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Industrial Policies for Innovation: A Cost-Benefit Framework

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ABSTRACT: When and how should governments use industrial policy to direct innovation to specific sectors? This paper develops a framework to analyze the costs and benefits of industrial policies for innovation. The framework is based on a model of endogenous innovation with a sectoral network of knowledge spillovers (Liu and Ma 2023), extended to capture implementation frictions and alternative policy goals. Simulations show that implementing sector-specific fiscal support is only preferable to sector-neutral support under restrictive conditions—when externalities are well measured (e.g., greenhouse gas emissions), domestic knowledge spillovers of targeted sectors are high (typically in larger economies), and administrative capacity is strong (including to avoid misallocation to politically connected sectors). If any of these conditions are not fully met, welfare impacts of industrial policy quickly become negative. The optimal allocation of support entails greater subsidies to greener sectors, but other factors such as cross-sector knowledge spillovers matter. For a sample of technologically advanced economies, existing industrial policies seem to be directing innovation to broadly the right sectors, but to an excessive degree in most economies, including China and the United States.

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WORKING PAPERS

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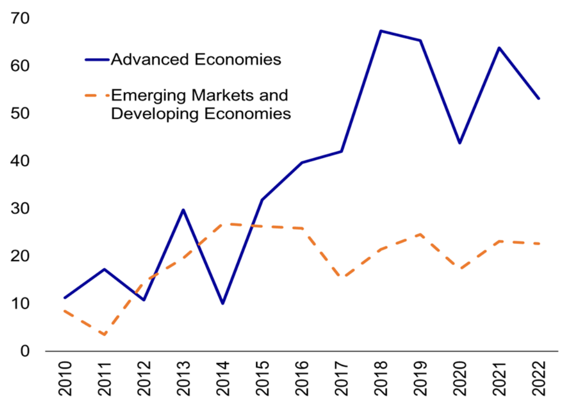
Contents

I. Introduction

The recent strategic push for industrial policies in large economies (Figure 1, panel 1) has brought to the fore the question of whether and under what conditions governments should direct fiscal support toward innovation in specific sectors or technologies. Recent industrial policy initiatives in advanced economies, such as the CHIPS Act and Inflation Reduction Act in the United States, the Green Deal Industrial Plan in the European Union, the New Direction on Economy and Industrial Policy in Japan, and the K-Chips Act in Korea, as well as longstanding policies in emerging market economies like China, share a strong emphasis on innovation in specific sectors, among other objectives. Most packages include fiscal incentives for innovation in green and advanced technology sectors (such as AI and semiconductors) (Figure 1, panel 2), with a heavy reliance on costly subsidies.

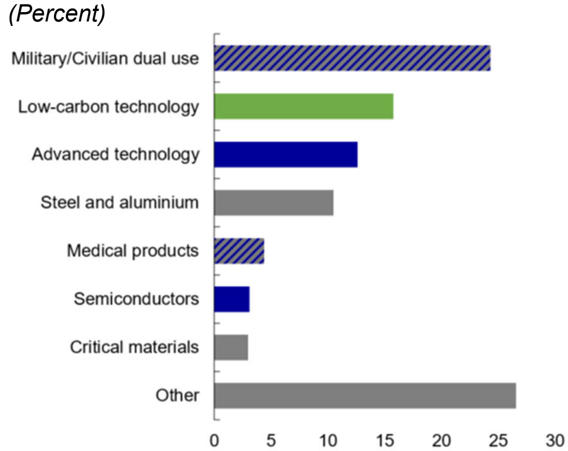
Figure 1. Increasing Use of Industrial Policies for Innovation

1. Share of Industrial Policies
(Percent of total trade policies)



Sources: Juhász et al. (2022), using the Global Trade Alert database.

2. Industrial Policies by Sector, 2023
(Percent)



Sources: Evenett et al. (2024); and IMF Staff estimates.
Note: Classification based on Evenett et al. (2024). Green sectors are highlighted in green, and high-tech sectors in blue. Sectors with blue and gray stripes include technologies that are both advanced and non-advanced.

Technologically advanced economies may want to direct the course of innovation for various reasons, including addressing market failures—externalities related to climate and public health, knowledge spillovers to other sectors, supply chain resilience, or national security. However, historical experience suggests that getting industrial policy right is a tall order (IMF 2024a). Whereas policies may help some firms become more productive, they can also lead to an inefficient allocation of resources. Indeed, an abundance of failed programs in economies with strong institutions shows that it is difficult to avoid policy mistakes. Even when projects succeed in transforming industries, they can incur high fiscal costs and, in some cases, generate negative cross-border spillovers.

This paper develops a framework to assess conditions under which sector-specific fiscal support for innovation ("industrial policy") is preferable to sector-neutral support ("horizontal policy"). The framework builds upon a model of endogenous innovation with a sectoral network of knowledge spillovers from Liu and Ma (2023). In this model, the key benefit of sector-specific support is that it allows to direct innovation towards sectors generating higher knowledge spillovers to other domestic sectors (measured by cross-sector patent citations). This, in turn, raises economy-wide innovation, productivity growth, and welfare.

The main contribution of our paper is to add two extensions to the model that are relevant for evaluating industrial policy. First, we consider different forms of policy implementation frictions—either random policy mistakes or political capture by certain sectors—that lead to misallocation of innovation inputs across sectors. Second, we allow for the government to pursue alternative policy goals such as supporting green innovation. We then quantify how these factors affect the welfare implications of industrial policy, and use the extended framework to describe optimal industrial policy and assess existing policies in different economies.

The simulations show that a large, advanced economy (for example, the United States), optimally targeting support to sectors with larger knowledge spillovers can increase welfare by almost 3 percent compared to an equivalent amount of sector-neutral support. The welfare gains can rise to up to 6 percent when the government considers green innovation goals and redirects support to sectors with a higher share of green patents. Implementation frictions, however, quickly turn the potential benefits of industrial policies into losses, making sector-neutral support preferable. Benefits are also limited for sectors and economies that rely more on foreign knowledge spillovers, as these are less likely to be affected by domestic innovation policy.

Overall, the results suggest that industrial policy for innovation can only be beneficial under fairly restrictive conditions. First, externalities must be correctly identified and precisely measured (for example, carbon emissions). Second, domestic knowledge spillovers from innovation in targeted sectors must be strong. And third, government capacity must be high enough to prevent misallocation (for example, to politically connected sectors).

The framework also sheds light on how to optimally allocate innovation inputs across sectors when the above conditions are in place. While greener sectors should receive more support, there is no one-to-one rule, as the degree to which innovation in each sector spills over to other sectors also plays a big role. Conversely, sectors projected to be more exposed to AI do not necessarily warrant stronger innovation support. Regarding existing policies, we find that leading economies tend to direct innovation support to broadly the right sectors (from the lens of our framework), with a positive correlation of 0.3-0.7 between the actual (observed) and model-implied optimal distributions. However, the intensity of industrial policies, as reflected in the concentration of innovators in certain sectors, is excessive in most economies, and particularly so in China and the United States. In those economies, scaling back the intensity of industrial policies would reduce misallocation and increase productivity growth.

This paper contributes to three separate branches of the economic literature. First, it is related to the research on how innovation policy should interact with knowledge spillovers (Aghion et al., 2005; Bloom, Schankerman, and Van Reenen, 2013, Bloom, Van Reenen, and Williams, 2019; Hopenhayn and Squintani, 2021; Sollaci, 2022; Liu and Ma, 2023). Specifically, most of this literature focuses on finding an optimal innovation policy and measuring its potential benefits. In contrast, we study the welfare effects of possible implementation frictions, showing that even relatively small deviations from the optimal policy can significantly diminish the gains from government intervention.

Second, the paper relates to studies on resource misallocation (Restuccia and Rogerson, 2008; Hsieh and Klenow, 2009; David and Venkateswaran, 2019; Baqaee and Farhi, 2020; Bils, Klenow, and Ruane, 2021), particularly the work that links it with economic growth (Peters, 2013; Garcia-Macia, 2017; Hsieh et al., 2019). In this case, we find that resource misallocation can arise from policy implementation frictions, ranging from policymaker mistakes, lack of clarity on the government's or society's ultimate goals (which can sometimes be contradictory), or through political capture (Acemoglu et al., 2016; Choi et al., 2021; Akcigit, Baslandze, and Lotti, 2023).

Lastly, given the focus on sector-specific subsidies, this paper also contributes to the growing literature on industrial policy (Liu, 2019; Evenett et al., 2024; Juhasz et al., 2022; Juhasz et al., 2023). The paper provides an integrated framework to assess the dynamic implications of industrial policy for innovation across the economy, complementing recent model-based analysis focused on specific industries (Barwick, Kalouptsidi, and Zahur, 2023; Barwick et al., 2024). This exercise cautions against the widespread use of policies to redirect resources towards targeted sectors, unless a strong set of institutional conditions is in place.

The rest of the paper is organized as follows. Section II describes the model. Section III discusses the data and calibration. Section IV presents the simulation results, including the welfare effects of industrial policy under various implementation frictions, levels of economic openness, and alternative goals, as well as the optimal distribution of innovation support across sectors and the assessment of existing policies. Section V concludes.

II. Model

Our theoretical framework builds upon a model of endogenous innovation with a sectoral network of spillovers from Liu and Ma (2023). In this 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 framework also accounts for the share of foreign inflows of knowledge by sector, as foreign innovation is less likely to be affected by domestic innovation policy. We extend this model to (1) capture differences in implementation capacity, whereby governments with weaker institutions make policy mistakes or divert subsidies to politically connected sectors, and (2) account for negative externalities from climate change, which call for redirecting innovation to greener sectors.

