Online Annex 2.1. Model of Industrial Policy for Innovation[1]

This Annex describes the model of endogenous innovation with a sectoral network used to obtain the results in Figures 2.3, 2.4, and 2.5 of the main text and presents additional results.

A model of endogenous innovation with a sectoral network based on Liu and Ma (2023) is considered. In the model, it is optimal for governments to subsidize relatively more the R&D of sectors that are more central in the innovation network, as they generate higher innovation spillovers to other sectors. The model is extended to: (1) account for negative externalities from climate change, which call for redirecting innovation to greener sectors, and (2) capture differences in implementation capacity, whereby governments with weaker institutions divert subsidies to politically connected sectors. The model also accounts for foreign inflows of knowledge by sector, which are less likely to be affected by domestic innovation policy.

Set-up

Innovation in each sector i benefits from the stock of knowledge of all other sectors $i = 1, \dots, K$. Cross-sector knowledge spillovers can come from both domestic and foreign firms. The arrival rate of an innovation to a firm in sector i, during period t, and that hires s_{it} scientists is

$$n_{it} = s_{it}\eta_i \frac{\chi_{it}}{q_{it}}, \quad \chi_{it} = \prod_{j=1}^{K}\left[\left(q_{jt}\right)^{x_{ij}}\left(q_{jt}^{f}\right)^{1-x_{ij}}\right]^{\omega_{ij}},$$

where η_i is sector-specific productivity and χ_{it} are the spillovers. The stock of knowledge in each sector is given by $\{q_{it}\}_{i=1}^{K}$ for domestic innovation, and $\left\{q_{it}^{f}\right\}_{i=1}^{K}$ for foreign innovation, with x_{ij} representing the share of spillovers coming from domestic knowledge. Finally, ω_{ij} represents the elasticity of spillovers from sector j to sector i.

The remainder of the model follows a straightforward quality ladder: innovations increase the quality of a good variety $q_{it}(\nu)$ by a factor of $\lambda > 0$ (note that $\ln q_{it} = \int \ln q_{it}(\nu)\, d\nu$), making the innovating firm the technology leader in a product and thus able to price all competitors out. A sectoral good is then produced by aggregating all good varieties and production labor ℓ_{it}: $\ln y_{it} = \int_0^1 \ln\left(q_{it}(\nu)\ell_{it}(\nu)\right) d\nu$. The final good is produced as

$$y_t = \prod_{i=1}^{K} y_{it}^{\beta_i}, \quad \sum_{i=1}^{K}\beta_i = 1.$$

A trade balance is imposed so that countries can import foreign goods by exporting unconsumed domestic production. For a given intertemporal discount rate ρ, the government's welfare function thus consists of maximizing the present discounted value of a representative household's utility:

[1] Prepared by Alexandre Balduino Sollaci.

$$V_t = \int_t^{\infty} e^{-\rho(s-t)} \ln y_s \, ds.$$

Equilibrium

Three main equilibrium results from the model are relevant (see proofs in Liu and Ma 2023). First, in the absence of industrial policy (sector-specific R&D subsidies in this case), the allocation of scientists to each sector is proportional to the sector's share in total output:

$$\boldsymbol{s} = \boldsymbol{\beta},$$

where $\boldsymbol{s} = [s_{it}]$ is the vector of scientist shares and $\boldsymbol{\beta} = [\beta_i]$ is the vector of elasticities. The total number of scientists is set to 1 for ease of exposition. In contrast, the allocation that maximizes the government's welfare function is

$$(\boldsymbol{s}^*)' = \boldsymbol{\beta}' \left(\boldsymbol{I} - \frac{\boldsymbol{\Omega} \circ \boldsymbol{X}}{1 + \rho/\lambda}\right)^{-1} \times \frac{1}{\xi}$$

where $\boldsymbol{\Omega} = [\omega_{ij}]$ is the matrix of spillover elasticities and $\boldsymbol{X} = [x_{ij}]$ are the shares of domestic spillovers. The operator $\circ$ indicates a Hadamard (or element-wise) product, and ξ is a scaling factor to guarantee that $(\boldsymbol{s}^*)'\boldsymbol{1} = 1$. This optimal allocation can be implemented via a set of sector-specific subsidies/taxes to R&D investment (scientists).[2]

Finally, the consumption-equivalent welfare impact (i.e., the amount that consumption would have to change to generate the same impact on welfare) of moving between two invariant R&D allocations, say from $\boldsymbol{s_0}$ to $\boldsymbol{s_1}$, is

$$W = \exp\left(\xi \frac{\lambda}{\rho} \, (\boldsymbol{s}^*)' \times (\ln \boldsymbol{s_1} - \ln \boldsymbol{s_0})\right),$$

where, again, $\boldsymbol{s}^*$ is the vector containing the welfare maximizing allocation[3] and ξ is the scaling factor from above. Note that this calculation compares V_t under two different balanced growth paths (induced by the different distributions of R&D resources).

Extensions to the Model

Two extensions to the government's problem are considered. First, there is a possibility of political capture, in the sense that the government can favor a larger allocation of resources to politically connected sectors. Let

[2] It can be shown that a sector-neutral subsidy does not change the share of scientists in any sector; and because the total number of scientists is fixed, a sector-neutral subsidy does not have any effect on the aggregate amount of innovation in the economy. This is one drawback from the simplicity of the model; for this reason, all comparisons made here are framed as "having a sector-specific subsidy" versus "having a sector-neutral subsidy."

[3] Note that $\boldsymbol{s}^* = \arg\max_{\boldsymbol{x}} (\boldsymbol{s}^*)' \times (\ln \boldsymbol{x} - \ln \boldsymbol{s_0}) \;\; s.t. \;\; \boldsymbol{x}'\boldsymbol{1} = 1$.

$\{\phi_i\}_{i=1}^K$, $\sum_{i=1}^K \phi_i = 1$ index the extent of "political clout" a given sector has and denote by θ the weight that the government assigns to political favoritism. The government's objective function becomes:

$$V_t^{pc} = \int_t^{\infty} e^{-\rho(s-t)} \sum_{i=1}^{K} (\beta_i + \theta\phi_i) \ln y_{is}\, ds.$$

Under this objective function, the government still cares about the total output of the economy but favors higher output in more politically connected sectors. The parameter θ governs the extent to which those sectors are favored relative to the "optimal" weight (note that when $\theta = 0$ the objective function reverts to case with no political capture). Since the only change in the problem are the weights on the output of each sector, the R&D allocation that maximizes this function is

$$(\boldsymbol{s}^{\boldsymbol{pc}})' = (\boldsymbol{\beta} + \theta\boldsymbol{\phi})' \left(\boldsymbol{I} - \frac{\boldsymbol{\Omega}\circ\boldsymbol{X}}{1+\rho/\lambda}\right)^{-1} \times \frac{1}{\xi^{pc}},$$

where again ξ^{pc} is a scaling factor. Plugging into the results above, the consumption-equivalent welfare gains from a policy that implements this allocation (starting from no industrial policy) is

$$W^{pv} = \exp\left(\xi \frac{\lambda}{\rho} (\boldsymbol{s}^*)' \times (\ln \boldsymbol{s}^{\boldsymbol{pc}} - \ln \boldsymbol{s})\right).$$

Second, the government is also allowed to include alternative goals into its objective function, specifically a preference for green innovation. In order to keep the possibility of political capture and maintain symmetry with the problem above, the government's objective function with green innovation goals is given by

$$V_t^{gg} = \int_t^{\infty} e^{-\rho(s-t)} \sum_{i=1}^{K} (\tilde{\beta}_i + \theta\phi_i) \ln y_{is}\, ds.$$

where $\tilde{\beta}_i = \frac{\alpha_i + \beta_i}{\sum_i \alpha_i + \beta_i}$ and α_i is proportional to the share of green innovation carried out in sector i.

Calibration

Sectors are defined at the 3-digit International Patent Classification (IPC) level. The calibration follows Liu and Ma (2023) in setting $\rho = \lambda = 0.5$. Country-specific parameters are chosen to match the features of a representative large economy (e.g., the *United States*) and small open economy (e.g., *the Netherlands*) at the technology frontier.

The vector $\boldsymbol{\beta}$ matches the share of value added in each sector using the World Input-Output Dataset (WIOD). Industry codes are matched to IPC categories following Liu and Ma (2023).[4] The value-added shares are remarkably stable over time, and thus the calibration uses an average over available years.

[4] The data were kindly supplied by the authors.

The matrix of spillover elasticities is calibrated using patent shares from the Google Patents Database, given by

$$\omega_{ij} = \frac{Cites_{ij}}{\sum_k Cites_{ik}}.$$

These shares are shown for select sectors (IPC D07—C21) in Online Annex Figure 2.1.1. Three features can be seen in the figure. First, patents in any given sector tend to cite patents in the same sector much more than patents across other sectors, indicating that within-sector spillovers are larger than cross-sector spillovers (indicated by the diagonal in the matrix). Second, similar sectors tend to provide more spillovers to each other, as shown by the light blue regions around the main diagonal indicating three "groups" of sectors (chemistry, metallurgy, and textiles). And third, the direction of spillovers is relevant, shown by the fact that basic science sectors (such as chemistry-related group) provide spillovers to all other sectors in the figure, but the reverse is not true. The cross-sector citation shares are also very stable across time and across countries. As a result, the calibration uses a single matrix $\mathbf{\Omega}$ for all simulations.

