Shaping Innovation:
Can Industrial Policies Boost Patent Applications?

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Abstract

This paper estimates the effects of industrial policies (IPs) on innovation. We implement a global empirical analysis and address endogeneity in policy targeting with an instrumental variable strategy. Protectionist IPs temporarily increase received foreign patent applications but have no effect on domestic applications within four years. In contrast, removing trade barriers results in larger and more persistent knowledge transfers. Effects vary by policy instrument, country income level, and targeted sector. Protectionist export-oriented IPs yield larger knowledge transfers than domestic subsidies. Protectionist IPs disproportionately attract foreign patenting in emerging markets and developing economies, while removing trade barriers encourages advanced economies to patent abroad. Policies applied to infant industries such as low-carbon technologies significantly boost domestic patenting in the medium term. Finally, foreign patenting responses vary along the innovation network, with larger effects for innovation-central sectors and positive spillovers to knowledge-providing sectors. Overall, our results suggest that careful IP design is essential to maximize innovation.

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1 Introduction

Industrial policies (IPs)–defined as targeted interventions to change the structure of economic activity (Juhász et al., 2024)–have taken center stage in the global policy agenda. After a period of decline during the liberalization wave of the 1990s, IPs have seen a resurgence since 2017 in both advanced and emerging economies (Evenett et al., 2024). In addition to competitiveness objectives, the recent wave of IPs began as countries grappled with heightened geopolitical tensions, calls for self-reliance in industries critical for national security (e.g., semiconductors), increased vulnerabilities in global value chains, and a need to accelerate the green transition.

The recent resurgence of IPs has reignited policy debates on their effectiveness, including their potential to foster innovation, one of the main engines of productivity growth. In theory, IPs can boost innovation by supporting investments in R&D, overcoming market failures, and mitigating coordination problems. Yet, IPs may also reallocate resources in a non-welfare-enhancing way by supporting targeted firms at the expense of more productive or innovative ones, exert negative externalities across sectors, or distort countries' relative competitiveness. In practice, the literature suggests a mixed track record for industrial policies (Aghion et al., 2015; Harrison, 2024; Lane, n.d.). Two opposite examples are often alluded to when presenting arguments against and in favor of IPs–the import-substitution IPs in Latin America and the export-oriented IPs in East Asia in the 1960s and 1970s. The former was linked to limited long-run productivity growth (Rodrigues, 2010), whereas the latter likely supported rapid export-led growth and productivity improvements (Krueger, 1997; Rodrik, 2009; Hu and Jefferson, 2009; Cherif and Hassanov, 2019; Branstetter et al., 2005). These contrasting cases illustrate the considerable heterogeneity in the effectiveness of IPs documented in the literature. They also suggest that, although IPs hold potential, their effectiveness may depend on a large set of conditions, including appropriate targeting and design, institutional quality, and implementation conditions (Aghion et al., 2015; Harrison, 2024; Juhász and Lane, 2024b,a; OECD, 2025; Baquié et al., 2025).

We contribute to this debate by providing, to the best of our knowledge, the first global cross-sectoral empirical analysis of the impact of IPs on innovation. Leveraging the novel classification of IPs by Juhász et al. (2025), who identify IPs within the Global Trade Alert (GTA) database (Evenett and Fritz, 2020), and the sector- and country-level patent data from the INPACT-S dataset (LaBelle et al., 2024), we assemble a unique dataset containing information on patents and IPs for 177 countries, 31 manufacturing sectors, from 2009 to 2019. This dataset enables us to shed light on how IPs foster innovation.

Our methodology employs the local projection approach to estimate the dynamic response of patent filings to the implementation of IPs at various horizons. To address the endogeneity of policy targeting–the possibility that policymakers implement IPs in sectors already experiencing an innovation boom–we pursue an instrumental variable (IV) strategy inspired by the shift-share literature. Specifically, we construct a novel instrumental variable based on changes in IPs in other sectors and politically distant countries. This approach allows for causal interpretation of the local projection coefficients and addresses identification concerns in earlier empirical literature (Juhász and Lane, 2024b).

Our results, in line with the earlier theoretical or country- or sector-specific empirical literature, point to a nuanced relationship between IPs and innovation. First, protectionist IPs are, on average, associated with a temporary increase in foreign patent applications: one additional policy leads to a 1.4 percent increase in foreign patent filings within the first two years, but the effect dissipates thereafter. This quick and short-lived boost in foreign patent applications suggests that foreign inventors may expedite the filing of innovations already in the pipeline in response to protectionist policies, leading to a front-loading of technological transfers rather than the generation of new innovations in the considered time frame. By contrast, liberalizing policies–mainly lifting import barriers–appear to generate larger and more persistent effects. In addition, both protectionist and liberalizing IPs have no significant effects on domestic patenting, suggesting that, on average, new innovation by domestic firms takes more than four years to materialize and that targeting promising sectors is essential to unleash innovation.

Beyond average effects, we find that the link between IPs and foreign patenting varies across IP instruments and country income groups. We show that export incentives and domestic subsidies are the primary drivers of the short-term increase in foreign patenting following protectionist IPs. Export-oriented policies yield slightly higher and more delayed effects, although the results are less precise. In terms of country characteristics, the average effect of protectionist IPs appears to be driven by emerging markets and developing economies (EMDEs), where protectionist IPs boost received foreign patent applications. Conversely, liberalizing IPs in advanced economies (AEs) are associated with increased cross-border patenting by domestic inventors, with AE-based inventors disseminating innovations worldwide. This rise in patenting may result from firms gaining access to cheaper or higher-quality imported inputs that foster innovation or from intensified product market competition following import liberalization that prompts firms to patent more (Goldberg et al., 2009; Amiti and Konings, 2007; Bloom et al., 2011).