A. Set-up

There is a representative consumer with preferences given by

$$V_t = \int_t^{\infty} e^{-\rho(s-t)} \ln C\left(c_s^d, c_s^f\right) ds\,, \tag{1}$$

where ρ is the intertemporal discount rate, $C(.)$ a constant returns to scale preference aggregator, c_s^d a bundle of domestically produced goods, and c_s^f a bundle of foreign goods. Imports of foreign goods are financed by exporting domestic production, and under trade balance we have

$$p_t^f c_t^f = y_t - c_t^d, \tag{2}$$

where the price of the domestic bundle is normalized to 1 (note that economies import and export bundles of goods, removing incentives for a social planner to use R&D allocation to manipulate the terms of trade).

Domestic production is given by

$$y_t = \prod_{i=1}^{K} y_{it}^{\beta_i}\,, \quad \sum_{i=1}^{K} \beta_i = 1 \tag{3}$$

Where $i = 1, \dots, K$ indexes sectors and y_{it} is a sectoral good, produced by aggregating all varieties ν of goods within a sector

$$\ln y_{it} = \int_0^1 \ln\left(q_{it}(\nu)\ell_{it}(\nu)\right) d\nu, \tag{4}$$

with $\ell_{it}(\nu)$ representing the number of production workers hired in variety ν of sector i, and $q_{it}(\nu)$ is the quality of the same variety.

Innovation in each sector benefits from the stock of knowledge of all other sectors, measured as the average quality of all varieties of goods within the sector:

$$\ln q_{it} = \int_0^1 \ln q_{it}(\nu)\, d\nu. \tag{5}$$

Cross-sector knowledge spillovers can come from both domestic and foreign firms. Thus, a firm in sector i that hires s_{it} scientists will have an arrival rate of innovation given by

$$n_{it} = s_{it}\eta_i \frac{\chi_{it}}{q_{it}}\ , \tag{6}$$

where η_i is a sector-specific productivity parameter and χ_{it} represent cross-sectoral knowledge spillovers

$$\chi_{it} = \prod_{j=1}^{K} \left[\left(q_{jt}\right)^{x_{ij}} \left(q_{jt}^{f}\right)^{1-x_{ij}} \right]^{\omega_{ij}}, \qquad \sum_{j=1}^{K} \omega_{ij} = 1. \tag{7}$$

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. Note that the condition $\sum_{j=1}^{K} \omega_{ij} = 1$ imposes constant returns to scale in innovation. However, some sectors may generate more research spillovers than others, i.e., $\sum_{i=1}^{K} \omega_{ij} \neq 1$.

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 $\lambda > 0$, making the innovating firm the technology leader in a product and thus able to price all competitors out. This results in a deterministic law of motion for each sector's knowledge stock

$$\frac{\dot{q}_{it}}{q_{it}} = \lambda \ln\left(\frac{n_{it}}{q_{it}}\right). \tag{8}$$

B. Optimal R&D Allocation and Decentralized Equilibrium

Three main equilibrium results from the model are relevant for the current paper (see proofs and more details in Liu and Ma, 2023): the optimal R&D allocation, the equilibrium allocation in a decentralized economy, and the welfare impact of changing the R&D allocation. To obtain the optimal allocation, we solve a central planner problem, given by

$$V^* = \max_{\{s_{it}, \ell_{it}\}} \int_0^\infty e^{\rho t} \ln C\left(c_t^d, c_t^f\right)\ dt \tag{9}$$

subject to the economy's production function of innovation, the goods (sectoral and final) production function, the trade balance, and the law of motion of domestic knowledge

$$\dot{q}_{it}/_{q_{it}} = \lambda \ln\left(\frac{n_{it}}{q_{it}}\right), \tag{10}$$

obtained from aggregating the innovation upon all varieties ν within a sector.

The solution to this problem is given by an allocation of production workers $\{\ell_{it} \propto \beta_i\}_{i=i}^{K}$ and an allocation of scientists

$$(\boldsymbol{s}^*)' = \boldsymbol{\beta}' \left(\boldsymbol{I} - \frac{\boldsymbol{\Omega} \circ \boldsymbol{X}}{1 + \frac{\rho}{\lambda}} \right)^{-1} \times \frac{1}{\xi} \tag{11}$$

where $\boldsymbol{s} = [s_{it}]$ is the vector of scientist shares, $\boldsymbol{\beta} = [\beta_i]$ is the vector of final good production elasticities, $\boldsymbol{\Omega} = [\omega_{ij}]$ is the matrix of spillover elasticities, and $\boldsymbol{X} = [x_{ij}]$ are the shares of domestic spillovers. The operator ° indicates a Hadamard (or element-wise) product, and ξ is a scaling factor to guarantee that $(\boldsymbol{s}^*)'\boldsymbol{1} = 1$ (the total number of scientists is set to 1 for ease of exposition).

In contrast, in a decentralized economy equilibrium (i.e., in the absence of any policy intervention) the allocation of scientists to each sector is proportional to the sector's share in total output:[1]

$$\boldsymbol{s} = \boldsymbol{\beta}. \tag{12}$$

Note this result is intuitive: this is what the social planner's allocation would look like if there were no cross-sector innovation spillovers (i.e., the term $\boldsymbol{\Omega} \circ \boldsymbol{X} \propto \boldsymbol{I}$ so that sectors only get spillovers from their own innovation), or if the planner infinitely discounted the future ($\rho \to \infty$), thus neglecting any benefits from current R&D to future innovation.

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 any two time-invariant R&D allocations, say from $\boldsymbol{s_0}$ to $\boldsymbol{s_1}$, is

$$W(\boldsymbol{s_1}, \boldsymbol{s_0}) = V(\boldsymbol{s_1}) - V(\boldsymbol{s_0}) = \exp\left(\xi \frac{\lambda}{\rho} (\boldsymbol{s}^*)' \times (\ln \boldsymbol{s_1} - \ln \boldsymbol{s_0}) \right), \tag{13}$$

where, again, $\boldsymbol{s}^*$ is the vector containing the welfare maximizing allocation[2] and ξ the scaling factor from above. Note that this calculation compares total welfare under two different balanced growth paths (induced by the different distributions of R&D resources).

C. Industrial Policy

The optimal allocation of R&D defined above comes from a social planner's problem, where the only constraints to the problem are given by the physical limitations of production functions. As such, this allocation is not a function of any particular policy that might be used to implement it—as long as the government's goals are the same as the planner above.

[1] See Annex A for an example of a decentralized equilibrium.

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

Bearing that in mind, we still show that the optimal allocation *can* be implemented by a government using conventional policies: in this case an R&D subsidy. We assume that governments can choose the rate of subsidies or taxes to innovation inputs (scientist wages) in each sector, with the government budget balanced by lump-sum transfers or taxes (see Annex A for details). "Industrial policy" refers to innovation policies with subsidy or tax rates that vary by sector, while "horizontal policy" refers to policies that set the same subsidy or tax rates for all sectors.

An allocation of scientists to sectors $\hat{\boldsymbol{s}}$ can be implemented via combinations of sector-specific subsidies $\{\sigma_i\}$:

$$\frac{\frac{\beta_i}{1-\sigma_i}}{\sum_{j=1}^{K}\frac{\beta_j}{1-\sigma_j}} = \hat{s}_{it}, \tag{14}$$

where a negative σ_i represents a tax.

The above implies 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 (any resulting increase in the demand for scientists is offset by a corresponding increase in scientists' wages). Thus, only the distribution of subsidies/taxes across sectors matters, not their level, and "horizontal policy" leads to the decentralized economy equilibrium described above.[3,4]

In what follows, we use the decentralized economy as a benchmark to analyze the implications of various types of industrial policies. In the absence of implementation frictions, the government uses industrial policy to maximize V_t and replicates the social planner allocation.

D. Implementation Frictions

In reality, implementation frictions may distort government's policies. Next, we extend the model to consider two types of such frictions. First, we allow for the possibility of political capture, in the sense that the government can favor a larger allocation of resources to politically connected sectors.

[3] This also means that the combination of subsidies and taxes can be set so that lump-sum transfers/taxes are zero without loss of generality.

[4] In practice, however, horizontal policies can affect aggregate innovation. This can happen both by increasing the supply of scientists relative to other occupations, or because different sectors might be exposed to structural fundamentals like education and infrastructure on different degrees. Thus, horizontal policies that affect these fundamentals might still have an effect on the distribution of innovation across sectors.

Second, governments might simply make random mistakes in implementation. In this case, the sectoral allocation is still distorted, but not necessarily towards preferred sectors.

Political Capture. Let $\{\phi_i\}_{i=1}^{K}$, $\sum_{i=1}^{K}\phi_i = 1$ 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:[5]

$$V_t^{pc} = \int_t^{\infty} e^{-\rho(s-t)} \sum_{i=1}^{K} (\beta_i + \theta\phi_i) \ln y_{is}\, ds\,. \tag{15}$$

Under this objective function, the government still cares about the utility of the representative consumer (which weights each sector by β_i) but favors higher output in more politically connected sectors. The parameter θ governs the extent to which those sectors are favored relative to the social planner's weight (note that when $\theta = 0$ the objective function reverts to the 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

$$(\boldsymbol{s^{pc}})' = (\boldsymbol{\beta} + \theta\boldsymbol{\phi})' \left(\boldsymbol{I} - \frac{\boldsymbol{\Omega}\circ\boldsymbol{X}}{1+\frac{\rho}{\lambda}}\right)^{-1} \times \frac{1}{\xi^{pc}}\,, \tag{16}$$

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

$$W^{pc} = \exp\left(\xi\frac{\lambda}{\rho}\,(\boldsymbol{s}^*)' \times (\ln \boldsymbol{s^{pc}} - \ln \boldsymbol{s})\right). \tag{17}$$

Mistakes. Implementation errors need not be "malicious" or serve ulterior motives to misallocate resources. Consider, for example, a collection of random distortions $\{\psi_i\}_{i=1}^{K}$ in the government's objective function

$$V_t^{m} = \int_t^{\infty} e^{-\rho(s-t)} \sum_{i=1}^{K} (\beta_i + \theta\psi_i) \ln y_{is}\, ds\,. \tag{18}$$

As with political capture, these distortions change the optimal weights attributed to each sector in the government's objective function, and θ controls the size of such mistakes. By symmetry, the same equilibrium conditions as with political capture apply, with $\boldsymbol{\psi}$ replacing $\boldsymbol{\phi}$**.**

[5] Following Liu and Ma (2023), define $\bar{C}(y_t, p_t^f) = \max_{c_t^d, c_t^f} C(c_t^d, c_t^f)\ s.t.\, y_t - c_t^d = p_t^f c_t^f$. Since $C(.)$ features constant returns to scale, we can re-write the maximized consumption aggregator as $\bar{C}(y_t, p_t^f) = y_t C^*(p_t^f)$ for some function $C^*(.)$. Given the logarithmic preferences and the fact that p_t^f is taken as given, maximizing the representative consumer's objective function V_t is the same as maximizing $\int_t^{\infty} e^{-\rho(s-t)} \ln y_s\, ds$. Plugging in the production function for y_t and adding the weights on political capture results in the objective function above.