Online Annex Figure 2.1.1. Sectoral Citation Network, Select Sectors, United States

(Percent of citations of other sectors)

organic chemistry	49.3	6.2	2.0	2.2	0.6	2.4	0.1	0.0	0.0	0.1	0.3	0.2	0.0	0.0	0.1	0.0	0.0	0.0	0.0	0.3	0.0	0
organic macromolecular compounds	6.5	58.7	4.2	0.8	0.3	0.3	0.0	0.1	0.0	0.1	0.3	0.2	0.0	0.0	0.6	0.0	0.0	0.1	0.0	1.0	0.0	0.
dyes, paints, polishes, natural resins & adhesives	4.7	14.4	40.4	1.0	0.7	0.3	0.0	0.0	0.1	0.1	1.0	0.3	0.1	0.0	0.1	0.0	0.0	0.1	0.0	1.2	0.0	0
petroleum, gas or coke industries	9.4	4.3	1.5	51.8	0.4	0.2	0.0	0.0	0.3	0.3	0.5	0.1	0.0	0.0	0.2	0.0	0.0	0.0	0.0	0.2	0.0	0
animal or vegetable oils & fats	7.1	3.5	3.0	1.0	46.1	1.0	0.0	0.1	0.0	0.1	1.8	0.1	0.0	0.0	0.2	0.0	0.0	0.1	0.0	3.6	0.0	0
biochemistry, beer, microbiology & enzymology	8.9	1.8	0.4	0.2	0.7	43.5	0.3	0.1	0.0	0.1	0.1	0.1	0.0	0.1	0.2	0.0	0.0	0.0	0.0	0.2	0.0	0.
sugar industry	4.4	3.9	0.4	0.4	0.6	5.5	41.4	0.0	0.1	0.1	0.1	0.0	0.0	0.0	0.7	0.0	0.0	0.2	0.0	0.2	0.0	2
skins, hides & pelts or leather	3.1	9.0	2.5	0.1	0.6	0.5	0.0	50.1	0.0	0.0	0.1	0.1	0.1	0.0	0.3	0.1	0.0	0.4	0.3	5.9	0.0	0
metallurgy of iron	0.3	0.4	0.2	0.7	0.0	0.1	0.0	0.0	48.9	10.5	2.3	0.3	0.1	0.0	0.1	0.0	0.0	0.0	0.0	0.2	0.0	0
metallurgy, ferrous or non-ferrous alloys	0.4	0.5	0.3	0.3	0.1	0.1	0.0	0.0	6.6	50.0	2.1	1.1	0.4	0.0	0.1	0.0	0.0	0.0	0.0	0.1	0.0	0
coating metallic material	1.1	1.3	1.4	0.6	0.6	0.1	0.0	0.0	1.0	1.9	39.7	2.6	1.4	0.0	0.1	0.0	0.0	0.1	0.0	0.3	0.0	0
electrolytic or electrophoretic processes	1.6	1.8	0.8	0.2	0.1	0.1	0.0	0.0	0.2	1.6	5.0	52.3	0.2	0.0	0.1	0.0	0.0	0.1	0.0	0.1	0.0	0
crystal growth	0.4	0.5	0.7	0.1	0.0	0.2	0.0	0.0	0.3	1.6	5.7	0.3	39.0	0.0	0.1	0.0	0.0	0.0	0.0	0.1	0.0	0
combinatorial technology	4.6	0.6	0.2	0.0	0.0	13.9	0.0	0.0	0.0	0.1	1.3	0.0	0.0	1.4	0.0	0.0	0.0	0.0	0.0	0.1	0.0	0
natural or man-made threads or fibres	0.7	6.5	0.4	0.3	0.1	0.2	0.0	0.0	0.1	0.1	0.2	0.1	0.1	0.0	52.9	3.9	0.4	2.1	0.1	2.3	0.2	0
yarns	0.4	2.4	0.3	0.0	0.0	0.1	0.0	0.0	0.1	0.1	0.1	0.1	0.0	0.0	14.6	46.3	2.0	2.3	0.1	3.4	1.1	0
weaving	0.3	0.8	0.2	0.1	0.0	0.1	0.0	0.0	0.0	0.1	0.1	0.1	0.0	0.0	1.7	2.0	61.7	2.7	0.6	2.2	0.1	2
braiding	0.3	2.4	0.4	0.1	0.2	0.1	0.0	0.0	0.0	0.1	0.1	0.1	0.0	0.0	4.0	1.3	1.7	49.6	0.9	2.5	0.2	1
sewing	0.2	0.3	0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.1	0.0	0.0	0.0	0.0	0.2	0.1	0.7	1.2	72.9	1.2	0.0	0
textiles	1.5	4.9	1.8	0.2	2.1	0.2	0.0	0.2	0.1	0.1	0.3	0.1	0.0	0.0	1.6	0.5	0.5	0.9	0.3	50.1	0.0	1.
ropes & cables	0.2	1.1	0.3	0.1	0.3	0.1	0.0	0.0	0.4	0.6	0.4	0.2	0.0	0.0	2.2	2.4	0.3	1.3	0.1	0.7	39.0	0
paper-making	0.9	5.4	1.5	0.2	0.4	0.4	0.1	0.1	0.1	0.1	0.2	0.1	0.0	0.0	0.8	0.1	1.3	1.0	0.0	2.4	0.0	49

Sources: IMF Staff calculations and Liu and Ma (2023).

Note: Sectors on the left are the ones citing, columns indicate the sector cited (same order as row). Blue entries indicate larger shares, and diagonal entries self-citations.

The matrix of foreign spillovers $\boldsymbol{X}$ is calibrated using PatStats to calculate the share of foreign citations in each ij sector pair. To attribute patents to a country, patents are assigned to country where most of its inventors reside. In case of a tie, assignment is based on the country of the patent authority that published the patent. If it coincides with any of the country majorities across inventors, the patent is attributed that country; if not, it is left as undetermined. This is done for each country-year pair, and each x_{ij} is set to the average ij citation share between 2010 and 2020. Figure 2.4 in the main text shows the average across sectors by country. The degree of political connectedness is proxied by market power in each sector, as estimated by Diez, Fan, and Villegas-Sánchez (2021). These estimates are matched to IPC categories using the probabilistic crosswalk by Lybbert and Zolas (2019). For symmetry with the value-added shares, political connectedness is defined as

$$\phi_i = \frac{\mu_i - 1}{\sum_i \mu_i - 1}$$

where μ_i is the sector's average markup.

The share of green patents is obtained by computing the number of patents at each 4-digit IPC category. Each of those 4-digit sectors is then matched to the IPC Green Inventory, which tracks patents related to green innovation. The share of green patents for each 3-digit sector is then computed as the ratio of the number of patents classified as green technology (i.e., classified into a green 4-digit IPC category) over the total number of patents in the 3-digit sector.

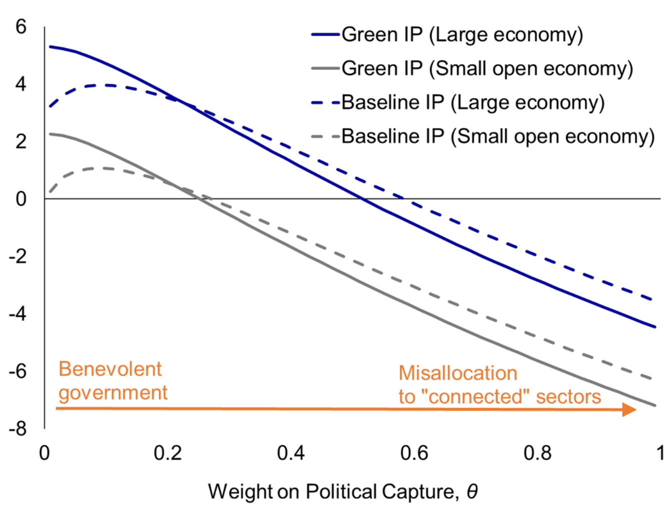
The weights $\{\alpha_i\}$ are proportional to the share of green patents, but normalized such that the welfare gains from green IP are 2 percentage points larger than the gains from "regular" IP (measured using the objective function that includes green innovation as an explicit goal). This welfare increase matches the estimated cost of climate inaction in the meta-analysis by Tol (2024), comparing global warming of 4°C relative to 1.5°C.

Lastly, the exposure to Artificial Intelligence across sectors is obtained from Felten, Raj, and Seamans (2021), normalized to be contained within [0,1]. Their data is once again matched to IPC categories using the crosswalks by Lybbert and Zolas (2019).

Additional Results

Online Annex Figure 2.1.2. Welfare Gains of Industrial Policy with Green Goals

(Consumption-equivalent change relative to no industrial policy, percent)



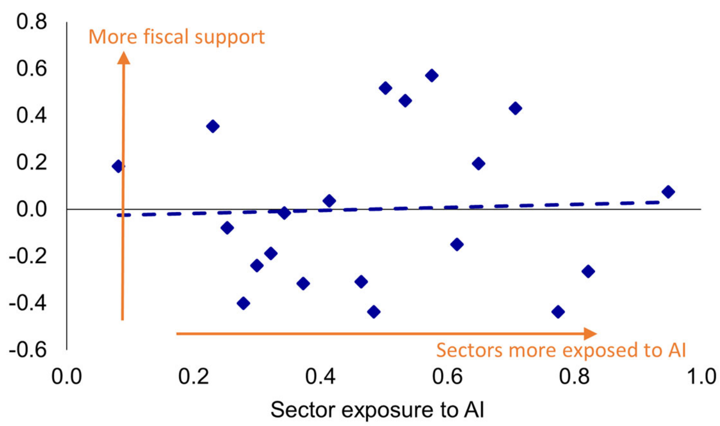
Sources: IMF Staff simulations, Liu and Ma (2023), PatStats, IPC green inventory, Diez, Fan, and Villegas-Sánchez (2021).
Note: spillovers (measured by patent citation linkages) and (in dashed line) emission reduction goals but may favor politically connected sectors (proxied by sector markups). The government chooses sectoral R&D subsidies to capture cross-sector knowledge spillovers (measured by patent citation linkages) and (in dashed line) emission reduction goals but may favor politically connected sectors (proxied by sector markups). The lines in the charts show differences relative to sector-neutral support.

Online Annex Figure 2.1.2 compares the welfare effects from "regular" and "green" IP when green innovation is included in the objective function. Note this differs from the baseline in Figure 2.3, which does not include green objectives. As expected, green IP has a larger welfare impact than regular IP when there is no political capture;[5] in addition, as political capture increases, the gains from green IP decrease.

Interestingly, because green sectors have slightly higher market power than brown sectors, an increase in political capture can increase the welfare impact of "regular" IP (note, however, that this is only possible because regular IP is sub-optimal to begin with). Also, this effect is not monotonic, and if sufficiently large, political capture still leads to negative welfare gains from policy.

Online Annex Figure 2.1.3 shows the correlation between optimal R&D support and AI exposure at the sector level, using data on projected AI exposure from Felten, Raj, and Seamans (2021). As discussed in the main text, the correlation is close to zero, as on average sectors more exposed to AI do not generate higher research spillovers to other sectors and are not greener either.

Online Annex Figure 2.1.3. Optimal R&D Support by Sector's AI exposure
(Change in R&D relative to no industrial policy, in logs)



Sources: IMF Staff simulations, Liu and Ma (2023), PatStats, IPC green inventory, Diez, Fan, and Villegas-Sánchez (2021), and Felten, Raj, and Seamans (2021).
Note: The dashed line shows the average increase in a sector's AI support (relative to uniform support) as the green intensity of the sector increases. Sectors are aggregated into 20 bins and the y-axis is rescaled to a zero mean.

