country Fixed Effects	Yes	Yes	Yes	Yes

Source: IMF staff calculations.

Note: Robust standard errors are reported in parentheses. EMDE is a dummy variable where the reference group is advanced economies. EMDE = emerging market and developing economy; Log = natural logarithm. ***, **, and * indicate statistical significance at 1, 5, and 10 percent, respectively.

The estimation results in columns (3) and (4) show that knowledge diffusion is stronger to EMDEs, with both types of knowledge (basic and applied) being critical for innovation. This result corroborates the finding that EMDEs tend to cite foreign research more than home-grown research (see panel 3 of Figure 3.5 in the chapter). The robustness of these findings is tested by re-estimating column (1)-(4) while removing the included countries one-by-one. For column (2)-(4) the sign and significance is robust to this check, while the coefficient on basic research interacted with the EMDE dummy becomes insignificant when removing China from the sample.

Annex 3.4 Production Functions for Goods

This Annex describes the methodology used to analyze the relationship between innovation and productivity.

Empirical Framework

The analysis is based on the following panel specification:

$$lny_{i,t} = \beta lns_{i,t} + \delta lnc_{i,t} + \lambda lnh_{i,t} + \varepsilon_{i,t}, \qquad (3.3)$$

where $y_{i,t}$ is output per worker (productivity) for country i in year t, $s_{i,t}$ is the stock of patents, $c_{i,t}$ is the stock of capital per worker, and $h_{i,t}$ is an index for human capital.[1] The coefficient of interest is β and captures the elasticity of productivity to the stock of patents. The stock of patents is computed using the annual flow of new patents along with a depreciation factor of 10 percent, while human capital is measured by the human capital index from the *Penn World Tables*. Country and time fixed effects are also included. Time fixed effects should capital elements common for all countries at each point in time, such as the global stock of patents.

Equation (3.3) is estimated using annual data for 138 advanced and emerging market and developing economies depending on data availability covering the period 1980 to 2017. Compared to Annex 3.3 a wider set of countries is included because the variables used in equation (3.3) are available for more countries. Robust standard errors are reported using the Huber/White/sandwich estimator.

Baseline Results

Table 3.4.1 reports the baseline results of equation 3.3. Column (1) reports the specification estimated with pooled ordinary least squares. In this specification the estimated elasticity of output per worker to the stock of patents is 0.057. This implies that a 1 percent increase in the stock of patents is associated with an 0.057 percent increase in output per worker. The estimated elasticity between output per worker, the capital stock per worker and the human capital index, respectively, is also positive albeit not significant for the human capital stock. In column (2), country fixed effects are added, which slightly increases the estimated elasticity on the patent stock to 0.063 percent. In column (3), time fixed effect is also added yielding an estimated elasticity on the patent stock of 0.055. In column (4), the coefficients on the capital stock per employee and the human capital index are restricted to sum to one which yields a coefficient on the patent stock of 0.048. Column (5) applies the regression using non-overlapping 5-year averages of the observations to mitigate potential year-to-year volatility due to business cycle effects. Overall, it is reassuring that the choice of estimation method does not affect the estimated elasticity much. In column (6) to (8), the dependent variable is changes from output per worker to TFP[2] Column (5) reports the results estimated without country or time fixed

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[1] A potential concern about this specification is non-stationarity. However, tests for stationarity have been done for the linear combination between output per worker, the patent stock, capital stock per worker, and the human capital index. These point to stationarity.

[2] For these specifications, capital per worker is dropped as independent variable because TFP is derived as the part of output not explained by utilized labor or capital.

effects. In column (6) country fixed effects are added, and column (7) further adds time fixed effects. For all specifications the estimated elasticities are close to those achieved using output per worker (column 1-4), except for column (7) which yields an insignificant elasticity.