E. Alternative Goals

Finally, we also allow the government to add alternative goals in its objective function—specifically a preference for green innovation.[6] 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

$$V_t^{gg} = \int_t^{\infty} e^{-\rho(s-t)} \sum_{i=1}^{K} \left(\tilde{\beta}_i + \theta\phi_i\right) \ln y_{is} \, ds \,. \tag{19}$$

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. Note that in this case the social planner's weight on each sector is no longer given by the consumption elasticity β_i but by $\tilde{\beta}_i$. The same results as above follow with $\tilde{\boldsymbol{\beta}}$ replacing $\boldsymbol{\beta}$.

We end this section with a word about the interpretation of the following results. As is the case with any model, the framework we use in this paper is a simplification of reality. Several generalizations of the model are already covered by Liu and Ma (2023), including: mobility between production workers and scientists (instead of there being a fixed supply of both), having an endogenous innovation network, sector-specific innovation step-sizes, and allowing for large open economies (that internalize that their policy decisions might affect innovation in other economies). In general, the basic results of the model remain unchanged. Nevertheless, due to the constraints such as a balanced growth path equilibrium, or the absence of switching costs between sectors, our results are better understood as long-run impacts of industrial policy, focusing on the distribution of innovation resources (not their level).

III. Data and Calibration

We calibrate the model separately for 7 highly innovative economies, ranging from small open economies to large economies: Germany, Japan, Korea, Mainland China, the Netherlands, Taiwan Province of China (P.O.C.), and the United States. Sectors are defined at the 3-digit International Patent Classification (IPC) level, giving us a total of 117 sectors (after removing sectors where there are no patents in any of the economies in the sample). The calibration of parameters in the baseline model (without extensions) follows Liu and Ma (2023). Table 1 summarizes the parameters and data used for calibration, which are explained in more detail below.

[6] While the ultimate goal would be to mitigate damages from climate change, for tractability this model does not model climate change or greenhouse gas emissions, and instead focuses on the allocation of innovation resources to greener sectors.

Table 1. Calibrated Parameters

Parameter	Interpretation	Data/source	Value
λ	Innovation step size	Liu and Ma (2023)	0.5
ρ	Discount rate	Liu and Ma (2023)	0.5
β_i	Elasticity of consumption	World Input-Output Database	Share of value added
ω_{ij}	Elasticity of spillover	PatStats	Share of citations
x_{ij}	Share of domestic spillovers	PatStats	Share of domestic citations
ϕ_i	Political connectedness	Díez, Fan, and Villegas-Sánchez (2021)	Normalized markup
α_i	Share of green innovation	PatStats, IPC Green Inventory	Share of green patents

The vector $\boldsymbol{\beta}$ matches the share of value added in each sector using the World Input-Output Dataset (WIOD, Timmer et al., 2015). These data are available only until 2014, but the value added shares are remarkably stable over time. Industry codes in the WIOD are matched to IPC categories using the concordance developed by Liu and Ma (2023), who kindly supplied their data. The sector value added shares are calculated separately for each of the economies in the sample.

The matrix of spillover elasticities $\boldsymbol{\Omega}$ is calibrated using patent shares from the PatStats database, given by

$$\omega_{ij} = \frac{Cites_{ij}}{\sum_k Cites_{ik}}. \tag{20}$$

Figure 2 shows those shares for select sectors (IPC C21—D06, spanning in broad terms: organic chemistry and related industries, metallurgy and related processes, and fibers and textiles) in the United States. 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 (indicated by the dark blue 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 most other sectors in the figure, but the reverse is not true.

As is the case with value added, the cross-sector citation shares are very stable across time. An average across 2015-2019 is used for consistency with the shares of foreign spillovers (see below; using other time periods yields very similar results). The network of citations is also highly correlated across economies, although we do find differences across economies in how "specialized" some sectors are. For example, citations in the United States tend to be more "spread" across other sectors (i.e., the off-diagonal citation shares are larger) than in other economies in our sample: the median share of self-citations across sectors in the United States is about 38 percent, while the same number in other economies is closer to 50 percent. In general (for a non-degenerate distribution), more spread-out spillovers across sectors tend to increase the potential gains from industrial policy.

Figure 2. Sectoral Citation Network, Select Sectors, the United States

(Percent of citations of other sectors)

organic chemistry	22.7	5.0	4.4	2.2	0.6	9.1	0.1	0.0	0.0	0.0	0.6	0.2	0.1	0.5	0.0	0.0	0.0	0.0	0.0	0.1
organic macromolecular compounds	6.3	44.6	6.8	1.0	1.0	0.9	0.0	0.0	0.0	0.0	0.2	0.2	0.0	0.0	0.4	0.0	0.0	0.1	0.0	0.2
dyes, paints, polishes, natural resins & adhesives	7.3	12.9	28.7	1.2	1.5	0.5	0.0	0.0	0.0	0.1	1.6	0.2	0.5	0.0	0.0	0.0	0.0	0.0	0.0	0.2
petroleum, gas or coke industries	10.9	9.9	2.0	47.5	0.6	0.4	0.1	0.0	0.1	0.2	0.5	0.1	0.0	0.0	0.0	0.1	0.0	0.0	0.0	0.1
animal or vegetable oils & fats	7.0	2.6	2.8	0.5	43.6	7.4	0.0	0.0	0.0	0.0	1.0	0.1	0.0	0.0	0.1	0.0	0.0	0.0	0.0	1.5
biochemistry, beer, microbiology & enzymology	13.1	0.5	0.5	0.2	2.1	37.1	0.1	0.0	0.0	0.0	0.0	0.0	0.0	1.3	0.0	0.0	0.0	0.0	0.0	0.1
sugar industry	7.8	7.2	1.0	3.4	1.9	25.9	12.1	0.0	0.0	0.0	0.3	0.0	0.0	0.0	0.1	0.0	0.0	0.0	0.0	0.3
skins, hides & pelts or leather	5.2	23.8	4.2	0.0	6.0	0.5	0.0	8.0	0.0	0.2	0.0	0.0	0.0	0.0	1.1	0.0	0.0	0.7	0.0	3.6
metallurgy of iron	0.1	0.0	0.1	0.5	0.0	0.0	0.0	0.0	23.6	16.8	4.6	0.3	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
metallurgy, ferrous or non-ferrous alloys	0.4	0.4	0.4	0.2	0.0	0.1	0.0	0.0	3.8	34.9	3.5	2.7	0.5	0.0	0.0	0.0	0.0	0.0	0.0	0.0
coating metallic material	0.7	0.6	1.4	0.2	0.2	0.1	0.0	0.0	0.2	0.4	32.3	1.0	1.9	0.0	0.0	0.0	0.0	0.0	0.0	0.0
electrolytic or electrophoretic processes	1.6	1.4	1.0	0.3	0.2	0.7	0.0	0.0	0.1	1.2	3.5	29.6	0.1	0.0	0.1	0.0	0.0	0.0	0.0	0.0
crystal growth	0.2	0.2	1.3	0.3	0.0	0.6	0.0	0.0	0.0	0.2	7.1	0.3	33.5	0.0	0.3	0.0	0.0	0.0	0.1	0.0
combinatorial technology	13.3	0.2	0.2	0.0	0.0	39.6	0.0	0.0	0.0	0.0	0.1	0.1	0.0	5.2	0.0	0.0	0.0	0.0	0.0	0.0
natural or man-made threads or fibres	1.0	14.2	1.3	0.2	0.3	0.2	0.0	0.0	0.0	0.0	0.4	0.4	0.0	0.0	26.5	3.8	0.9	5.2	0.0	2.3
yarns	0.4	9.1	0.5	0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	15.7	21.7	5.5	5.5	0.4	3.6
weaving	0.1	2.5	0.3	0.0	0.0	0.0	0.0	0.0	0.0	0.1	0.3	0.1	0.0	0.0	1.9	3.3	32.8	6.1	0.2	2.7
braiding	0.3	2.5	0.7	0.0	0.3	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	3.5	1.3	1.9	34.3	0.9	1.1
sewing	0.0	0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.6	0.6	0.7	1.4	68.8	1.4
textiles	0.1	1.3	0.6	0.1	0.6	0.0	0.0	0.1	0.0	0.0	0.1	0.0	0.0	0.0	0.9	0.5	0.2	0.5	0.5	53.4

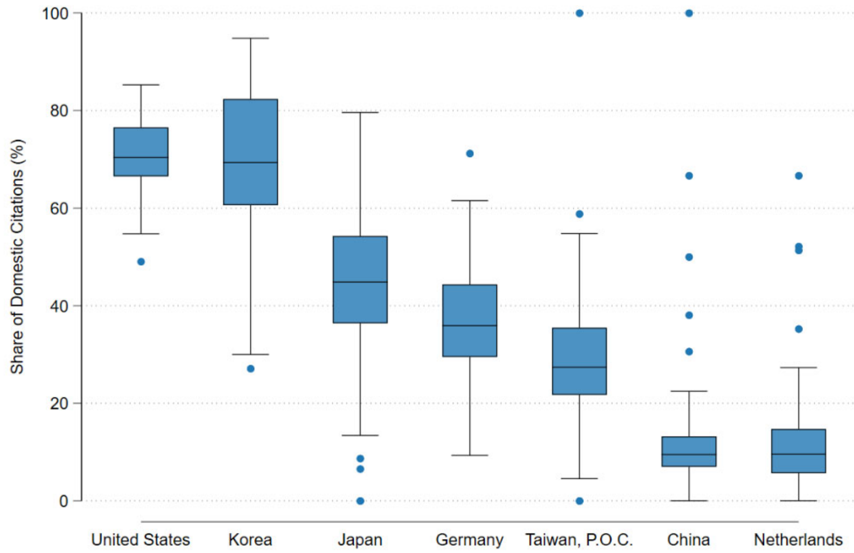
Sources: European Patent Office PatStats and IMF staff calculations.
Note: Sectors on the left are the ones citing, columns indicate the sector cited (same order as row). Blue entries indicate larger shares, and diagonal entries are sector self-citations.