[5] Note that these effects are larger than in Figure 2.3 because adding green innovation in the objective function moves the optimal allocation of resources farther from the allocation without industrial policy.

Online Annex 2.2. Literature Review on Fiscal Instruments for Innovation[6]

This annex lists the literature sources on the effectiveness of fiscal instruments for innovation and describes the estimated effects of R&D tax incentives on total R&D, as well as the effects of total R&D on GDP and debt.

Literature Sources

Online Annex Table 2.2.1 lists the literature sources used to compile Table 2.2 in the main text.

Online Annex Table 2.2.1. Sources on Budgetary Instruments to Promote Innovation

Instrument	Sources of Literature Estimates
R&D tax incentives	Castellacci and Lie (2015), Appelt, Galindo-Rueda, and González Cabral (2019), Gaillard-Ladinska, Non, and Straathof (2019), and Blandinieres and Steinbrenner (2021).
Patent boxes (intellectual property regimes)	Karkinsky and Riedel (2012), Griffith, Miller, and O'Connell (2014), Alstadsæter and others (2018), Gaessler, Hall, and Harhoff (2021), Knoll and others (2021), and Schwab and Todtenhaupt (2021).
R&D grants	Hussinger (2008), Bronzini and Iachini (2014), Black (2015), Dimos and Pugh (2016), Howell (2017), Santoleri and others (2022), and Moretti, Steinwender, and Van Reenen (2023).
Public R&D	Levy and Terleckyi (1983), Jaffe (1989), Woodward, Figueiredo, and Guimaraes (2006), Becker (2015), and Azoulay and others (2019).
Moonshot projects	Schweiger, Stepanov, and Zacchia (2022), Gross and Sampat (2023), and Kantor and Whalley (2023).
Across instruments	Bloom, Van Reenen, and Williams (2019), Bryan and Williams (2021), and Akcigit and Stantcheva (2022).

Impact of R&D Tax Incentives on Total R&D

The estimates for R&D tax incentives presented in Table 2.2 draw primarily on two recent meta-studies (Castelacci and Lie 2015; Blandinieres and Steinbrenner 2021).[7] The combined dataset includes more than 1,200 estimates from around 85 studies published over the last two to three decades. To ensure comparability with other estimates in Table 2.2, only studies that calculate an elasticity of business R&D expenditure to the user cost of R&D are retained, and duplicate entries and outliers[8] are removed, leaving a total of 234 estimates from 28 studies published between 1993 and 2019. Estimates are averaged within each study to avoid bias towards publications with many estimates. This approach produces an overall (unweighted) average elasticity of R&D expenditure to the user cost of R&D of -0.81, with 25th and 75th percentiles equal to -1.13 and -0.13, respectively.

Next, these elasticities are translated into the incrementality ratio (IR), i.e., the dollar increase in R&D expenditure per dollar of foregone tax revenue. Following Thomson (2017) and Appelt, Galindo-

[6] Prepared by Tibor Hanappi and Roberto Piazza.

[7] Authors of both studies have shared the data underlying their meta-regression analyses.

[8] Outliers are defined as the upper and lower 2 percentiles of the distribution of coefficient estimates (9 observations).

Rueda, and González Cabral (2019), the IR is defined as the marginal change in business R&D induced by a marginal change in tax expenditure for R&D support, with the cost of tax support approximated as the product of the implied marginal subsidy rate and business R&D:

$$IR = \left(\frac{1}{1-\tau}\right)\frac{\beta_{UC}}{-UC+\beta_{UC}(1-UC)},$$

where (τ) is the corporate income tax rate, UC the user cost of R&D, and β_{UC} the elasticity of R&D expenditure to the user cost of R&D. To improve comparability across studies with different samples, the two exogenous parameters—τ and UC—are held constant to derive the IR based on the set of elasticity estimates (β_{UC}). The GDP-weighted sample means $\tau = 0.3$ and $UC = 0.89$, calculated from the OECD's MSTI database for the period 2000-2021, are combined with the (unweighted) average elasticity estimate ($\beta_{UC} = -0.81$) to derive an IR of 1.18, with the 25th and 75th percentiles at 1.58 and 0.2, respectively.

Online Annex 2.3. Panel Regression Analysis of Fiscal Instruments for Innovation[9]

This annex describes the empirical approach used to derive the new estimates shown in Table 2.2.

Regression Specification

A cross-country panel regression analysis allows for comparison of the effectiveness of different fiscal instruments to support innovation in a unified set-up. It considers tax incentives to business R&D, patent boxes or intellectual property regimes (IPRs), which offer preferential tax treatment to income from protected intellectual property assets (e.g., patents, trademarks, or copyrights), and government R&D. The analysis also differentiates the impact of IPRs before and after 2015, when an international agreement was reached (G20/OECD project on Base Erosion and Profit Shifting (BEPS)) to ensure that tax benefits from IPRs can only be accessed if there is substantial R&D activity located in the respective jurisdiction ('nexus approach').[10]

The regression model estimates the elasticities of R&D expenditure financed by businesses (RD) with respect to various policy and macroeconomic factors:

$$lnRD_{ct} = \alpha + \beta_{UC} * lnUC_{ct} + \beta_{IPR} * D_{ct}^{IBR} + \beta_{Nexus} * D_{ct}^{Nexus} + \beta_{Gov} * lnGovRD_{ct}$$
$$+x'_{ct-1}\gamma_x + \delta_c + \delta_t + \epsilon_{ct}.$$

The coefficient β_{UC} captures the elasticity with respect to the user cost of capital, defined as the B-index (UC), i.e., the pre-tax return required for firms to break even following a marginal increase in their R&D expenditure.[11] However, UC only covers R&D tax incentives. The impacts of IPRs on R&D expenditure are captured by two binary indicator variables: one capturing the existence of an IPR (D_{ct}^{IBR}) and the other capturing compliance with the nexus approach (D_{ct}^{Nexus}). A measure of government-financed expenditure on R&D ($GovRD$), excluding public grants to business,[12] is also included to capture spillovers from government R&D into business R&D.

In addition, a vector of control variables is added (x'_{ct-1}) to capture lagged time-varying effects on R&D expenditure at the country level, including GDP per capita, nominal interest rates, inflation, corporate tax rates, and inward FDI positions. Finally, the specification includes country and year fixed effects.

[9] Prepared by Tibor Hanappi.

[10] Although some IPRs included development conditions—i.e., requirements to locate R&D activities in the respective jurisdiction—before 2015, this was only a minority and conditions were often not very stringent. With BEPS Action 5, widespread adoption of the nexus approach was achieved in 2016.

[11] In principle, the B-index is firm-specific, but to operationalize it as a policy indicator it is typically computed for a representative firm based on a stylized investment project, which is held constant across countries and scenarios. The implied subsidy rate for R&D expenditures is defined as one minus the B-index. The B-index is also closely related to forward-looking effective tax rates (Devereux and Griffith 2004). A more detailed discussion can be found here and in OECD (2019).

[12] This variable is calculated by subtracting government grants to business—government-financed BERD—from government-financed GERD.

To translate the estimated elasticities for business R&D from the above specification into the dollar-to-dollar impacts on total R&D (incrementality ratios) shown in Table 2.2, the current values of regressors are used (cross-country average), coupled with the assumption that government R&D is exogenous to business R&D.

Data

The regression is estimated with data sourced mainly from the OECD's MSTI and R&D Tax Incentives databases. The combined dataset yields a relatively balanced panel of 40 countries over 2000-2021 (804 observations) (Online Annex Table 2.2.3).[13]

The main variables of interest are 'Gross Domestic Expenditure on Research and Experimental Development' (GERD), capturing all R&D expenditures carried out within each country each year, as well as its sectoral components. Specifically, GERD can be broken down into: 'Higher Education Expenditure on R&D' (HERD), 'Government Expenditure on R&D' (GOVERD), and 'Business Expenditure on R&D' (BERD). In addition to the sectoral split, it is also possible to distinguish the financing sources. In the regression, the dependent variable is the business-financed component of BERD, which excludes business expenditures on R&D that are directly funded by the government, while government R&D is defined as government-financed GERD minus government financed BERD.[14]

The R&D Tax Incentives database is another important source since it includes a time series of the tax component of the R&D user cost, commonly referred to as the B-index (Warda, 2001; OECD, 2013), covering 49 countries since 2000, thus yielding a large overlap with the MSTI data. The data for IPRs is sourced from González Cabral and others (2023b).[15]

Online Annex Table 2.3.1. Sample Country Coverage

Australia, Austria, Belgium, Canada, Chile, China, Colombia, Costa Rica, Czech Republic, Denmark, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Israel, Italy, Japan, Korea, Latvia, Lithuania, Luxembourg, Mexico, Netherlands, Norway, Poland, Portugal, Romania, Russia, Slovak Republic, Slovenia, South Africa, Spain, Sweden, Switzerland, United Kingdom, and United States.

Results

The results are summarized in Online Annex Table 2.3.2 and illustrated in Online Annex Figure 2.3.1, with specification (3) being the preferred one used to derive the estimates presented in Table 2.2. The estimated coefficients for the R&D user cost are strongly significant, ranging between -0.5 and -0.6 in specifications (1) to (3), which are based on the full sample period. Since the variables are defined in log-terms, the coefficient estimate for the R&D user cost can be directly interpreted as the R&D elasticity. Using the estimate from

[13] Missing values are imputed for countries that only report these variables on a bi-annual basis, as well as for a small number of other countries.

[14] Note that only a share of HERD and GOVERD is government-funded, with the rest funded by the private sector.

[15] As described in detail in OECD (2023c), IPRs are a complex set of interacting rules. Although the choice of indicators implies some loss of information, the chosen approach is an improvement compared to the previous literature that typically focused only on expenditure- or income-base tax incentive regimes (Shehaj and Weichenrieder 2021).

specification (3), -0.55, implies an incrementality ratio (IR) of 0.8 based on average values for the statutory rate and the user cost (see Online Annex 2.2). Using the 25th and 75th percentile of the estimated coefficient implies an IR ranging between 0.7 and 0.9 (reported in Table 2.2). A one percent increase in R&D expenditure by the government is estimated to have significant positive effects on business-financed R&D of around 13 percent in specification (3), implying an IR for total R&D of 1.35 evaluated at the sample mean.[16] Based on the 25th and 75th percentiles, this corresponds to an IR ranging between 1.2 and 1.5.