Annex Table 3.4.1. Productivity and Innovation

	Output per Worker					Total Factor Productivity		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log(Patent Stock)	0.057***	0.063***	0.055***	0.046***	0.048***	0.048***	0.041***	0.047***
	(0.014)	(0.015)	(0.015)	(0.005)	(0.009)	(0.009)	(0.011)	(0.013)
Log(Capital Stock per Employed)	0.514***	0.498***	0.465***	0.468***	0.479***	0.479***		
	(0.038)	(0.040)	(0.042)	(0.019)	(0.030)	(0.030)		
Log(Human Capital Index)	0.017	-0.031	-0.215	0.532***	0.521***	0.521***	-0.106	-0.121
	(0.188)	(0.202)	(0.263)	(0.019)	(0.030)	(0.030)	(0.112)	(0.132)
Constant	3.961***	4.170***	4.746***	4.332***	4.140***	4.140***	-0.207**	-0.230***
	(0.354)	(0.366)	(0.429)	(0.223)	(0.360)	(0.360)	(0.082)	(0.079)
Number of Observations	4680	4680	4680	4,680	886	886	3866	3866
Number of Countries	138	138	138	138	138	138	114	114
Country Fixed Effects	No	Yes	Yes	Yes	Yes	Yes	No	Yes
Time Fixed Effects	No	No	Yes	Yes	Yes	Yes	No	No
Coefficient Restriction	No	No	No	Yes	Yes	Yes	No	No
Sample	All	All	All	All	All	All	All	All

Source: IMF staff calculations.

Note: The estimations are based on a sample of countries from 1980 to 2017. Robust standard errors are reported in parentheses. Log = natural logarithm. ***, **, and * indicate statistical significance at 1, 5, and 10 percent, respectively.

Results with Institutional Interactions

Analysis reported in Table 3.4.2-3.4.3 is meant to investigate whether certain institutional features may strengthen the relationship between innovation and productivity. Specifically, columns (1) to (6) in Table 3.4.2 and 3.4.3 augment the baseline specification with additional institutional variables interacted with the patent stock. Following Coe and others (2009), the institutional variables are split into three groups (low, middle, and high) based on the average value for each country. These are used to create dummy variables for low and high level that are then interacted with the patent stock. In Table 3.4.2, the institutional variables include contract viability (column 1), financial development (column 2), intellectual property protection (column 3), quality of overall infrastructure (column 4), quality of the education system (column 5), and control of corruption (column 6). In Table 3.4.3, the institutional interactions include government effectiveness (column 1), political stability (column 2), rule of law (column 3), regulatory quality (column 4), voice and accountability (column 5), and years of schooling (column 6).

The interactions are only significant for financial development and years of schooling, where high levels are associated with a larger elasticity. The interaction is also significant for government effectiveness, where low levels are associated with a significantly lower elasticity.

Annex Table 3.4.2. Productivity and Innovation with Institutional Interactions

	X = Contract Viability	X = Financial Development	X = Intellectual Property Protection	X = Quality of Overall Infrastructure	X = Quality of the Education System	X = Control of Corruption
	(1)	(2)	(3)	(4)	(5)	(6)
Log(Patent Stock)	0.047**	0.025	0.055***	0.064***	0.069***	0.058***
	(0.021)	(0.019)	(0.015)	(0.017)	(0.014)	(0.015)
Log(Human Capital Index)	-0.206	-0.196	-0.204	-0.201	-0.173	-0.200
	(0.273)	(0.261)	(0.264)	(0.265)	(0.272)	(0.282)
Log(Capital Stock per Employed)	0.465***	0.466***	0.465***	0.465***	0.464***	0.465***
	(0.042)	(0.041)	(0.042)	(0.040)	(0.041)	(0.042)
Log(Patent Stock) × High X	0.012	0.038**	0.001	-0.011	-0.024	-0.003
	(0.020)	(0.017)	(0.018)	(0.018)	(0.017)	(0.019)
Log(Patent Stock) × Low X	0.016	-0.005	-0.008	-0.060	-0.052	-0.022
	(0.029)	(0.093)	(0.043)	(0.040)	(0.039)	(0.039)
Constant	4.735***	4.751***	4.739***	4.761***	4.763***	4.750***
	(0.409)	(0.426)	(0.422)	(0.410)	(0.422)	(0.432)
Number of Observations	4,680	4,680	4,680	4,680	4,680	4,680
Number of Countries	138	138	138	138	138	138
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Coefficient Restriction	No	No	No	No	No	No
Sample	All	All	All	All	All	All

Source: IMF staff calculations.