The matrix of foreign spillovers $\boldsymbol{X}$ is calibrated with the share of foreign citations in each ij sector pair averaged over 2015-2019, also using PatStats. This time frame is chosen to avoid including the pandemic years in the sample, which might have temporarily shifted the innovation investments in most economies. In addition, we avoid including years before 2015 because there have been significant shifts in the share of domestic citations in some economies (even in this timeframe; see figures below).

We assign patents to an economy based on the location where most of its inventors reside. In case of a tie between two economies, assignment is based on the economy of the patent authority that published the patent: if it coincides with any of the economy majorities across inventors, the patent is attributed that economy; if not, it is left as undetermined. Figure 3 shows the distribution of the share of domestic citations across sectors by economy, with a median ranging from about 70 percent in the United States to about 10 percent in many European advanced economies. Figure 4 shows the evolution of this share: while it has been, on average, stable for most economies, there is a significant increase in domestic citations in Korea and Taiwan P.O.C.

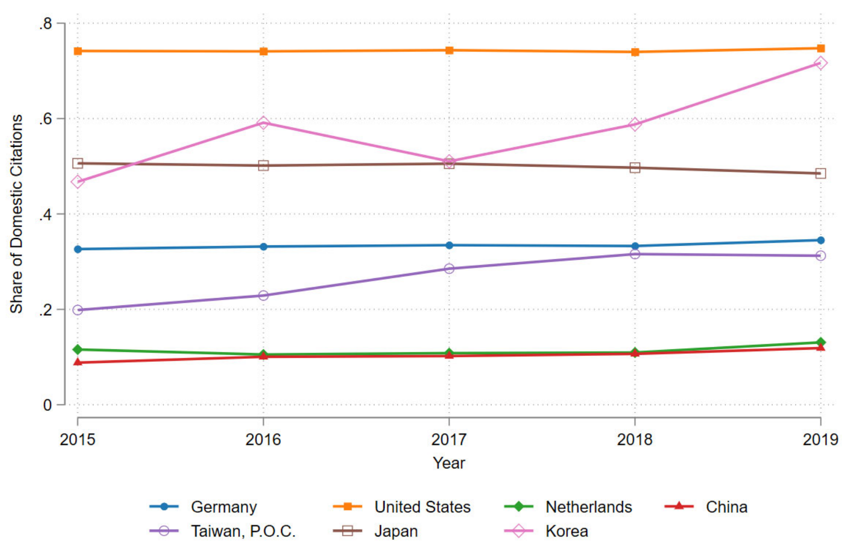
Figure 3. Domestic Knowledge Spillovers, Select Economies

(Patent citations from own economy, percent of total)



Sources: European Patent Office PatStats and IMF staff calculations.
Note: Each box spans the 25th, 50th (middle line), and 75th percentiles of the share of domestic citations across sectors for each country in the sample, between 2015 and 2019. The whiskers show the upper and lower adjacent values (defined as the 75th or 25th percentiles plus/minus 1.5 times the inter-quantile range) and the dots are outside values (observations above or below the adjacent values).

Figure 4. Evolution of the Average Share of Domestic Citations



Sources: European Patent Office PatStats and IMF staff calculations.
Note: The chart on the shows the share of domestic patent citations for each country and year in our sample.

The degree of political connectedness is proxied by two alternative measures. First, we employ the average size of markups in each sector, estimated by Díez, Fan, and Villegas-Sánchez (2021) using firm-level data from the Orbis dataset. Intuitively, firms operating in sectors with higher markups should have more resources and incentives to invest in political connects, as they would capture a higher share of benefits provided by the government (due to lower competition).

The average markup within each industry is matched to its corresponding IPC categories using the probabilistic crosswalk by Lybbert and Zolas (2019). For symmetry with the value-added shares, political connectedness is defined as

$$\phi_i = \frac{\mu_i - 1}{\sum_i \mu_i - 1} \tag{20}$$

where μ_i is the sector's average markup. For ease of comparison, the vector of mistakes ψ_i is bootstrapped from the observed distribution of the ϕ_i shocks, but with random sampling to ensure independence of policy mistakes relative to sector characteristics.

However, market power across sectors might also capture other industry characteristics that are unrelated to political connectedness. To address this issue, we employ a second measure of political influence: the share of lobbying expenditures. In this case, we equate ϕ_i to the sectoral share of lobbying expenses in the United States between 1999 and 2020, calculated using the LobbyView dataset (Kim, 2018). Once again, the industry codes are matched to the IPC sectors using the crosswalk by Lybbert and Zolas (2019).

While lobbying expenses are arguably more directly related to political influence, this measure also comes with caveats. First, it is only available for the United States, and likely reflects particular institutional features of that country. Second, some of the largest lobbying expenses come from sectors that do not patent (e.g., banking) and are therefore excluded from the analysis. As such, both measures of political connectedness should be seen as complementary; and as we will show below, lead to similar results in our framework.

The share of green patents is obtained by computing the number of patents at each 4-digit IPC category listed in the IPC green inventory, which identifies sectors 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, averaged between 2010 and 2020.

The weights $\{\alpha_i\}$ are proportional to the share of green patents, but normalized such that the welfare gains from green industrial policy are 2 percentage points larger than the gains from "regular" industrial policy (measured using the objective function that includes green innovation as an explicit goal). Specifically, we define $\alpha_i = \kappa g_i$, where g_i is the share of green patents in sector i and κ is a constant. Let $\boldsymbol{s^{gg}}$ be the optimal allocation of scientists when the government has green goals and there are no implementation frictions—i.e., it maximizes the objective function $V_t^{gg}\big|_{\theta=0}$. The constant κ is chosen so that

$$W^{gg}(\boldsymbol{s^{gg}}, \boldsymbol{s}^*) = \exp\left(\xi^{gg}\frac{\lambda}{\rho}\,(\boldsymbol{s^{gg}})' \times (\ln \boldsymbol{s^{gg}} - \ln \boldsymbol{s}^*)\right) = 1.02\,. \tag{21}$$

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. Due to the uncertainty around this number and the possibility that margins other than higher innovation on green sectors contribute to emission reductions, we also consider an alternative calibration where this gain is reduced to 1 percentage point instead.[7]

IV. Results

A. Implementation Frictions

The framework presented above allows us to simulate the welfare implications of industrial policy for innovation (i.e., reallocating scientists across sectors, for example through targeted subsidies). For a large, advanced economy like the United States, targeting support to sectors with larger knowledge spillovers can increase welfare by just under 3 percent (in consumption equivalent terms) compared with an equivalent amount of sector-neutral support (Figure 5). As explained above, those gains come from aligning the amount of research done in a sector with the amount of spillovers that research produces, thereby increasing the productivity of the whole economy. Those gains, however, assume no misallocation of fiscal support.

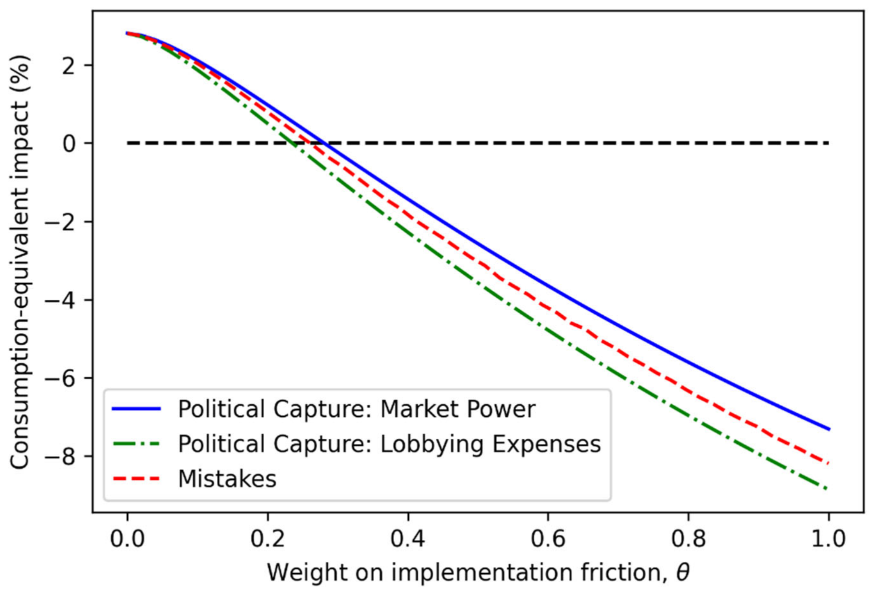
Implementation challenges can lower the economic and social benefits of industrial policy. The model simulations show that as the degree of political capture increases, industrial policy can quickly result in welfare losses. Our analysis starts by employing sectoral markups to proxy for a sector's political influence (see above), in line with evidence that firms with larger market shares tend to employ more politicians per worker (Ackigit, Baslandze, and Lotti, 2023), and political connections can drive the market valuation of listed firms and allocation of government spending (Acemoglu et

[7] Note that those numbers are still a relatively conservative estimate of the cost of climate inaction, with recent research finding the welfare cost to be over 30 percent (Bilal and Känzig, 2024).

al., 2016; Choi, Penciakova, and Saffie, 2021). As shown in the figure, as the government gives more weight to political influence in the design of industrial policy, the welfare gains diminish. When the weight θ reaches about 0.3 (30 percent of the weight given to the sector consumption elasticities), welfare gains from industrial policy turn into losses.[8]

Figure 5. Simulated Welfare Impact of Industrial Policy, the United States

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



Sources: European Patent Office PatStats, World Input-Output Database, Díez Fan, and Villegas-Sánchez (2021), Kim (2018), and IMF staff calculations.