Online Annex Table 2.3.2. Estimation Results

Dependent variable: business financed BERD	(1)	(2)	(3)	(4)
Public R&D (excluding grants)	0.10	0.10	0.13*	0.23**
	(0.07)	(0.07)	(0.07)	(0.10)
Statutory CIT Rate	0.03	0.23	0.32	0.35
	(0.40)	(0.39)	(0.39)	(0.50)
User Cost of R&D	-0.57***	-0.54***	-0.55***	-0.39***
(Taking only R&D incentives into account)	(0.12)	(0.12)	(0.11)	(0.15)
Intellectual Property Regime (IPR)		0.13***	0.10**	0.08**
		(0.04)	(0.04)	(0.03)
IPR with Nexus Requirement (y/n)			0.23***	
			(0.04)	
GDP per Capita (lagged)	0.97***	0.95***	0.97***	0.65***
	(0.13)	(0.13)	(0.13)	(0.17)
Inward FDI Position (lagged)	-0.07***	-0.08***	-0.08***	-0.31***
	(0.02)	(0.02)	(0.02)	(0.10)
Inflation (lagged)	0.01**	0.01**	0.01**	0.01*
	(0.01)	(0.01)	(0.01)	(0.01)
Nominal Interest Rate (lagged)	0.01	0.01	0.01	0.01
	(0.01)	(0.01)	(0.01)	(0.01)
Number of observations	804	804	804	569
R-squared	0.99	0.99	0.99	0.99

Source: IMF Staff calculations, OECD Main Science and Technology Indicators database, OECD R&D Tax Incentives database, González Cabral and others (2023b).
Note: Staff estimates are based on an OLS panel regression with country and year fixed effects, controlling for macroeconomic factors and the corporate income tax rate. The sample covers 40 OECD and non-OECD economies including China, Romania, Russia, and South Africa over 2000–21. Values in parentheses indicate standard errors. The results from specification (3) are used to derive the staff estimates in Table 2.2 of the main text.

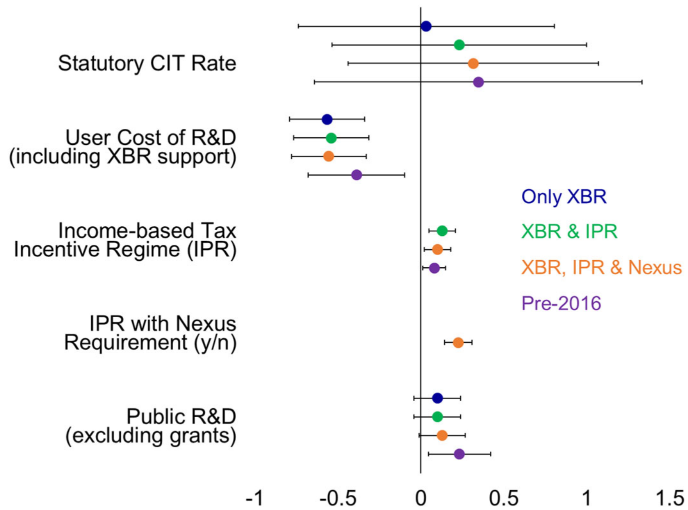
Specification (2) shows that introducing an IPR is associated with a significant increase of about 13 percent in R&D expenditure. Specification (3) shows the combined effect of IPR with nexus requirement is larger, implying an increase in R&D expenditure of up to 33 percent with development condition.[17] Specification (4) is identical to (3) except that it is limited to years prior to 2016, when the nexus approach became widely

[16] Government-financed GERD (excluding business grants) is around USD 7.7 billion on average; business-financed BERD is around USD 21.2 billion on average.

[17] However, information on the cost of IBR in terms of revenue forgone is limited, making comparison to the other instruments difficult. For further descriptive information on a limited number of regimes see Appelt and others (2023).

implemented. In this last regression the IPR indicator is smaller and less significant, suggesting that BEPS Action 5 did strengthen the link between IPRs and R&D expenditure. Taken together, the results suggest that IPRs are less effective in cases where there are no development conditions; and that adopting the nexus approach has positive effects on local R&D expenditure.

Online Annex Figure 2.3.1. Regression Estimates



Source: IMF Staff calculations, OECD Main Science and Technology Indicators database, OECD R&D Tax Incentives database, González Cabral and others (2023b).
Note: Staff estimates are based on an OLS panel regression with country and year fixed effects, controlling for macroeconomic factors and the corporate income tax rate. The sample covers 40 OECD and non-OECD economies including CHN, RUS and ZAF over 2000–21.

Online Annex 2.4. Analysis of Intellectual Property Regimes[18]

This annex describes the empirical approach and results of the analysis of the introduction of intellectual property tax regimes using a quasi-experimental regression.

Empirical Approach

To complement the panel regression approach (Online Annex 2.3), the impacts of intellectual property regimes (IPRs) on R&D expenditures are further analyzed based on a quasi-experimental estimation approach using Synthetic Difference-in-Difference (SDID) (Arkhangelsky and others 2021). This approach addresses concerns about the endogeneity of tax policy instruments (with respect to R&D expenditures) and is increasingly favored by the literature, although it requires for a comparison of effects before and after the year a new policy is introduced, rather than comparing the effects of various instruments over time.

SDID combines advantages of Difference-in-Difference (DiD) and Synthetic Control Methods (SCM). As with the DiD estimator, SDID can accommodate level differences in the outcome variable before the treatment; and, like SCM, it is much less reliant on the parallel trend assumption due to the similar matching procedure used to create a synthetic control unit. The SDID estimator is defined as follows, using unit-weighs ($\widehat{\omega_i}^{SDID}$) and time-weights ($\widehat{\lambda_t}^{SDID}$) as well as control variables ($x_{ct}^{\prime}$), time and country fixed effects:

$$\left(\hat{\beta}^{SDID}, \hat{\alpha}, \widehat{\delta_c}, \widehat{\delta_t}\right) = argmin_{\beta,\alpha,\delta_i,\delta_t}\left\{\sum_{i=1}^{N}\sum_{t=1}^{T}\left(lnRD_{ct} - \alpha - \beta^{SDID}D_{ct} - x_{ct}^{\prime}\gamma_x - \delta_c - \delta_t\right)^2 \widehat{\omega_i}^{SDID}\widehat{\lambda_t}^{SDID}\right\}$$

The coefficient of interest is $\hat{\beta}^{SDID}$, which measures the causal effect of a binary treatment (D_{it}), i.e., the introduction of an IPR, on R&D expenditure, corresponding to the average treatment effect on the treated (ATT).

For comparability with the approach in Online Annex 2.3, a log-log specification is used, and the control variables are retained, including the B-index, except for inflation and interest rates which are missing for some of the countries in the sample. Public R&D (the sum of higher-education and government R&D) is used instead of government-financed GERD to ensure that variation in private spending on higher education is also captured.

Data

The SDID estimator requires a balanced panel. Using the same sample described in Online Annex 2.3, the balanced panel consists of 28 countries from 2000 to 2021 (616 observations). 15 of these countries have adopted an IPR over the sample period (Figure 2.8). Sample differences should be kept in mind when comparing the results with those in Online Annex 2.3.

[18] Prepared by Tibor Hanappi.

Online Annex Table 2.4.1. Sample Country Coverage

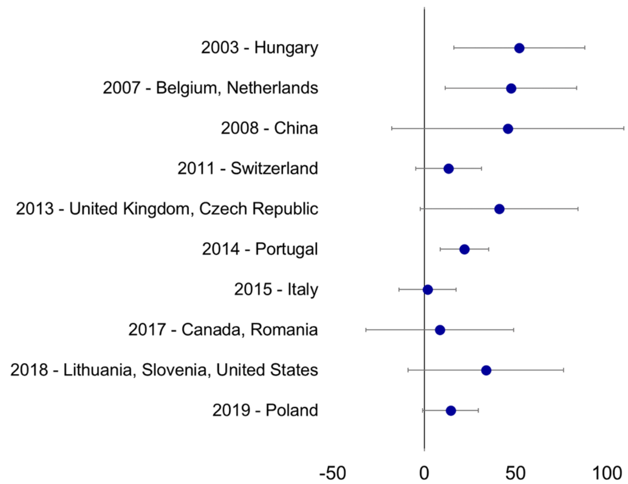
No IPR	Australia, Austria, Denmark, Estonia, Finland, Germany, Iceland, Lithuania, Mexico, New Zealand, Norway, Slovenia, Sweden
IPR	Belgium, Canada, China, Czech Republic, Hungary, Italy, Latvia, Netherlands, Poland, Portugal, Romania, Slovak Republic, Switzerland, United Kingdom, United States.

Results

The individual estimates for each adoption year are illustrated in Online Annex Figure 2.4.1. A weighted-average ATT is also estimated capturing the combined effect under staggered IPR adoption.[19]

Several additional insights emerge from this analysis. First, on average, introducing an IPR increases R&D expenditure by 35 percent, higher than the 12 percent estimated in Online Annex Table 2.3.2 specification (2), possibly due to the removal of endogeneity bias or differences in sample composition. However, the SDID estimate is similar to the combined effect in the panel regression if the effect of development conditions is included, adding up to around 33 percent. Looking across countries, some of the earlier adopters (*Hungary*, *Belgium*, *Netherlands*, *UK*, *Czech Republic*) benefited from larger positive effects, suggesting first-mover advantages. Intangible assets are highly mobile and there is no reason to relocate them again once they have been transferred to a low tax jurisdiction. Conversely, IPRs in other countries, especially those not deemed compliant with the nexus approach (e.g., the *United States*, *China* and *Romania*), have less certain impacts on R&D expenditures. Bringing these results together with those in Online Annex 2.3 strengthens the view that heterogeneity in IPR design as well as regarding the international and domestic context is crucial. While IPRs implemented after 2015 appear to have had mostly insignificant impacts, the results are consistent with a significant positive impact of the nexus approach stemming from existing IPRs becoming compliant around 2016. Apart from a first-mover advantage that seems to have existed in the early 2000s, newly introduced regimes are more likely to have an impact on R&D expenditure if they comply with the nexus approach, such as the regime in *Poland* introduced in 2019, with smaller but significant positive impacts (at the 90 percent confidence level).

Online Annex Figure 2.4.1. Impact on R&D Expenditure of Introducing an IPR



Source: IMF Staff calculations, OECD Main Science and Technology Indicators database, OECD R&D Tax Incentives database, González Cabral and others (2023).
Note: Staff estimates are based on a synthetic difference-in-difference estimation, controlling for macroeconomic factors, the corporate income tax rate, government, and higher education spending on R&D. The sample covers 28 OECD and non-OECD economies over 2000-21. Whiskers show 95-percent confidence intervals, with bootstrapped standard errors.