Note: The estimations are based on a sample of countries from 1980 to 2017. Robust standard errors are reported in parentheses. Log = natural logarithm. ***, **, and * indicate statistical significance at 1, 5, and 10 percent, respectively.

Annex Table 3.4.3. Productivity and Innovation with Institutional Interactions, Continued

	X = Government Effectiveness	X = Political Stability	X = Rule of Law	X = Regulatory Quality	X = Voice and Accountability	X = Years of Schooling
	(1)	(2)	(3)	(4)	(5)	(6)
Log(Patent Stock)	0.065***	0.075***	0.060***	0.057***	0.040*	0.050***
	(0.016)	(0.020)	(0.016)	(0.016)	(0.020)	(0.018)
Log(Human Capital Index)	-0.214	-0.224	-0.177	-0.184	-0.194	0.026
	(0.274)	(0.271)	(0.278)	(0.275)	(0.280)	(0.297)
Log(Capital Stock per Employed)	0.460***	0.464***	0.462***	0.465***	0.469***	0.473***
	(0.040)	(0.042)	(0.042)	(0.041)	(0.042)	(0.041)
Log(Patent Stock) × High X	-0.017	-0.023	-0.006	-0.002	0.021	0.044**
	(0.018)	(0.022)	(0.018)	(0.018)	(0.024)	(0.022)
Log(Patent Stock) × Low X	-0.134**	-0.028	-0.048	-0.037	0.029	-0.043
	(0.056)	(0.021)	(0.043)	(0.057)	(0.022)	(0.029)
Constant	4.872***	4.745***	4.776***	4.738***	4.683***	4.458***
	(0.419)	(0.418)	(0.436)	(0.420)	(0.442)	(0.413)
Number of Observations	4,680	4,680	4,680	4,680	4,680	4,680
Number of Countries	138	138	138	138	138	138
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Coefficient Restriction	No	No	No	No	No	No
Sample	All	All	All	All	All	All

Source: IMF staff calculations.

Note: The estimations are based on a sample of countries from 1980 to 2017. Robust standard errors are reported in parentheses. Log = natural logarithm. ***, **, and * indicate statistical significance at 1, 5, and 10 percent, respectively.

Annex 3.5 Policy Experiments

This annex makes use of estimates in Annex 3.3 and 3.4 to conduct two policy experiments. First, it computes the effect on productivity of increasing own and foreign research stocks (Figure 3.7.1 in the main chapter). Second, it calculates the effect on global innovation and productivity of scientific decoupling between the United States and China (Figure 3.7.2 in the main chapter).

The Effect of Higher Research Stocks on Productivity

The effect on productivity of increasing research stocks is investigated by combining the estimated elasticities (i) from research stocks to patenting activity (Annex 3.3), and (ii) from patent stocks to productivity (Annex 3.4). Specifically, the estimated effect of an X percent increase in the stock of basic research is

$$X \times \eta_{\{b^i,p\}} \times \eta_{\{p,y\}}, \qquad i \in \{o, f\}$$

where $\eta_{\{b^i,p\}}$ is the elasticity from own (i=o) or foreign (i=f) basic research to patenting activity, while $\eta_{\{p,y\}}$ is the estimated elasticity from the domestic stock of patents to output per worker. It is assumed that the research stock is permanently increased, which permanently increase the flow and thus also stock of patents. Baseline parameters from Section 3.3 and Section 3.4 are used for parametrization of $\eta_{\{b^i,p\}}$, $\eta_{\{b^o,p\}}$, and $\eta_{\{p,y\}}$;they are set to 0.674, 1.358, and 0.046. A 10 percent increase in the stock of own and foreign basic research thus yields a productivity increase of 0.31 and 0.62, respectively.