Note: political capture measured using normalized sector markups from Díez, Fan, and Villegas-Sánchez (2021) and the share of lobbying expenses, calculated from the LobbyView database (Kim, 2018). Mistakes are generated by reshuffling markups across sectors, eliminating any systematic relationship between markups and political clout.

Next, we repeat the exercise above using an alternative measure of political influence: the share of lobbying expenses across sectors in the United States. As shown in Figure 5, the welfare gains are qualitatively similar to the exercise that uses markups to proxy for political connectedness. Quantitatively, the distortions towards sectors with more market power are less costly than distortions towards sectors that spend more on lobbying—likely because sectors with large innovation spillovers also have more market power (since some level of market power is needed to encourage firms to innovate). The difference is, however, small when compared to the total welfare

[8] As a quantitative benchmark, a weight θ=0.5 leads to a misallocation of resources equivalent to 10 percent of the overall misallocation gap between the United States and large emerging market economies (Hsieh and Klenow 2009).

effects of such distortions. Indeed, it appears that the measure of political influence is less important than the weight that it is given when implementing the policy.

More broadly, the effectiveness of industrial policies can also be hindered by information asymmetries between the government and firms, such as mislabeling of projects, inefficient government administration, inertia in policies (Juhász, Lane, and Rodrik 2023), and uncertainty about—or mismeasurement of—the social benefits. The dashed red line in Figure 5 considers precisely this case, where political influence ϕ_i is replaced by a random shock ψ_i (see section II.D). For ease of comparison with the results involving political capture, the shocks ψ_i are randomly drawn from the observed vector $\{\phi_i\}$, thus preserving the same distribution (but eliminating systematic correlation between $\{\psi_i\}$ and political influence). To construct the expected welfare loss from mistakes, we draw the shock ψ_i for each sector and calculate the welfare loss from the resulting allocation of resources. For each value of θ, we repeat this process 500 times and average the resulting welfare loss to calculate the values shown in the figure.

The results, perhaps surprisingly, show that mistakes are just as harmful to welfare as political capture. In fact, they can be slightly worse than the calibration of political capture with markups, because there is a small positive correlation between market power (i.e., political influence) and the spillovers produced by sectors in the United States. It is, of course, possible that the "size" of shocks relative to mistakes is lower than those relative to political capture (that is, $E[\psi_i] < E[\phi_i]$), making their welfare impact lower (equivalent of having a lower θ for mistakes). But in practice it is likely that both shocks have the potential to affect industrial policy design, making transparency and institutional capacity extremely important for the success of such undertaking.

B. Economy Openness

Not all economies benefit equally from industrial policy. The ability to influence cross-sector knowledge spillovers is generally more limited in small or more open economies because a larger share of their knowledge flows come from abroad (Figure 6). More open economies are also less able to complement R&D support with production or demand-side subsidies, as they are more integrated in global markets and supply chains.

Figure 6 illustrates this point by comparing the potential welfare gains (under no implementation frictions) in seven economies with varying degrees of domestic spillovers (measured by share of domestic citations across sectors). Note that in this exercise the consumption elasticities $\boldsymbol{\beta}$, the spillover matrix $\boldsymbol{\Omega}$, and share of domestic citations $\boldsymbol{X}$ are all economy specific. However, differences in domestic citations are undoubtedly the biggest driver of the variation in welfare gains.

Our results indicate that the United States has the largest potential gains from redirecting innovation, as about 70 percent of its patent citations are domestic; Korea and Japan follow, with the second and third largest shares of domestic citations as well. Note that the welfare results shown are economy-bound, not global. This is why the share of domestic citations becomes important: if most knowledge spillovers come from patents produced in other economies, domestic policies cannot directly affect those knowledge flows and lose effectiveness. This suggests that smaller economies, which usually have a low share of domestic citations, can coordinate their policies to account for the knowledge spillovers between each other (an example is the European Union Horizon Europe program) and become more effective in promoting welfare.

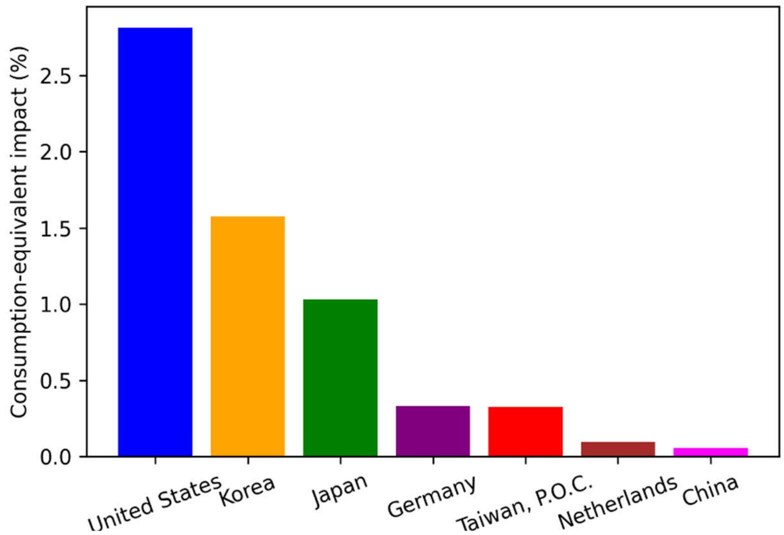
Our analysis also implies another avenue for potential welfare gains: even if the average share of domestic citations is small, its distribution also matters—especially if it is concentrated among a few sectors where the economy has a comparative advantage in innovation. This can help to explain why the model predicts similar welfare gains from industrial policy for economies like Taiwan P.O.C. and Germany: even though the average share of domestic citations in Germany is quite a bit larger than in Taiwan P.O.C., the latter focuses its innovation efforts on a few key sectors where companies already have a comparative advantage and thus have a very high share of domestic citations. This idea also provides a potential explanation for the apparent success of industrial policies in some Asian tigers in the past (Cherif and Hasanov, 2019).

An important corollary of these findings is that geoeconomic fragmentation could be self-reinforcing and hard to reverse. This is because less open, technologically advanced economies tend to have higher domestic spillovers, and, as such, greater incentives to implement industrial policies, which often entail preferential treatment for domestic industries (Evenett et al., 2024; IMF, 2024b). As the majority of the stock of knowledge is imported even for most economies at the technology frontier, policies discriminating against foreign firms can prove self-defeating, and trigger costly retaliation.

Finally, we note that results presented here assume that governments take the path of foreign innovation as given. For large economies, knowledge spillovers to other economies could be beneficial if they improve the quality of imported products. On the other hand, knowledge spillovers could allow competitors to gain global market shares, spurring economies to restrict knowledge outflows (Garcia-Macia and Goyal, 2020). As such, assuming that governments account for foreign knowledge spillovers could either amplify or mitigate the gains from industrial policy.

Figure 6. Simulated Welfare Impact of Industrial Policy, Select Economies

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



Sources: European Patent Office PatStats, World Input-Output Database, and IMF staff calculations

Note: The figure shows potential welfare gains from the optimal industrial policy assuming there are no implementation frictions.

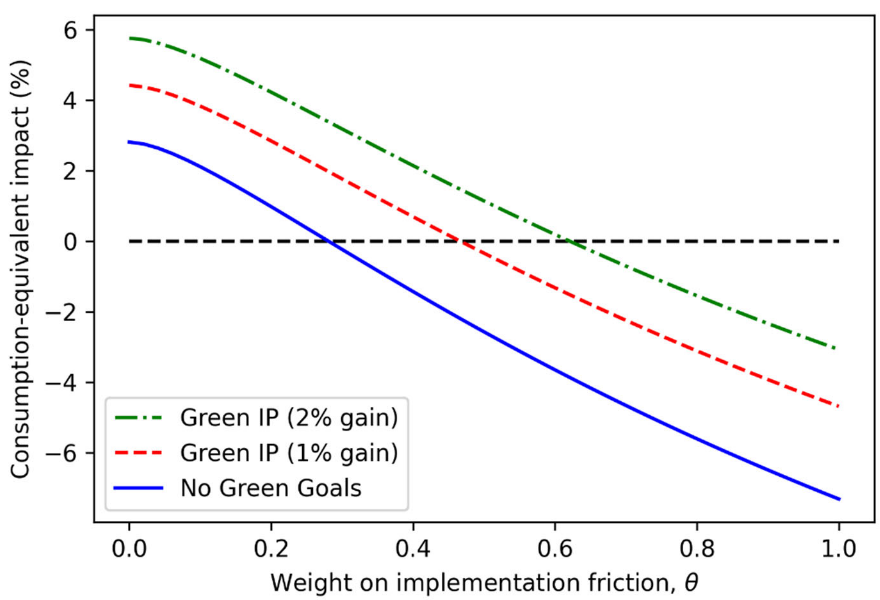
C. Alternative Goals

Next, we ask how welfare is impacted if industrial policy also aims to address other market failures, such as increasing innovation in greener sectors (which provide externalities related to mitigating climate change). Figure 7 repeats the exercise shown in Figure 5, but under alternative objective functions. The baseline (no green goals) curve shows the welfare effect of implementing the policies discussed above (it is the same as the blue line in Figure 5). The two other curves indicate the welfare gains from incorporating green innovation into the government's objective function, under the two alternative calibrations: one that increases the welfare gain relative to "regular" industrial policy (under no implementation frictions) by 2 percentage points (Tol, 2024), and one that increases it by 1 percentage point.