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[19] Each year-specific estimate is derived by comparing the IBR-adopting countries to their synthetic control, which is constructed using only countries that are not (yet) treated. To construct the weighted average, each year-specific effect is weighted by the share of treated periods within the overall timeframe.

Online Annex 2.5. Impacts of Total R&D on GDP and Debt[20]

This annex describes the calculations of impacts of total R&D on GDP and debt-to-GDP reported in the main text.

GDP Impact

To obtain the impact of an additional dollar of total R&D on output, values from the empirical and model-based literature are combined with additional calculations to translate commonly estimated elasticities into dollar-to-dollar impacts.

Consider a Cobb-Douglas production function with labor augmenting technology A_t. Following Bloom and others (2020), the growth rate of technology is assumed to depend on the amount S_t of R&D researchers:

$$\frac{\dot{A}_t}{A_t} = A_t^{-\beta} S_t.$$

where β is a constant parameter.

Define $R_t = w_t^S S_t$ as the R&D expenditure on researcher salaries. Along a path with constant technological growth and wages proportional to output (Y), output is given by:

$$\ln Y_t = \kappa + \gamma \ln \frac{R_t}{Y_t} + \alpha_1 \ln L_t + \alpha_2 \ln K_t \,, \qquad (1)$$

where L is labor, K is capital, R/Y is the R&D intensity, and Greek letters are constant parameters. The parameter of interest in equation (1) is γ, the output elasticity of R&D intensity:

$$\gamma = \frac{d \ln Y}{d \ln R/Y} = \epsilon_{Y,R/Y}.$$

This elasticity is commonly estimated in the literature. A meta-analysis of the empirical literature (OECD 2015) finds estimates of $\epsilon_{Y,R/Y}$ for business R&D centered around 0.1, but focusing on the specification closest to equation (1) would suggest a value closer to 0.2.[21] A value of $\gamma = 0.2$ is also implied by the calibration in Bloom and others (2020), assuming constant returns to scale in capital and labor and a labor share of 0.6.[22]

While the model reflects the long run elasticity, the empirical studies surveyed in OECD (2015) combine short- and long-run elasticities. Long-run elasticities are more likely to capture the effect of R&D through productivity, as innovation takes time to materialize, while short-run elasticities may reflect aggregate demand effects of policies (and can vary more across policy tools). Still, estimates of short- and long-run elasticities are found to be similar.

To translate the elasticity $\epsilon_{Y,R/Y}$ into dollar-to-dollar impacts, it is useful to first derive the elasticity of output to R&D ($\epsilon_{Y,R}$). Applying some algebra yields:

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[20] Prepared by Roberto Piazza.

[21] See Table 5, column 4 in OECD (2015), adding up the constant, the midpoint between the coefficients for “Unit Industry” and “Unit Economy”, and the coefficients for “Within unit variation”, “Value added”, and “R&D intensity.

[22] Considering the endogenous increase in physical capital from a higher TFP level would lead to a greater output response in the new balanced growth path (by about 1.5*γ assuming a fixed interest rate).

$$\epsilon_{Y,R} = \frac{\epsilon_{Y,R/Y}}{1 + \epsilon_{Y,R/Y}}.$$

Next, a reference country needs to be chosen to input nominal values of output and R&D. Taking the *United States* as a reference (where in 2021 total R&D expenditure was USD 709 billion and output USD 23.3 trillion) and a midpoint for $\epsilon_{Y,R/Y} = 0.15$, the impact of an additional dollar of R&D on GDP equals:

$$\epsilon_{Y,R} * \frac{Y}{R} = \frac{0.15}{1 + 0.15} * \frac{23.3}{0.7} = 4.3$$

or about 4 additional dollars of GDP.

Given the most effective fiscal instruments are found to lead to at least 0.8 additional dollars of R&D per dollar of fiscal cost (Table 2.2), the long-term fiscal multiplier is estimated to be 3 to 4, erring on the lower end as scaling up R&D support can face diminishing returns.

Debt-to-GDP Impact

The multiplier can also be used to derive the impact on the debt-to-GDP ratio over the long term. Assuming that nominal interest rates are similar to nominal growth rates, in line with past data in advanced economies, and that nominal revenue increases in proportion with GDP, the effect of an increase in annual fiscal support to R&D by x percentage points of GDP would lead to a change in the debt-to-GDP ratio (d) by year h equal to:

$$d_{t+5} = \frac{d_t + hx * \left(1 - \frac{m * \tau}{2}\right)}{1 + m * x}$$

where m is the fiscal multiplier derived above and τ the revenue share to GDP.

Using the 2023 values in advanced economies (January 2024 WEO vintage) for $d_{2023} = 110$ and $\tau = 0.35$, a midpoint for $m = 3.5$, and a time horizon $h = 8$ years (consistent with a policy mix favoring fundamental research, which pays off over a longer horizon (IMF 2021)), an increase in R&D support of 0.5 percentage points of GDP per year leads to a decrease in debt-to-GDP by year 8 of 0.4 percentage point of GDP.

The calculation abstracts from the short-term demand impact from increased spending on GDP and assumes for simplicity that GDP increases linearly to its long-term level. A faster GDP pick-up would lead to a larger reduction in debt-to-GDP. Further, this does not represent a full cost-benefit analysis, which would also discount for risk, and account for tax distortions, administrative and compliance costs, and benefits not captured by GDP.

Online Annex 2.6 Accelerating Technology Diffusion Across Countries[23]

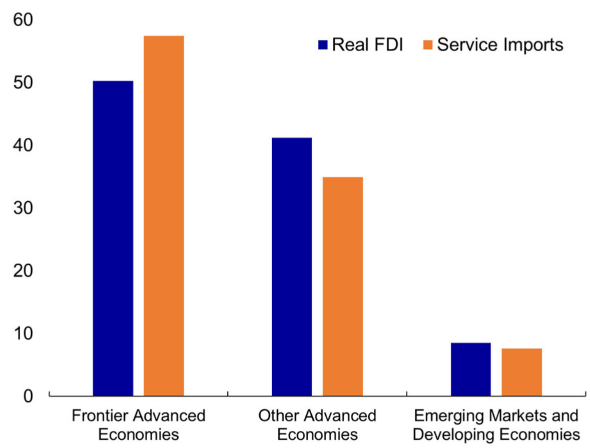
This annex presents the details on the data and methodology used to analyze technology diffusion across countries through service trade and real FDI channels.

The analysis first describes the data sets for service imports and real FDI. It then quantifies knowledge spillovers from frontier economies via service imports and real FDI, following Eugster and others (2022). Next it estimates determinants of these flows into emerging market and developing economies (EMDEs), focusing on factors that fiscal policies can influence. It then quantifies the impact of enhanced policies on lifting innovation, productivity, and GDP by stimulating service imports and real FDI.

Service Imports and Real FDI in Accelerating Diffusion

Data. Data on bilateral inward real FDI positions between 2009 and 2017 are part of the global FDI network database (Damgaard, Elkjaer and Johannesen 2024). Statistics on international trade in services are provided by the Balanced Trade in Services (BaTIS) Database compiled by the Organization for Economic Co-operation and Development (OECD) and the World Trade Organization (WTO). The dataset covers all services suppliers indirect cross-border trade but does not include sales of local services through offshore affiliates. The analysis is restricted to countries with non-missing bilateral flows of services from 2009 to 2021. The technology frontier includes the top seven countries according to the UNCTAD Frontier Technology Readiness Index (*United States*, *United Kingdom*, *Germany*, *Korea*, *France*, *Netherlands*, and *Sweden*). Together, they account for half of the world's R&D spending, half of real FDI and 60 percent of service imports for an average developing country in our sample (Online Annex Figure 2.6.1).

Online Annex Figure 2.6.1. Contribution of Frontier Economies to Real FDI and Services Imports of EMDEs
(Percent of total)



Sources: Damgaard, Elkjaer and Johannesen (2024), OECD-WTO BaTIS; and IMF staff calculations.
Note: The figure shows average shares of inward real FDI positions and services imports of 21 EMDEs counties over 2009-2017 originating from corresponding country groups. Frontier countries include *the United States*, *the United Kingdom*, *Germany*, *Korea*, *France*, *the Netherlands*, and *Sweden*.

Specification. To examine the impact of knowledge flows from frontier economies on patent and productivity growth in the recipient economies, a dynamic panel regression is estimated for 32 countries (22 non-frontier AEs and 10 emerging markets and developing economies) over 2009-2017:

$$logY_{rt} = \beta logR_{rt-1} + \delta log\left(\sum_i \omega_{rit-1} R_{it-1}\right) + \sum_p logY_{rt-p} + \lambda X_{rt} + \alpha_r + \eta_t + \varepsilon_{rt}$$

[23] Prepared by Alexandra Solovyeva and Parijat Lal.

where Y_{rt} the dependent variable measures the recipient country's innovation activity (the number of patent families – a collection of patent applications covering the same or similar technical content), total factor productivity (welfare-relevant TFP), or labor productivity (output per worker); R_{rt} and R_{it} are R&D stocks of recipient country and frontier countries, respectively.[24] The set ω_{rit} captures time-varying knowledge linkages between frontier and recipient economies, measured by the recipient country's imports of services from the frontier economy i and the bilateral inward real FDI position of the recipient economy *(r)* originating from the frontier economy i (both expressed as a share of the recipient's GDP). The regression also controls for the recipient country's real GDP growth, denoted by X_{rt}, and includes lags of the corresponding dependent variable, as well as recipient-country and year fixed effects.

Results. Estimation results show that knowledge flows from the frontier economies play a significant role in boosting domestic innovation and productivity (Online Annex Table 2.6.1)[25]. Knowledge spillovers via the real FDI channel stimulate domestic patent activity. On average, a 1 percent increase in the foreign real-FDI-weighted R&D stock is associated with about 0.1 percent increase in the number of patent families in the recipient country. The elasticities of both TFP and labor productivity with respect to the foreign real-FDI-weighted R&D stock are estimated at around 0.03, lower than patents but still positive and significant. Compared to real FDI, spillovers of traditional FDI on patent activity and labor productivity are estimated to be weaker. Turning to service imports, it is estimated to enhance technological transfer and boost domestic TFP and labor productivity—with an elasticity of about 0.015—has a stronger impact on diffusion than imports of goods.