Scientific Decoupling

The potential effects on innovation and productivity of scientific decoupling are investigated through construction of counter-factual stocks of foreign research. Specifically, the intensity of scientific citations between the two countries is reduced gradually, which reduces the stock of foreign basic knowledge for both countries (Table 3.5.1). In the empirical framework above, this reduces annual innovation through equation (3.2), and in turn reduces productivity through equation (3.3). Specifically, the effect on the annual flow of patents from a reduction in the stock of foreign basic knowledge can be written as

$$\Delta ln(p_{i,t}) = \gamma_1 \Delta ln\left(\sum_{j \neq i} w_{ij}^{(b)} b_{j,t}\right)$$

while the change in productivity can be expressed as

$$\Delta lny_{i,t} = \beta \Delta lns_{i,t}.$$

To translate the reduction in the annual flow of patents ($p_{i,t}$) to the stock of patents ($s_{i,t}$), it is assumed that the change in the stock of foreign basic knowledge is permanent. Finally, the country-specific results are weighted by global patent and employment shares to translate into global results.

Table 3.5.1 illustrates these effects for various degrees of decoupling. Columns (1) and (2) show the change in the stock of basic foreign knowledge for China and the United States, respectively.

Columns (3) and (4) convert this drop in foreign basic research into a drop in the annual flow of patents using the estimated elasticity of patents with respect to foreign basic research.[3] Column (5) computes the global effect by applying the sample shares of annual patenting activity. Columns (6) and (7) compute the resulting effect on productivity by applying by applying the estimated elasticity of productivity with respect to patent stocks. Finally, column (8) denotes the computed effect on global productivity by applying the employment shares for China and the United States.

Annex Table 3.5.1. Estimated Effect of Scientific Decoupling on Global Innovation and Productivity

	Foreign Basic Knowledge (Percentage change)		Annual Flow of Patents (Percentage change)			Output per Worker (Percentage change)		
	China	USA	China	USA	Global	China	USA	Global
Decoupling (Percent)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
10	-3.21	-0.55	-4.37	-0.74	-0.41	-0.20	-0.03	-0.06
20	-6.54	-1.09	-8.88	-1.49	-0.83	-0.41	-0.07	-0.12
30	-9.97	-1.65	-13.54	-2.24	-1.25	-0.62	-0.10	-0.18
40	-13.53	-2.20	-18.37	-2.99	-1.69	-0.85	-0.14	-0.25
50	-17.22	-2.76	-23.38	-3.75	-2.13	-1.08	-0.17	-0.32
60	-21.05	-3.32	-28.58	-4.51	-2.58	-1.31	-0.21	-0.39
70	-25.03	-3.89	-33.99	-5.28	-3.04	-1.56	-0.24	-0.46
80	-29.18	-4.45	-39.62	-6.05	-3.51	-1.82	-0.28	-0.54
90	-33.51	-5.02	-45.50	-6.82	-3.99	-2.09	-0.31	-0.62
100	-38.03	-5.60	-51.64	-7.60	-4.48	-2.38	-0.35	-0.70

Source: IMF staff calculations.

Note: The table shows the estimated effect on global innovation (measured as the flow of new patents) and productivity of a given reduction (in percent) of citations between the United States and China. To construct the "Global" effect on annual patents, patent shares of 32 percent and 4 percent are used for USA and China (sample shares in 2016). To construct the "Global" effect on output per worker, employment shares of 6 percent and 29 percent are used for USA and China (sample shares in 2016). An estimated elasticity of 1.358 is used for patents with respect to the stock of foreign basic knowledge, and an estimated elasticity of 0.046 of productivity with respect to the stock of patents.

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[3] Here it is assumed that a given drop in patent application translates into a proportional drop in granted patents.

Annex 3.6 Policy Analysis

The model used in the chapter is a version of Akcigit et al. 2021, re-estimated to comparable data across three advanced economies. This Annex outlines the basics of the model and covers more detail on the re-estimation process discussed in the main body of the chapter.

The Model

For an in-depth presentation of the model, the reader is referred to Akcigit et al. 2021. Here, the annex focusses on the microeconomic structure of firms as this determines their incentives for distinct basic and applied research.

The framework is a multi-firm, multi-industry, multi-product model. Each firm sells potentially many products. These products are grouped by industry, of which there are a fixed number, M. Industries, in turn, are differentiated from each other in two ways. First, products within an industry are closer mutual substitutes than products in different industries. Second, the effects of basic and applied research vary across industries. As a result, cross-market presence is the key determinant of individual firms' incentives for applied and basic research – firms selling a wider range of different types of product have greater incentives for basic research (more on this below).