Considering green innovation goals increases the potential for industrial policy to generate welfare gains, which can rise to up to 6 percent absent implementation frictions. This is not an obvious result, however, as it depends on the sector-level correlation between green intensity (measured by the share of green patents) and the strength of knowledge spillovers. For a sufficiently negative correlation, adding green goals may lead to a *decline* in welfare, as it would require targeting conflicting objectives.

Note also that Figure 7 plots welfare gains under three alternative scenarios that include three *alternative objective functions*—recall from Section II that the welfare gain from moving between two allocations $\boldsymbol{s_1}$ and $\boldsymbol{s_0}$ depends on the optimal allocation under the current objective function, $\boldsymbol{s}^*$. Since the objective function for the government is different in each case in the figure, so is the optimal allocation $\boldsymbol{s}^*$. This is why the increase in welfare shown in the figure when $\theta = 0$ is larger than 1 and 2 percent for the orange and green curves, respectively. In those cases, welfare increases because adding green innovation in the objective function moves the optimal allocation of resources farther away from the allocation without industrial policy. Annex B discusses the welfare effects of green industrial policy for a fixed parametrization of the objective function, showing the impact of implementing the baseline industrial policy when the government has green goals.

Figure 7. Welfare Gains of Industrial Policy with Green Goals
(Consumption-equivalent change relative to no industrial policy, percent)



Sources: European Patent Office PatStats, World Input-Output Database, Díez, Fan, and Villegas-Sánchez (2021), IPC Green Inventory, and IMF staff calculations.
Note: The figure shows the welfare gains from the optimal industrial policy under three scenarios: two scenarios where the government explicitly includes green innovation as one of its goals (scenario 1 increases welfare of the optimal policy by 2 percentage points relative to climate inaction, while scenario 2 increases welfare by 1 percentage point), and one scenario where green innovation is not an explicit goal. Implementation friction is measured by political favoritism towards sectors with higher average markups, as estimated by Díez, Fan, and Villegas-Sánchez (2021).

Another result of including green goals into the objective function is that it slightly attenuates the negative effects of political capture: the welfare curves that incorporate green goals are slightly flatter. This is due to a small but positive correlation between market power (our measure of political influence) and green intensity of a sector. Taken together, these features allow for positive welfare gains under a broader range of weights on political influence: $\theta > 0.5$ for the 1-percentage-point calibration, and $\theta > 0.7$ for the other.

D. Allocating Support Across Sectors

So far, we have mostly discussed the net welfare effects of industrial policy. But our framework also allows to shed light on how industrial policy should allocate R&D across sectors. We continue to assume that the government has green goals in its objective function and explore the distribution of scientists across sectors under optimal policies.
Figure 8 shows that while greener sectors do receive higher support, the relationship is not one-to-one: the degree to which innovation in each sector benefits other sectors also plays a big role. Not all green sectors are equally central in terms of their knowledge spillovers, and knowledge can spill over between green and brown sectors over time, diluting the effects of targeting green sectors.

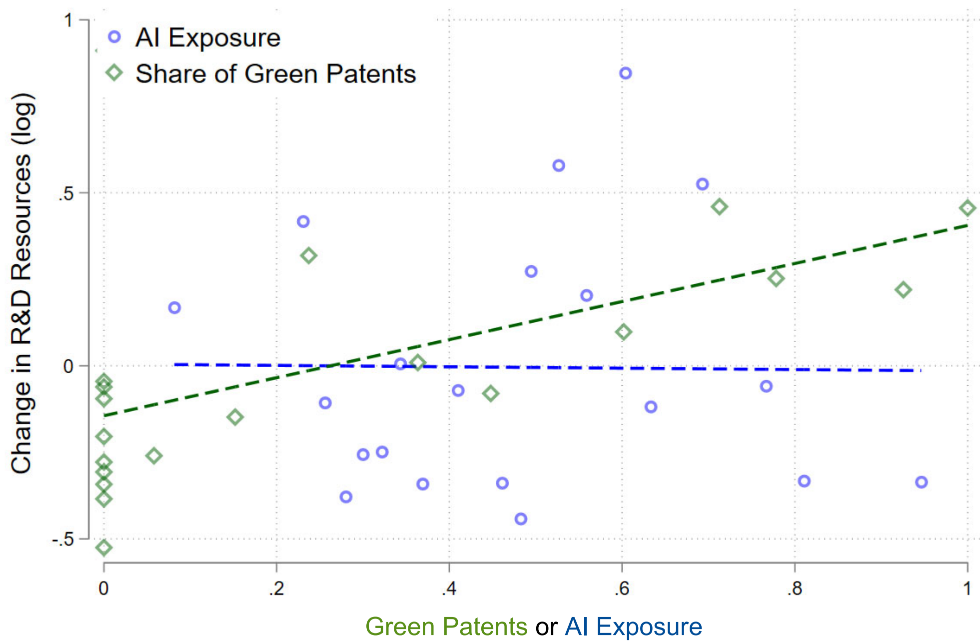
Another important point to keep in mind is that green innovation is only one of multiple (and sometimes contradictory) objectives that governments might have. To that end, having clear objectives from the start becomes extremely important for the success of industrial policy. To make that point, we look at another important goal for innovation policy across large economies: artificial intelligence (AI).[9]

Figure 8 also correlates the level of support given to sectors under the optimal policy (with green goals) and their exposure to AI, obtained from Felten, Raj, and Seamans (2021).[10] The simulation results show that, in contrast to green sectors, sectors currently projected to be more exposed to AI may not necessarily warrant higher fiscal support. This result is partly because sectors more exposed to AI are not necessarily greener, highlighting that different potential goals for industrial policy do not necessarily correlate. However, and perhaps more surprising, this also indicates that sectors more exposed to AI do not necessarily produce more spillovers to other sectors (of course, innovation in AI technology itself could lead to higher research spillovers, but a disaggregation of AI inputs by sector is not currently available in the data).

[9] For example, through initiatives such as AI Next and AI Institutes in the United States, or the European Union's Partnership on AI, Data and Robotics, among others. In addition, much of industrial policy has also indirectly targeted AI through some of its key inputs, such as semiconductors.

[10] The index of exposure is normalized so that it is contained in the interval [0,1], and the data is matched to IPC categories using the crosswalks by Lybbert and Zolas (2019).

Figure 8. Optimal R&D Support by Sector's Share of Green Patents and AI exposure
(Change in R&D relative to no industrial policy, in logs)



Sources: European Patent Office PatStats, IPC green inventory, Felten, Raj, and Seamans (2021) index of AI exposure, and IMF staff calculations.
Notes: The dashed line shows the average increase in a sector's R&D support (relative to uniform support) as the green intensity (green) or the AI exposure (blue) of the sector increases. AI exposure is measured using a normalized version of the index by Felten, Raj, and Seamans (2021). Sectors are aggregated into 20 bins and the y-axis is rescaled to a zero mean.

E. Assessing Existing Policies

Lastly, we use the framework to assess the existing distribution of R&D in the economies in our sample. For this exercise, we look at how the optimal model-generated distribution of scientists (under the specification that includes green goals, but assuming no implementation frictions) compares with the actual distribution of inventors (patent authors) in each economy of our sample.[11] The share of inventors in each economy-sector are again calculated using PatStats by matching the names of all authors in a given patent to their addresses.[12]

[11] The same exercise was run under the specification without green goals, leading to very similar findings.
[12] Because the publication of a patent is a fundamentally stochastic event, some inventors might not publish patents every year. To avoid bias from undercounting the number of scientists working in a sector, we "fill the gap year" for each inventor—for example, if a person published a patent in year t and another patent in year $t+k$, we assume that person is also actively working in R&D in all years $t+j,\ 0<j<k$. Also note that an inventor that publishes patents in different sectors will contribute to the count of scientists working in all of those sectors; the same is true for inventors that have addresses in multiple economies.

The first 2 columns of Table 2 compare the concentration of inventors in the data and in the model-generated optimal distribution by calculating the Herfindahl-Hirschman index (HHI) using 3-digit IPC sectors. While the implied concentration is at first glance not that high (the United States Department of Justice considers markets with an HHI below 1000 to be not concentrated[13]), note that our calculation is based on relatively broad sectors on the economy, and not firms within specific markets. More importantly, we find large differences between the optimal and current concentration in many economies.

The third column in the table shows the ratio between the HHI under the optimal industrial policy and the HHI of the current distribution of inventors. In the case of the two largest economies in our sample—the United States and China, which are also the largest investors in industrial policy—sectoral concentration would fall by half if the optimal policy was adopted. This suggests that both economies' current policies are diverting too many resources to a few chosen sectors, at least relative to the amount of knowledge spillovers that those sectors produce. In terms of concentration, the European economies in the sample (Germany and the Netherlands) are currently similar to—or even less concentrated than—what the model suggests as the optimal policy. Other Asian economies (Japan, Korean, and Taiwan P.O.C.) are in between the above-mentioned cases. An important caveat is that some of the "excess" concentration in the data could be due to certain sectors being intrinsically more "patentable" than others, rather than to the effect of policies. Yet, such sectoral differences in patentability are likely to be similar across economies, and should not explain the large differences in concentration observed across economies.