Online Annex Table 2.6.1. Technology Diffusion through Real FDI and Service Imports

	Real FDI			Services imports		
	Log(Patent families)	Log(TFP)	Log(Labor productivity)	Log(Patent families)	Log(TFP)	Log(Labor productivity)
Lag Log(R&D stock)	0.677***	0.0334	0.118**	0.641***	0.00679	0.0851**
Lag Log(Foreign R&D stock)	0.115***	0.0306***	0.0263**	0.0558	0.0154***	0.0141**
GDP growth	0.00466	0.00495***	0.00663**	0.000114	0.00416**	0.00664***
Observations	188	188	188	192	192	192
AB AR(2)	0.610	0.175	0.229	0.542	0.117	0.133

Sources: Damgaard, Elkjaer and Johannesen (2024), OECD, OECD-WTO BaTIS, Penn World Tables, April 2023 IMF World Economic Outlook; and IMF staff calculations.
Note: The table shows estimated coefficients from a panel regression model for 32 countries over 2009-2017. Each coefficient estimate represents the impact of changes in (lagged) foreign R&D stock on the recipient country's innovation activity (log of patent families) and productivity (log of welfare-relevant TFP and log of labor productivity measured as output per worker). The foreign R&D stock is weighted by the bilateral knowledge linkages (inward real FDI position and services imports as a share of recipient country's GDP) between 7 frontier countries (*United States*, *United Kingdom*, *Germany*, *Korea*, *France*, *the Netherlands*, *Sweden*) and the recipient country. R&D stock is constructed using perpetual inventory method using gross domestic expenditure on R&D (Eugster and others 2022). Dynamic panel estimates are obtained using the Arellano-Bond estimator with two lags of the dependent variable. All columns include country and year fixed effects. AB AR(2) corresponds to results of the Arellano-Bond test for zero autocorrelation in first-differenced errors. Robust standard errors are clustered at the recipient-country level. ***, **, and * denote statistical significance at 1 percent, 5 percent, and 10 percent levels, respectively.

[24] R&D stock is calculated from gross expenditure on R&D from OECD Science, Technology and R&D Statistics using perpetual inventory method as in Eugster and others (2022).

[25] Estimation results are robust to a broader definition of the technology frontier (top 10 countries).

Determinants of Service Imports by EMDEs[26]

Specification. To analyze the determinants of service imports by emerging market and developing economies, the following augmented gravity model is estimated using a Poisson pseudo-maximum likelihood (PPML) estimator[27]:

$$Y_{eit} = \exp\left(\beta_0 + \sum_j \beta_j X_{it} + \sum_k \eta_k z_{ei}^k + \mu_{et} + \gamma_i\right) + \varepsilon_{eit},$$

where Y_{eit} represents the value of service imports into country i from exporter e in year t. The estimated coefficients of interest, X_{it}^j, are a set of j independent time-varying characteristics of the importer. Bilateral gravity variables for each importer-exporter pair, including distance, contiguity, common language, and common colonizer, are captured by z_{ei}^k, while exporter-year fixed effects μ_{et} are included to control for time-varying characteristics of the exporter. Finally, time-invariant characteristics of the importer are controlled for by adding importer fixed effects γ_i.

Data. Among the key potential determinants of services imports are the withholding tax (WHT) rate on payments to non-resident companies, which are relevant when the WHT rate in the importing country is higher than the CIT rate in the exporting country (as well as the CIT rate of the exporting country otherwise). These WHT rates come from the International Bureau of Fiscal Documentation (IBFD). Another relevant tax on service imports is the value added tax (VAT) in the importing country. Finally, the CIT rate for residents is pertinent, as a high CIT can incentivize higher imports by companies with affiliates in lower tax jurisdictions. A range of macroeconomic variables is also considered, as well as qualitative measures of government effectiveness, infrastructure, spending on education, and trade restrictiveness. Each of the indices used is standardized on a yearly basis.

Results. The results from the PPML estimation of services imports into 70 emerging market and developing economies over 2009-2021 are presented in Online Annex Table 2.6.2. First, a 1 percentage point (p.p.) increase in the CIT for residents is associated with a 1.6 percent increase in the value of imported services, a result that is statistically significant. As expected, there is a negative relationship between services imports and other relevant taxes, with a 1 p.p. increase in the WHT rate and VAT rate resulting in services imports falling by 0.7 percent and 6 percent, respectively. Measures of both government effectiveness and e-government are positively related to services imports. The point estimates suggest that a one standard deviation increase in the government effectiveness index yields around a 2 percent increase in imports, while the same change in the e-government index leads to an approximately 5 percent increase.

[26] This section is based on Klemm, Lal, and Liu (forthcoming).

[27] PPML estimation is preferred over the ordinary least squares (OLS) approach with a lagged dependent variable given the prevalence of zero imports between country pairs (Silva and Tenreyro 2006).

Online Annex Table 2.6.2. Determinants of Bilateral Services Imports
(Coefficient estimates)

Dependent variable: Bilateral services imports	(1)	(2)	(3)
Log(Nominal GDP)	0.854***	0.873***	0.924***
Log(Distance)	-0.847***	-0.846***	-0.851***
Contiguity	0.461***	0.458***	0.452***
Common Language	0.544***	0.543***	0.546***
Common Colonizer	0.731***	0.803***	0.723***
Log(Exchange Rate)	0.0120	0.0175**	0.0190*
Capital Account Openness Index	0.00382	0.00307	0.00247
Lagged Trade Openness (%)	0.00569***	0.00556***	0.00535***
Trade Restrictiveness Index (Non-Tariff)	-0.0145***	-0.0152***	-0.0137***
Rule of Law (above 75th percentile)	-0.0304	-0.0258	-0.0192
International Property Rights Index	0.00540	0.00181	0.00228
Estimated Education Spending (% of GDP)	0.129**	0.116*	0.158***
Government Effectiveness Score	0.0171**	0.0187**	0.0147*
Trade&Transport Infrastructure Index	0.00264	0.00166	0.000323
E-Gov Development Index	0.0529***	0.0527***	0.0547***
VAT Rate (%)	-0.0613***	-0.0497***	-0.0642***
CIT Rate for Residents (%)	0.0157***		0.0159***
Withholding Tax Rate (%)	-0.00658*		-0.00639**
Tax Rate Differential (%)		0.0147**	
Exporter CIT (%)			-0.00546***
Observations	15,258	14,402	14,445
Method	PPML	PPML	PPML
Importer FE	Yes	Yes	Yes
Exporter-Year FE	Yes	Yes	Yes

Sources: OECD-WTO BaTIS, GeoDist (CEPII), IMF WoRLD, IBFD, April 2023 IMF World Economic Outlook, World Bank, UN E-Government Knowledgebase, Property Rights Alliance, MATR; and IMF staff calculations.
Note: The table presents the estimated coefficients from panel regression models for 70 emerging markets and developing economies over 2009-2021. PPML corresponds to the Poisson pseudo-maximum likelihood estimator. The dependent variable is the monetary value of services imports. All index variables are standardized on an importer-country basis. Robust standard errors are clustered at the exporter-importer level. Standard errors are not reported here but are available from authors. ***, **, and * denote statistical significance at 1 percent, 5 percent, and 10 percent levels, respectively.

Determinants of real FDI to Emerging Market and Developing Economies

Specification and Data. To analyze the determinants of real FDI to emerging market and developing economies, the following augmented gravity model is estimated for 21 countries over 2009-2017:

$$log(realFDI_{rit}) = \beta_1 log(GDP_{rt}) + \beta_2 log(GDP_{it}) + \Lambda' X_{rit} + \Upsilon' Y_{rt} + \Gamma' P_{rt} + \Omega' CIT_{it} + \alpha_i + \eta_t + \epsilon_{rit},$$

where $realFDI_{rit}$ corresponds to the bilateral inward real FDI position (US$) of the recipient country *r* originating from the investor country *i*; GDP_{rt} (GDP_{it}) is the nominal GDP of the recipient (investor) country (US$); X_{rit} is a vector of bilateral distance indicators, including the log of distance between two countries, common border, common language, former colonial connection, and political distance[28]. Y_{rt} is a vector of recipient country's structural and institutional characteristics, including labor costs defined as the log

[28] Political distance reflects similarities between recipient and investor countries' UN General Assembly votes. It is defined as an absolute value of difference between ideal points calculated in Bailey and others (2017).

of average labor income per hour worked (US$, constant prices), trade openness (defined as the sum of recipient country's exports and imports as a share of GDP), level of financial development, the quality of governance (the rule of law and control of corruption), as well as the level of intellectual property rights protection. CIT_{it} denotes the statutory Corporate Income Tax (CIT) rate in the investor country. Finally, P_{rt} is a vector of fiscal policy variables or variables that can be affected by the fiscal policies, which includes government spending on education (as a share of GDP), statutory and effective CIT rates of the recipient country, the quality of trade and transport-related infrastructure, and the level of digital development of the public sector proxied by the UN E-Government Development Index. The regression also includes investor-country and year fixed effects, α_i and η_t respectively. All indices are standardized on a yearly basis.

Results. The baseline regression results are presented in column (1) of Online Annex Table 2.6.3.[29] Higher government spending on education is associated with higher real FDI, with a 1 percentage point of GDP increase in education spending associated with a 32 percent increase in real FDI. Similarly, real FDI is estimated to be larger in emerging market and developing economies with better physical infrastructure, as well as with more digitally developed public sector. In contrast to the analysis of FDI determinants in IMF (2016), which was based on the traditional FDI data, there is no significant association between real FDI and the level of statutory or effective CIT rate of the recipient country.[30] Most of standard gravity variables (such as geographical distance, common language, former colony) are statistically significant and have expected signs from the literature (Bergstrand and Egger 2007; Yotov and others 2016). Countries with lower labor costs and with more financially developed markets also tend to attract more real FDI.

[29] Although the issue of endogeneity in gravity models could arise due to the multilateral resistance, the sample span is a small window (2009-2017), so a set of year and investor-country fixed effects could mitigate this to some extent.

[30] Effective CIT rate is the average effective CIT rate calculated based on the BEA data on activities of U.S. multinational enterprises following the methodology in Blouin and Robinson (2021).