To be more concrete, we say that firm j sells Pj products in Mj industries, with $Mj<M$. and $Pj\geq Mj$. For example, a simple economy might have 5 industries in total, and a firm j might operate in two industries, with 5 products in the first and 2 in the second. In which case, $Mj =2$ and $Pj =7$.

Firms can conduct both basic and applied research within a given industry. Both types of research have increasing marginal cost and the within-industry effects are similar: both types of research increase the probability that firms will become more productive in that industry, although the particular product line where this occurs is random. However, only basic research has a cross-industry impact. Basic research in one industry raises the probability that productivity will increase in another industry, so long as the firm is already operating in that industry. As a result, large multi-industry firms can better capture the gains of basic research. This induces a correlation between firm size and basic research effort, in line with the data.

To return to the example of firm j above, either applied or basic research in either of the industries that they operate in will have a direct within-industry effect. For instance, if the firm sells products in industries numbered 1 and 2, applied research in industry 1 only raises the probability of productivity gains in industry 1. This can take the form either of an improvement to product they already sell (so Pj remains the same) or of supplanting a competitor's product (so Pj increases). Basic research in industry 1 has the same effect plus an additional cross-industry spillover, increasing the chance of improved productivity also in industries 2 through 5 (each with equal probability). Of these, the only place that the firm can make use of these gains is in industry 2. And so the firm benefits more from basic research if it operates in more industries.

Note that although basic research has a cross-industry spillover that applied research lacks, increasing marginal costs mean that firms will always do some of both types of research, increasing their research effort until marginal costs are equal.

Because the scope of the firm's activities determines the incentives for (the type of) innovation, the aggregate effect of pro-research policies depends on the distribution of firm sizes. More large firms mean a greater role for basic research all else equal.

The preceding is a somewhat simplified version of the main model mechanisms. There are several other further wrinkles in the final version (large "breakthrough" innovations, depreciation rates of product line efficiency varying with type of research, entry and exit of firms, expansion into new industries, and the like). However, the basic mechanism is governed by the trade-offs and incentives outlined here.

Estimation

Estimation involves matching some 30 moments in order to infer values for the 18 different parameters that govern the model solution. Given that the number of model moments exceeds the number of parameters, the model is over-identified. This means that there is a tension between matching the different aspects of the data. This tension is resolved by using an efficient weighting regime within the context of a simulated method of moments. For a given parameter combination, the model is solved and the steady-state density of firms simulated. The estimation routine then minimizes the divergence of the simulated results from the data, weighting them in proportion to their information about the model parameters. This weighting scheme means that deviations from the target moments are largest for moments which have the least information about the model's parameters

In their original paper, Akcigit and co-authors estimate the model using French data. This is appealing because French firms survey data is unique in its inclusion of questions about the explicit division of firms' research effort into basic and applied components. This provides information on the relationship between firm size and research effort and intensity, and pins down 16 of the data moments. In the absence of analogous data for other countries, the estimation procedure employed here assumes that this relationship is broadly representative of that elsewhere.

The country-specific variation in the estimation instead comes from key macroeconomic moments, summarized below. These conditions pin down a range of parameters relevant to the policy recommendations of the model including households' time preference and risk aversion, firms' entry and exit rates, and the probability of mergers.

The data for these aggregate moments come from three sources.:

- *Aggregate macroeconomic data* allow the calculation of three moments the return on sales, firm exit rate, and average aggregate growth. These pin down dynamics of the corporate sector, and so influence expected future profits and thus returns to (and hence incentives for) research.

- *National firm surveys* inform two further moments: the ages of small and large firms. These pin down the speed at which firms grow on average, and also affect firms' incentives to engage in research.
- *PATSTAT data* on individual citations to patents are aggregated to provide the last four moments: the average and standard deviation of the number of citations to public and private patents. These determine the public benefits of research, as they proxy for the positive spillovers from research.

Note that throughout, estimation is conditional on the average values observed for the size of public research and research subsidies. Of course, these moments are not fixed in the policy experiments presented in the chapter but instead vary when alternate policy scenarios are considered. Generally, the model matches the targeted moments well, similar to Akcigit et al. 2021, with a median absolute average error on growth rates of less than one half of one percent.