Finally, the last column in Table 2 shows that the correlation between the optimal and current distribution of inventors is relatively high in most cases. China again presents the lowest correlation between model and data, indicating that not only that few sectors are receiving disproportionate support, but also that those sectors are not necessarily the ones that produce the highest spillovers to the economy. In contrast, Korea and Taiwan P.O.C. display the largest correlation between observed and optimal distributions, likely reflecting their targeted support to sectors where they have a larger comparative advantage (and thus have larger domestic citations and larger spillovers from R&D). In this metric, the United States is around the middle of the distribution, displaying a considerably larger correlation than the economies at the bottom, but also with significant room for improvement.

[13] See https://www.justice.gov/atr/herfindahl-hirschman-index.

Table 2. Optimality of Existing Industrial Policies for Innovation, Select Economies

Economy	Observed HHI	Optimal HHI	HHI Ratio (Optimal/Observed)	Correlation (Optimal, Observed)
China	557	278	0.50	0.31
United States	528	264	0.50	0.56
Taiwan, P.O.C.	497	388	0.78	0.70
Japan	367	320	0.87	0.56
Korea	372	270	0.73	0.71
Netherlands	343	355	1.03	0.35
Germany	302	325	1.07	0.60

Sources: European Patent Office PatStats, World Input-Output Database, IPC Green Inventory, and IMF staff calculations.
Notes: HHI = Herfindahl-Hirschman concentration index at the 3-digit IPC sector level. A higher HHI indicates that innovation (as measured by patents) is more concentrated in a few sectors.

V. Conclusions

This paper develops a framework to assess the net benefits of industrial policy for innovation. Overall, the results suggest governments should be cautious. Even as multiple social goals—most prominently emissions reductions—call for higher innovation in some sectors than others, implementing industrial policies effectively is challenging. It requires sufficient information—including on the nature of market failures and structure of the economy—, administrative capacity, and influence over global innovation flows.

Tentative evidence suggests that leading economies are directing innovation to broadly the right sectors, but to an excessive degree in most cases. Governments deploying industrial policies should strengthen technical capacity to vet subsidized projects, establish clear benchmarks, conduct exhaustive assessment of fiscal costs and risks, recalibrate support as conditions change, and foster competition.

The framework in this paper provides general guidelines to assess industrial policies for innovation across sectors and economies. More granular research is needed to analyze concrete sectoral policies, as well as policies that employ instruments other than innovation subsidies (e.g., other types of subsidies and tax incentives, credit allocation, trade restrictions, or regulatory advantages), or differentiate between firms within a sector (e.g., national champions).

Finally, the framework also abstracts from strategic interaction between economies. In a context of growing geoeconomic fragmentation, strategic considerations may lead to policy actions that diverge from welfare maximization. All economies should avoid inward-looking policies that would stymie the world's innovative capacity and slow down technology diffusion and productivity growth.

References

Acemoglu, Daron, Simon Johnson, Amir Kermani, James Kwak, and Todd Mitton. 2016. "The Value of Connections in Turbulent Times: Evidence from the United States." *Journal of Financial Economics* 121 (2): 368–391.

Aghion, Philippe, Nick Bloom, Richard Blundell, Rachel Griffith, and Peter Howitt. 2005. "Competition and Innovation: An Inverted-U Relationship." The Quarterly Journal of Economics 120: 701–728

Akcigit, Ufuk, Salomé Baslandze, and Francesca Lotti. 2023. "Connecting to Power: Political Connections, Innovation, and Firm Dynamics." *Econometrica* 91 (2): 529–564.

Baqaee, David Rezza, and Emmanuel Farhi. 2020. "Productivity and Misallocation in General Equilibrium." *The Quarterly Journal of Economics* 135 (1):105–163.

Barwick, Panle Jia, Hyuk-soo Kwon, Shanjun Li, and Nahim Bin Zahur. 2024. "Driving Down the Cost: Learning By Doing and Government Policy in the Electric Vehicle Battery Industry." Working Paper, 2024.

Barwick, Panel Jia, Myrto Kalouptsidi, and Nahim Bin Zahur. 2023. "Industrial Policy Implementation: Empirical Evidence from China's Shipbuilding Industry." NBER Working Paper 26075.

Bilal, Adrien and Diego Känzig. 2024. "The Macroeconomic Impact of Climate Change: Global vs. Local Temperature." NBER Working Paper 32450.

Bils, Mark, Peter J. Klenow, and Cian Ruane. 2021. "Misallocation or Mismeasurement?" *Journal of Monetary Economics* 124S:S39-S56.

Bloom, Nicholas, Mark Schankerman, and John Van Reenen. 2013. "Identifying Technology Spillovers and Product Market Rivalry." *Econometrica* 81 (4):1347-1393.

Bloom, Nicholas, John Van Reenen, and Heidi Williams. 2019. "A Toolkit of Policies to Promote Innovation." *Journal of Economic Perspectives* 33 (3):163–84

Cherif, Reda, and Fuad Hasanov. 2019. "The Leap of the Tiger: Escaping the Middle-Income Trap to the Technological Frontier." *Global Policy* 10 (4): 497–511.

Choi, Joonkyu, Veronika Penciakova, and Felipe Saffie. 2021. "Political Connections, Allocation of Stimulus Spending, and the Jobs Multiplier." FEDS Working Paper No. 2021-005R1

David, Joel M., and Venky Venkateswaran. 2019. "The Sources of Capital Misallocation." *American Economic Review,* 109 (7): 2531–67.

Díez, Federico, Jiayue Fan, and Carolina Villegas-Sánchez. 2021. "Global declining competition?" *Journal of International Economics* (132).

Evenett, Simon, Adam Jakubik, Fernando Martín, and Michele Ruta. 2024. "The Return of Industrial Policy in Data". IMF Working Paper No. 2024/001.

Felten, Edward, Manav Raj, and Robert Seamans. 2021. "Occupational, Industry, and Geographic Exposure to Artificial Intelligence: A Novel Dataset and its Potential Uses." *Strategic Management Journal* 42 (12): 2195–2217

Garcia-Macia, Daniel. 2017. "The Financing of Ideas and the Great Deviation." IMF Working Paper 2017/176.

Garcia-Macia, Daniel, and Rishi Goyal. 2020. "Technological and Economic Decoupling in the Cyber Era." IMF Working Paper 20/257.

Hsieh, Chang-Tai, and Peter J. Klenow. 2009. "Misallocation and Manufacturing TFP in China and India." *The Quarterly Journal of Economics* 124 (4):1403–1448.

Hsieh, Chang-Tai, Erik Hurst, Charles I. Jones, and Peter J. Klenow. 2019. "The Allocation of Talent and U.S. Economic Growth." Econometrica 87(5):1439-1474.

Hopenhayn, Hugo, and Francesco Squintani. 2021. "On the Direction of Innovation." *Journal of Political Economy* 129 (7).

Kim, In Song. 2018. "LobbyView: Firm-level Lobbying & Congressional Bills Database." Working Paper.

Liu, Ernest. 2019. "Industrial Policies in Production Networks." *The Quarterly Journal of Economics* 134 (4):1883–1948.

Liu, Ernest, and Song Ma. 2023. "Innovation Networks and R&D Allocation." NBER Working Paper 29607

IMF. 2024a. "Expanding Frontiers: Fiscal Policies for Innovation and Technology Diffusion". April 2024 Fiscal Monitor, Chapter 2.

IMF. 2024b. "Industrial Policy Coverage in IMF Surveillance—Broad Considerations", IMF Policy Paper No. 2024/008.

Juhász, Réka, Nathan Lane, Emily Oehlsen, and Verónica C. Pérez. 2022. "The Who, What, When, and How of Industrial Policy: A Text-Based Approach." Working Paper.

Juhász, Réka, Nathan J. Lane, and Dani Rodrik. 2023. "The New Economics of Industrial Policy." NBER Working Paper 31538.

Lybbert, Travis, and Nikolas Zolas. 2019. “Getting Patents and Economic Data to Speak to Each Other: An ‘Algorithmic Links with Probabilities’ Approach for Joint Analyses of Patenting and Economic Activity.” *Research Policy*, 43.3 (2014): 530–542.

Maslej, Nestor, Loredana Fattorini, Erik Brynjolfsson, John Etchemendy, Katrina Ligett, Terah Lyons, James Manyika, Helen Ngo, Juan Carlos Niebles, Vanessa Parli, Yoav Shoham, Russell Wald, Jack Clark, and Raymond Perrault. 2023. “The AI Index 2023 Annual Report,” AI Index Steering Committee, Institute for Human-Centered AI, Stanford University, Stanford, CA.

Peters, Michael. 2020. “Heterogeneous Markups, Growth, and Endogenous Misallocation.” *Econometrica* 8(5):2037-2073.

Restuccia, Diego, and Richard Rogerson. 2008. “Policy Distortions and Aggregate Productivity with Heterogeneous Establishments.” *Review of Economic Dynamics* 11(4).

Sollaci, Alexandre. 2022. “Agglomeration, Innovation, and Spatial Reallocation: The Aggregate Effects of R&D Tax Credits.” IMF Working Paper 2022/131

Timmer, Marcel., Erik Dietzenbacher, Bart Los, Robert Stehrer, and Gaaitzen de Vries. 2015. “An Illustrated User Guide to the World Input–Output Database: The Case of Global Automotive Production.” *Review of International Economics*, 23: 575–605

Tol, Richard. 2024. “A Meta-Analysis of the Total Economic Impact of Climate Change.” *Energy Policy* 185.