Online Annex Table 2.6.3. Determinants of Bilateral Real FDI

(Coefficient estimates)

Dependent variable: Log(real bilateral FDI)	(1)	(2)
Log(Nominal GDP) recipient country	0.191**	0.200**
Log(Nominal GDP) investor country	-0.124	-0.119
Log(Distance)	-1.774***	-1.774***
Contiguity	0.395	0.395
Common language	1.405***	1.403***
Former colony	1.387***	1.387***
Fomerly same country	-0.132	-0.127
Political distance	0.110	0.111
Log(Average Hourly Labor Income)	-0.973***	-0.973***
Financial Development Index	0.0567***	0.0566***
Trade Openness	-0.00715***	-0.00725***
Rule of Law (above 75th percentile)	1.197***	1.097***
Control of Corruption (above 75th percentile)	-0.705**	-0.624*
Education Spending (% GDP)	0.321***	0.318***
Trade&Transport Infrastructure Index	0.198***	0.203***
E-Government Development Index	0.172***	0.173***
International Property Rights Index	-0.0228	-0.0219
Statutory CIT rate, investor country (%)	-0.0100	-0.0102
Statutory CIT rate (%)	0.0120	0.00873
Effective CIT rate (%)		0.00182
Observations	6,506	6,506
Year FE	Yes	Yes
Investor Country FE	Yes	Yes

Sources: BEA, Damgaard, Elkjaer and Johannesen (2024), GeoDist (CEPII), IMF WoRLD, MATR, OECD, Penn World Tables, Property Rights Alliance, April 2023 IMF World Economic Outlook, World Bank, UN E-Government Knowledgebase, Bailey et al. (2017); and IMF staff calculations.
Note: The table shows the estimated coefficients from panel regression models for 21 emerging markets and developing economies over 2009-2017. The dependent variable is log of bilateral inward real FDI position (US$). All index variables are standardized on a recipient-country basis. Robust standard errors are clustered at the recipient-investor level. Standard errors are not reported here but are available from authors. ***, **, and * denote statistical significance at 1 percent, 5 percent, and 10 percent levels, respectively.

Quantifying Impact of Enhanced Policies on Innovation, Productivity, and GDP

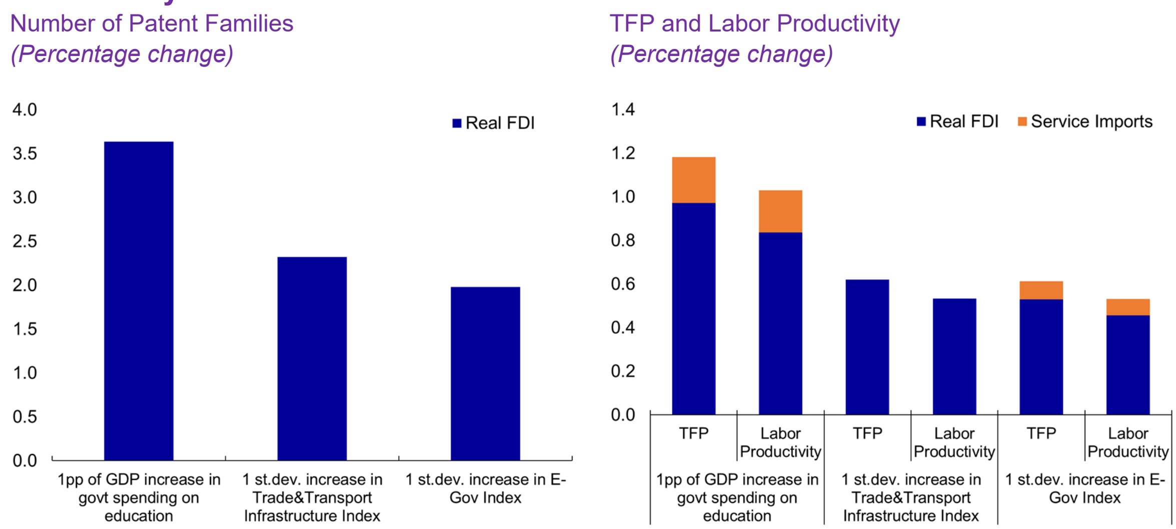
To quantify the implications of policies aimed at stimulating real FDI and service imports on patent activity and productivity in emerging market and developing economies, the estimated effect of policy changes on real FDI and service imports is combined with the associated changes in the corresponding knowledge linkage, and the estimated long-term impact of foreign R&D stock on domestic patents and productivity (from the knowledge diffusion regressions), ceteris paribus (Online Annex Figure 2.6.2). The estimates for the real FDI channel suggest that a 1 percentage point of GDP increase in education spending yields about 3.5 percent increase in the number of patent families, a 1 percent increase in both TFP, and a 0.8 percent increase in labor productivity.[31] A one standard deviation increase in indices of the quality of physical infrastructure and digital development of the public sector is associated with an increase in the number of patent families by 2 percent and that in productivity of about ½ percent, respectively. The impact of policies

[31] Government spending on education in emerging market and developing economies is about 5 percent of GDP on average, implying that a 1 percentage point of GDP increase is equivalent to a 20 percent increase in the monetary value of education spending.

on productivity through service imports channel is more modest but still positive and significant. An increase in spending on education by 1 percentage point of GDP yields a 0.2 percent increase in productivity, while a one standard deviation increase in E-Government development index is associated with a 0.08 percent increase in productivity.

Taken together, the positive impact of higher government spending on education and infrastructure on TFP can be sizeable. By applying the standard neoclassical growth accounting approach (Barro 1999), the impact of these policies on GDP growth is assessed. Assuming a Cobb-Douglas aggregate production function and that technological change is labor augmenting, GDP growth and TFP growth are proportional with a factor of $1/(1-\alpha)$, where α is the capital income share. Given that the average capital income share in emerging market and developing economies is about 37 percent (based on Penn World Table estimates), the cumulative increase in GDP growth from a 1 percentage point increase in government spending on education is about 1.9 percentage points, while the cumulative increase in GDP growth associated with improvements in the quality of trade and transport infrastructure by one standard deviation is 1 percentage point.

Online Annex Figure 2.6.2 Impact of Selected Policies on Innovation and Productivity in EMDEs



Sources: Damgaard, Elkjaer and Johannesen (2024), OECD-WTO BaTIS, OECD, Penn World Tables, April 2023 IMF World Economic Outlook, World Bank, UN E-Government Knowledgebase; and IMF staff calculations.
Note: Figures show the estimated impact of corresponding policy changes on patent growth, TFP and labor productivity in EMDEs through real FDI and services imports channels using estimates from knowledge diffusion regressions for patent families, TFP and labor productivity and augmented gravity equations for real FDI and services imports.

Online Annex 2.7. Accelerating Diffusion of Innovation across Firms – The Role of Government Policies[32]

This annex presents details on the empirical analysis examining the diffusion of innovation across firms shown in Figure 2.10.

Data

Innovation. To examine how innovation diffuses across the firm distribution, a measure of innovation is constructed using data from the European Patent Office's PATSTAT database. To distinguish high-value inventions from the large number of patents that get filed globally, patent growth is defined in terms of growth of international patent families, where a patent family consists of all the patents that cover the same invention, and the family contains patents that have been filed in more than one jurisdiction. In this manner, the patent growth measure is limited to capture 'high value' innovation (Probst and others 2021). IPC-NACE mapping provided by EUROSTAT is used to construct the measure of growth in high-value patent families at the level of the NACE 2 sector classification for all manufacturing sectors.

Firm-level Data. By matching sector level patent family growth to firm level data from the Orbis van Djik database, the impact of innovation in the firm's industry is assessed on its productivity growth. The cleaning steps follow Diez, Fan, and Villegas-Sánchez (2021), including converting all monetary variables into real variables industry deflators and investment deflators (for fixed assets), and keep only manufacturing firms over the 2005-2020 period. TFP is estimated following the methodology proposed by Ackerberg, Caves, and Frazer (2015). The estimation uses a gross output approach, with cost of goods sold and tangible fixed assets as inputs. The estimation is conducted pooling countries within a given 2-digit NACE sector. The country sample is limited to advanced and emerging economies for which sufficient data is available to enable total factor productivity (TFP) estimation. The final estimation sample consists of over 730,000 firms from 28 advanced and 15 emerging economies (See Online Annex Table 2.7.1 for details on country coverage).

Country-level Policy Variables. Data on the quality of physical infrastructure is obtained from the World Bank logistics performance index, which measures the quality of trade and transport-related infrastructure. Data on ICT adoption is from the World Bank Global Competitiveness Index's subindex of ICT adoption, which captures mobile, broadband, fiber internet subscriptions and internet usage. Level of human capital is proxied with the World Bank PISA science scores of a country, which measures the scientific literacy of 15-year olds. Measures of financial development, including the credit-to-GDP ratio and venture capital availability in an economy, are obtained from the IMF World Economic Outlook database and the World Bank Global Competitiveness Report, respectively.

[32] Prepared by Salma Khalid.

Online Annex Table 2.7.1 lists all the countries in the sample.

Online Annex Table 2.7.1. Country Coverage

Australia, Austria, Belgium, Bulgaria, China, Colombia, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iran, Ireland, Israel, Italy, Japan, Latvia, Lithuania, Malaysia, Mexico, Morocco, Netherlands, New Zealand, Norway, Philippines, Poland, Portugal, Romania, Russian Federation, Slovakia, Slovenia, Korea, Spain, Sweden, Switzerland, Thailand, Türkiye, United Kingdom, United States, Vietnam.

Sources: ORBIS, and IMF staff calculations.

Diffusion of Innovation Across Firms

Specification. The baseline specification evaluates the impact of frontier innovation in an industry (proxied by the NACE2 sector level high value patent growth) on growth of firm productivity, controlling for the productivity growth of frontier firms and the rate of convergence between the firm and the frontier:

$$\Delta\, ln(TFP)_{isct} = \theta_1 \boldsymbol{Z}_{it}[\Delta\, ln(TFP)_{Fst}] + \theta_2 \boldsymbol{Z}_{it}[TFPgap_{st-1}] + \theta_3 \boldsymbol{Z}_{it}[\Delta\, ln(Patents)_{st-1}] + \gamma X_{isct-1} + D_{t,c,s} + \varepsilon_{it}$$

$\Delta \ln(TFP)_{isct}$ is the growth of TFP of firm i, in sector s, of country c, at time t; $\Delta \ln(TFP)_{Fst}$ is the TFP growth of firms at the global frontier, where the global frontier is defined as the top 50 firms in the sector; $TFPgap_{ist-1}$ captures the gap to the frontier at the sector-decile level, where the gap is measured as the difference between the TFP at the frontier and the mean TFP in the country-sector decile of the TFP distribution in which the firm is located; $\Delta \ln(Patents)_{st-1}$ captures the change in the growth rate of high-value patent families in the firm's industry; X_{isct-1} is a vector of firm-level control variables including firm age and turnover-to-assets ratio; and $D_{t,c,s}$ is a vector of fixed effects at the firm, country-sector and country-year levels. $\boldsymbol{Z}_{it} = [1, I(bottom40_{isct} \neq 1)]$ is a *vector* of variables indicating position in the country-sector TFP distribution, where $I(bottom40_{isct} \neq 1)$ indicates that the firm is outside the bottom 40th percentile of the TFP distribution of their sector-country. $\theta = [\beta_{b40}, \beta_{nb40}]$ is the corresponding vector of coefficient estimates for the laggards and non-laggards, respectively. The key coefficients of interest $\theta_3 = [\beta_{b40}, \beta_{nb40}]$ capture the spillover effects from sector level patent growth on different portions of the firm TFP distribution. The summary statistics for the sample, including by laggard and non-laggard firms, is provided in Online Annex Table 2.7.2.

Online Annex Table 2.7.2. Sample Summary Statistics

Summary Statistics	AE	Non-AE
Number of countries	28	15
Number of firms	423,751	306,341
Laggard firms		
Age	21.51	13.21
Turnover/Assets	1.40	1.72
Debt/Assets	0.28	0.14
Shareholder Funds/Assets	0.31	0.38
Non-Laggard firms		
Age	21.61	13.71
Turnover/Assets	1.46	2.30
Debt/Assets	0.24	0.12
Shareholder Funds/Assets	0.37	0.46

Sources: ORBIS, and IMF staff calculations.

Results. Estimation results show a positive relationship between lagged patent growth across all firms in the industry and the TFP growth of individual firms, implying a diffusion of innovation from innovating firms in the industry to the average firm (Online Annex Table 2.7.3). A 1 percent increase in growth of high value patent families in the preceding year predicts an increase in the growth rate of firm-level TFP of 0.05 percent. The results also indicate disparity in the strength of diffusion in advanced economies with TFP growth among laggard firms increasing by 0.06 percent, relative to 0.03 percent among non-laggard firms. This pattern reflects diffusion of TFP growth from frontier firm TFP growth, wherein laggard firms show faster catch-up.

Online Annex Table 2.7.3. Diffusion of innovation to firm TFP growth

	Δ log TFP			
VARIABLES	All	All	AE	EM
Δ log TFP Frontier firms	0.23***	0.27***	0.24***	0.33***
Firms above 40th percentile of TFP distribution (Non-laggards)		0.19***	0.17***	0.22***
Δ log TFP Frontier firms * Non-laggards		-0.01**	-0.01***	-0.01
Lag gap to frontier (industry decile)	0.45***	0.52***	0.45***	0.65***
Lag gap to frontier * Non-laggards		-0.02***	-0.01**	-0.02
Lag Δ log high value patent families in industry	0.05***	0.06***	0.06***	0.06
Lag Δ log patent families * Non-laggards		-0.02	-0.03***	0.01
log(Firm age)	0.00	-0.00	0.00	-0.02***
log(Turnover/Assets)	0.03***	0.01***	0.02***	0.01***
Observations	5,651,428	5,651,428	3,739,424	1,912,004
R-squared	0.23	0.31	0.30	0.34
FE: Firm Country-Sector Country-Year FE				

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Sources: PATSTAT, ORBIS, IMF World Economic Outlook Database, and IMF staff calculations.
Note: The table represents the coefficient estimates from a panel regression model based on Bureau van Dijk ORBIS database. Sample consists of 43 countries, between 1995 and 2020. Data cleaning steps follow Diez Fan, and Villegas-Sánchez (2021). The dependent variable is log changes in total factor productivity. Frontier firms are defined as the top 50 most productive firms in a sector, across countries, while laggards are defined as belonging in the 40th percentile or below of the TFP distribution within each country and sector. High-value patent families consists of all patent families with patents that have been filed in more than one jurisdiction. Policy variables are defined at the country level and standardized across the sample countries. All regressions include firm level controls for firm age and turnover-to-assets. Robust standard errors are clustered at the country-sector level.

Diffusion of Innovation Across Firms: The Role of Policies

Specification. The baseline estimation equation is enhanced to explore how policy variables can influence the diffusion of innovation:

$$\Delta\, ln(TFP)_{isct} = \theta_1 Z_{it}[\Delta\, ln(TFP)_{Fst}] + \theta_2 Z_{it}[TFPgap_{st-1}] + \theta_3 Z_{it}[\Delta\, ln(Patents)_{st-1}] + \theta_3 Z_{it} * PolicyVar_c + \theta_3 Z_{it}[\Delta\, ln(Patents)_{st-1}] * PolicyVar_c + \gamma X_{isct-1} + D_{t,c,s} + \varepsilon_{it}$$

where $PolicyVar_c$ are country level variables capturing digital and physical infrastructure, human capital, and financial development. The policy variables are standardized at the country level, and controls include the impact of GDP per capita and its interactions with patent growth, for laggard and non-laggard firms in each regression, to capture the effect of overall differences in economic development.

Results. The results are summarized in Online Annex Table 2.7.4. Starting with physical infrastructure, the results show that laggard firms in economies with higher levels of infrastructure quality experience stronger TFP growth and therefore have stronger spillover benefits from patent growth in their industry. The coefficient estimates indicate that closing the infrastructure gap between the average emerging market economy and advanced economy in the sample will result in nearly doubling the impact of patent growth on laggard firm TFP, with a 1 percent increase in patent growth resulting in a 0.08 percent increase in TFP growth of laggard firms.[33] This gain is absent for non-laggard firms in the same economies, indicating that public policies that improve infrastructure quality may disproportionately benefit laggard firms.

Online Annex Table 2.7.4. Policy Impact on Diffusion of Innovation to Firm TFP

	Δ log TFP									
VARIABLES/POLICY VARIABLES	Infrastructure Quality		ICT Adoption		Mean PISA Scores		Credit to GDP		Venture Capital Availability	
Δ log TFP Frontier firms	0.23***	0.27***	0.23***	0.27***	0.22***	0.26***	0.23***	0.27***	0.23***	0.27***
Non-laggards		0.20***		0.19***		0.19***		0.20***		0.18***
Δ log TFP Frontier firms * Non-laggards		-0.01***		-0.01**		-0.01***		-0.01**		-0.01**
Lag gap to frontier (industry decile)	0.45***	0.52***	0.45***	0.52***	0.43***	0.50***	0.45***	0.52***	0.45***	0.52***
Lag gap to frontier * Non-laggards		-0.02***		-0.02***		-0.02***		-0.02***		-0.02***
log(Firm age)	0.00	-0.00	0.00	-0.00	0.00	-0.00	0.00	-0.00	0.00	-0.00
log(Turnover/Assets)	0.03***	0.01***	0.03***	0.01***	0.03***	0.01***	0.03***	0.01***	0.03***	0.01***
Lag Δ log high value patent families in industry	0.04***	0.04**	0.03*	0.04**	0.03*	0.05***	0.04***	0.03*	0.05***	0.06***
Lag Δ log patent families * Non-laggards		0.00		-0.01		-0.03***		0.02		-0.02*
Lag Δ log patent families * GDP per capita	-0.02	-0.03	-0.05	-0.07*	-0.04	-0.05	-0.03	-0.05	-0.02	-0.01
GDP per capita * Non-laggards		-0.04***		-0.02***		-0.02***		-0.02***		-0.05***
Lag Δ log patent families * GDP* Non-laggards		0.00		0.02		0.01		0.02*		-0.02
Lag Δ log patent families * Policy variable	0.01	0.04***	0.03*	0.03**	0.03*	0.02	0.01	0.04**	0.02	0.04**
Policy Variable * Non-laggards		-0.04***		-0.02***		-0.03***		-0.03***		-0.03***
Lag Δ log patent families * Policy var * Non-laggards		-0.05**		-0.01		0.01*		-0.06***		-0.03**
Observations	5,651,428	5,651,428	5,651,428	5,651,428	5,465,339	5,465,339	5,651,428	5,651,428	5,651,428	5,651,428
R-squared	0.23	0.32	0.23	0.31	0.22	0.31	0.23	0.32	0.23	0.32
FE: Firm Country-Sector Country-Year FE										

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Sources: PATSTAT, ORBIS, IMF World Economic Outlook Database, and IMF staff calculations.
Note: The table represents the coefficient estimates from a panel regression model based on Bureau van Dijk ORBIS database. Sample consists of countries. Sample consists of 43 countries, between 1995 and 2020. The dependent variable is log changes in total factor productivity. Frontier firms are defined as the top 50 most productive firms in a sector, across countries, while laggards are defined as belonging in the 40th percentile or below of the TFP distribution within each country and sector. High-value patent families consists of all patent families with patents that have been filed in more than one jurisdiction. Policy variables are defined at the country level and standardized across the sample countries. All regressions include firm level controls for firm age and turnover-to-assets ratio and country level controls for GDP per capita (standardized) and its respective interactions. Robust standard errors are clustered at the country-sector level.

A similar positive relationship is found between ICT adoption at the economy level and innovation diffusion, suggesting greater investment in ICT infrastructure also enhances the ability of firms to reap benefits from innovations in their sectors. Higher levels of human capital, as measured by the average PISA science scores in an economy, also predict stronger diffusion of innovation. However, this effect is not statistically different for laggard firms, suggesting that this is a benefit shared by all firms. Countries with higher R&D spending also see faster diffusion to laggard firms (not shown), suggesting a complementary role of innovation policies for adoption across firms.

Given the extensive literature on credit availability posing a constraint to firm growth, the analysis further looks at how credit availability may impact diffusion of innovation. Higher credit availability as measured by credit-to-GDP and higher availability of venture capital financing both predict greater diffusion of innovation to laggard firms. Since laggard firms are more likely to have lower shareholder financing (Online Annex Table

[33] The gap between the infrastructure index of advanced economies and emerging market economies in the estimation sample is equivalent to 1.38 standard deviations of the infrastructure index. Hence, the impact of closing the gap reflects an increase in laggard firm TFP growth of 1.38*0.04=0.06, where 0.04 is the coefficient estimate of the interaction term between lagged growth of patent families and the standardized infrastructure index. This reflects a near doubling of the impact found for the full sample in emerging market economies (Online Annex Table 2.6.3, column 3).

2.7.4), they are more likely to be credit-constrained, such that policy efforts to enhance credit availability asymmetrically benefits their productivity growth.

Overall, the results indicate that there is heterogeneity in the diffusion of innovation, with laggard firms experiencing slightly more TFP growth from innovation activity in their sector. Higher quality physical and digital infrastructure, human capital and greater credit availability are associated with stronger diffusion of innovation to laggard firms.

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