Annex

A. Decentralized Equilibrium and Implementation of the Optimal Policy

This section presents the decentralized version of the model in section II, and how R&D subsidies can implement the optimal allocation. We again closely follow Liu and Ma (2023) and solve for an illustrative decentralized equilibrium. Specifically, we make the following assumptions—which are clearly a simplification of reality, but enough to illustrate the main mechanisms at work:

- Each variety is produced by a distinct monopolist. Since all vintages of the same variety are perfect substitutes, the firm that produces that variety at the current highest quality is able to price its competitors out of the market by charging a markup $(1+\lambda)$ over its marginal cost.
- Firm size is limited to one variety. In other words, only entrants invest in innovation to "steal" a variety from a current incumbent. Once this happens, the entrant becomes the current monopolist and the incumbent exits.
- There is a continuum (measure 1) of potential entrants to each variety, who hire scientists to conduct R&D. A successful innovation improves on the quality of a randomly drawn variety/sector, so entrants are unable to target which variety they will innovation upon.
- The representative household supplies scientists and production labor to all sectors and firms, and receives the wage income and profits from the economy.

Cost minimization under the production function for the final good presented in section II implies that the share of expenditure in each sector equals its elasticity

$$\frac{p_{it}y_{it}}{y_t} = \beta_i.$$

In addition, each variety is produced using production labor according to $y_{it}(\nu) = q_{it}(\nu)\ell_{it}(\nu)$, which implies a marginal cost of $w_t^\ell / q_{it}(\nu)$, where w_t^ℓ is the labor of production workers. Since the monopolist charges a markup of $1+\lambda$ (to price its competitors out of the market), it follows that

$$p_{it}(\nu) = (1+\lambda)\frac{w_t^\ell}{q_{it}(\nu)},$$

which implies a profit of $p_{it}(\nu)y_{it}(\nu) - w_t^\ell \ell_{it}(\nu) = \lambda w_t^\ell \ell_{it}(\nu)$.

The sectoral good producer minimizes costs according to

$$\min_{\{y_{it}(\nu)\}_{\nu\in[0,1]}} \int_0^1 p_{it}(\nu)y_{it}(\nu)\,d\nu$$

$$s.t.\ \ \ln y_{it} = \int_0^1 \ln y_{it}(\nu)\,d\nu.$$

Plugging in the results above, this becomes

$$\min_{\{\ell_{it}(\nu)\}_{\nu\in[0,1]}} \int_0^1 (1+\lambda) w_t^\ell \ell_{it}(\nu)\, d\nu$$
$$s.t.\ \ \ln y_{it} = \int_0^1 \ln q_{it}(\nu)\, \ell_{it}(\nu)\, d\nu,$$

which gives the first order condition $(1+\lambda)w_t^\ell = \frac{\mu_{it}}{\ell_{it}(\nu)}$, where μ_{it} is the Lagrange multiplier on the constraint. Since neither μ_{it} nor w_t^ℓ vary across varieties, it follows that $\ell_{it}(\nu) \equiv \ell_{it}$ is constant across firms within a sector.

Finally, perfect competition on the production of the sectoral good implies

$$p_{it} y_{it} = \int_0^1 p_{it}(\nu) y_{it}(\nu)\, d\nu \Longrightarrow \ \ell_{it} = \beta_i \frac{y_t}{(1+\lambda) w_t^\ell}.$$

Given that the supply of production workers is constant at $\sum_{i=1}^K \ell_{it} = \bar{\ell}$, it follows that $\ell_{it} = \beta_i \bar{\ell}$ for all sectors. Profits made are thus

$$p_{it}(\nu) y_{it}(\nu) - w_t^\ell \ell_{it}(\nu) = \lambda w_t^\ell \ell_{it}(\nu) = \frac{\lambda}{1+\lambda} \beta_i y_t \equiv \pi_{it}.$$

Innovation and industrial policy. Let r be the interest rate and δ be the (constant) rate of innovation in a balanced growth path. The monopolist value is

$$V_{it} = \int_t^\infty e^{(r+\delta)(s-t)} \pi_{is}\, ds = \frac{\lambda}{1+\lambda} \beta_i \int_t^\infty e^{(r+\delta)(s-t)} y_s\, ds.$$

A potential entrant in sector i conducting R&D thus has value

$$V_{it}^e = \max_{s_{it}} \left\{ -(1-\sigma_i) w_t^s s_{it} + \ln\left(s_{it} \eta_i \frac{\chi_{it}}{q_{it}} \right) V_{it} \right\},$$

where σ_i is the R&D subsidy (or tax) applied to sector i, and w_t^s is the wage paid to scientists. This problem's first order condition is

$$s_{it} = \frac{V_{it}}{(1-\sigma_i) w_t^s},$$

which implies

$$\frac{s_{it}}{s_{jt}} = \frac{\beta_i/(1-\sigma_i)}{\beta_j/(1-\sigma_j)}.$$

And given that $\sum_{i=1}^K s_{it} = 1$, we find

$$s_{it} = \frac{\beta_i/(1-\sigma_i)}{\sum_{j=1}^K \beta_j/(1-\sigma_j)}.$$

This equation leads to two important results. First, in the fully decentralized equilibrium (where $\sigma_i = 0$ for all i), the allocation of scientists to each sector is proportional to its share of total output: $s_{it} = \beta_i$ for all sectors. Second, the government can implement any allocation of scientists $\{\hat{s}_{it}\}$ by choosing $\{\sigma_i\}$ such that

$$\frac{\beta_i/(1-\sigma_i)}{\sum_{j=1}^{K}\beta_j/(1-\sigma_j)} = \hat{s}_{it}.$$

In particular, the optimal allocation $\{s_i^*\}$ can be implemented by a set of sector-specific subsidies/taxes such that

$$\sigma_i = 1 - \frac{\beta_i}{s_i^*}\left(\sum_{i=1}^{K}\frac{\beta_i}{1-\sigma_i}\right)^{-1},$$

so that sectors that *should* have more scientists relative to the decentralized equilibrium are relatively more subsidized.

Government budget balance. The government budget constraint is given by

$$\sum_{i=1}^{K}\sigma_i w_t^s s_{it} = T_t,$$

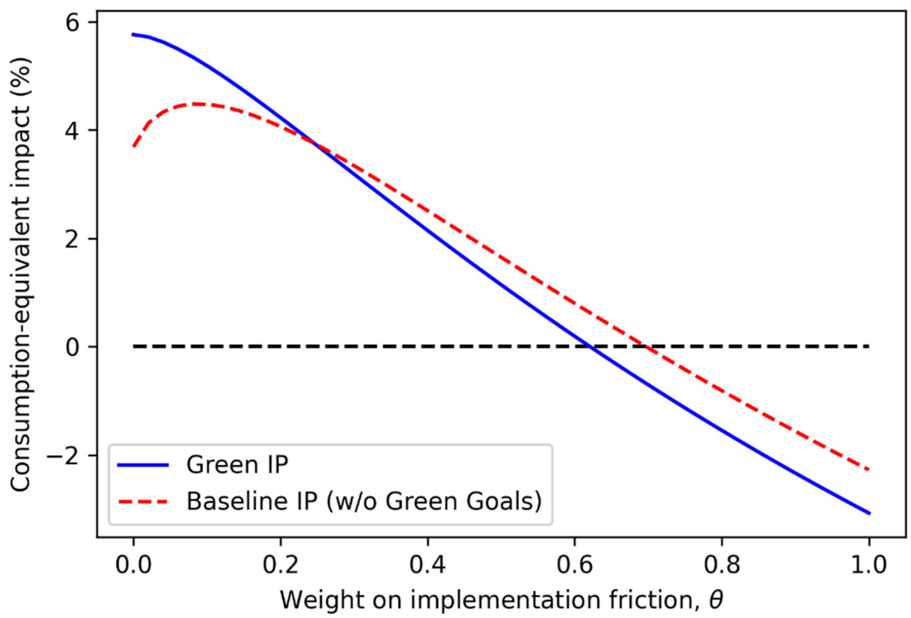
where T_t denotes a lump-sum transfer or tax (e.g., a corporate income tax that only scales down profits across firms but does not change R&D allocations).

B. Welfare Costs of Ignoring Green Goals

The analysis in section IV.C (Figure 7) shows the welfare impact of optimal policies under alternative government objective functions. This section shifts this perspective and shows the welfare consequences of implementing the "wrong" policy. We assume the government would like to have more green innovation and fixes its objective function assuming that green innovation would increase welfare by 2 percentage points when compared to the baseline industrial policy. What are the welfare consequences of implementing the baseline industrial policy anyway, including the potential for political capture?

Annex Figure B.1 answers this question. When there is no political capture ($\theta = 0$), the optimal policy increases welfare relative to the baseline industrial policy by 2 percent (by construction). But note that the baseline industrial policy also increases welfare (relative to a horizontal policy) by about 4 percent—higher than its base effect from Figure 6. The reason for this is that having green goals in the objective function moves the optimal allocation farther away from the no- industrial policy equilibrium (which is $s_i = \beta_i$ for all sectors.) Interestingly, the welfare impact of the baseline industrial policy is not monotonic on the weight on political capture. This is because green sectors happen to have slightly more market power (our measure of political connectedness) than brown sectors, so increasing the weight on political captures actually moves the allocation from the baseline industrial policy in the "correct" direction (i.e., towards greener sectors). This effect, however, only holds for low levels of political capture, and at a certain level political capture starts to decrease welfare as is the case for other policy configurations.

Figure B.1. Welfare Gains from Alternative Policies



Sources: European Patent Office PatStats, World Input-Output Database, Díez, Fan, and Villegas-Sánchez (2021), IPC Green Inventory, and authors' calculations.
Note: the figure shows the welfare impact of different policies *under the same welfare function*. Specifically, the government's objective function explicitly favors innovation in greener sectors. The blue curve indicates how welfare responds to political capture under a policy that takes the same green goals into account. The red dashed line shows the same evolution under a policy that does not take green goals into account (i.e., implements the "wrong" set of subsidies). Implementation friction is measured by political favoritism towards sectors with higher average markups, as estimated by Díez, Fan, and Villegas-Sánchez (2021).

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