Our results also highlight the role of targeting to spur domestic innovation by focusing on promising cases highlighted in the literature: infant industries, and in particular, low-carbon technologies (LCTs) (Melitz, 2005; Aghion et al., 2015; Criscuolo et al., 2019; Mazzucato, 2011; Aghion et al., 2016). When it comes to domestic patenting, our results suggest that IPs directed toward infant–young, leveraged, and frontier–industries are associated with increases in domestic patenting, consistent with evidence that targeted support can relax financing constraints and accelerate innovation in early-stage, high-potential sectors (Aghion et al., 2015; Criscuolo et al., 2019; Mazzucato, 2011). In particular, climate-related IPs disproportionately increase domestic patenting, particularly by encouraging new entrants (Aghion et al., 2016).

Finally, we investigate IPs' spillovers along the innovation network (Liu and Ma, 2021). To do so, we construct sectoral innovation networks using patent citations. This allows us to measure a sector's innovation centrality, and its exposure to IPs targeting other sectors that rely on its knowledge stock (downstream) or other sectors whose patents are cited by the sector's inventors (upstream). Consistent with the baseline findings, IPs do not affect domestic innovation within four years, irrespective of whether they target innovation-central, upstream, or downstream sectors. However, IPs targeting innovation-central sectors–those with high centrality in the country's knowledge network–generate larger increases in foreign patenting, likely reflecting patent optimization as foreign firms secure access and participation in frontier sectors that are both supported by government policy and underpin a potential wide range of downstream innovations. Moreover, when distinguishing sectors by the direction of knowledge flows, IPs in downstream sectors–those citing the considered technologies–increase foreign patent applications, potentially as foreign firms patent in expectation of increased demand for complementary knowledge-providing technologies. In contrast, IPs in upstream sectors–those supplying foundational knowledge–lower foreign filings, possibly as foreign firm expect that the increase in domestic innovation capacity in the knowledge-providing sectors will reduce their innovative edge in downstream sectors, and, in turn, their incentives to patent locally. These findings are consistent with the recent literature on IPs in the green transition suggesting that learning by doing may be substantial and that, to increase learning, targeting downstream sectors may be preferable to upstream ones (Aghion et al., 2025; Barwick et al., 2025).

Related Literature: Our paper contributes to three strands of literature. First, we contribute to the literature on the economic effects of industrial policy by examining its contribution to one of the primary drivers of growth: innovation. Theoretically, markets may under-invest in innovation due to externalities, market failures, and coordination problems, thereby creating room for strategic government intervention and industrial policy (Rodrik, 2009; Aghion et al., 2015). However, in practice, skepticism emerged from concerns about resource misallocation, poor targeting, rent-seeking, and capture (Krueger, 1990; Pack and Saggi, 2006). The early empirical literature on the effects of industrial policy offered mixed insights, reflecting methodological challenges, identification issues, and heterogeneity in effects (Juhász and Lane, 2024b). Nevertheless, successful case studies from East Asian economies, such as China, Korea, and Taiwan Province of China, highlighted the potential for industrial policies to contribute to industrial transformation, including through domestic innovation and knowledge transfers (World Bank, ed, 1993; Weiss, 2005; Branstetter et al., 2005; Chang, 2006; Hu and Jefferson, 2009; Aghion et al., 2015).

This paper extends the recent literature by offering, to our knowledge, the first global and cross-sectoral empirical analysis of industrial policy and innovation. Prior research in this area has been theoretical (Liu and Ma, 2021) or focused on specific countries, sectors, or policy instruments (Barwick et al., 2024, 2025). Our analysis draws on the machine-learning-based classification of IPs proposed by Juhász et al. (2025), which identifies relevant interventions within the Global Trade Alert (GTA) database (Evenett and Fritz, 2020), and combines it with sector- and country-level patenting data to study innovation outcomes globally. Other recent studies have leveraged the Global Trade Alert project data to examine the effects of IPs on other outcomes or in a country setting (Huang et al., 2025; Machado-Parente et al., 2025; Baquié et al., 2025; Barwick et al., 2024). We also propose a way to address a limitation of the earlier empirical work—the endogeneity of policy targeting—by applying an instrumental variable approach inspired by the shift-share literature (see Section 3.1).

Second, our analysis contributes to the literature on the targeting of industrial policies. Specifically, we empirically examine two sectors with promising rationales for IP intervention according to the literature: infant industries and LCTs. Using ORBIS data, we identify sectors–within specific countries–where firms are disproportionately young, leveraged, and operating at the technological frontier. Prior research suggests that targeting such sectors could enhance the effectiveness of IPs by relaxing financing constraints and facilitating early-stage innovation (Aghion et al., 2015; Criscuolo et al., 2019; Mazzucato, 2011; Melitz, 2005). Our empirical results support this view, showing that protectionist IPs targeting infant industries significantly boost domestic patenting activity. We then focus on a particular subset of infant industries–LCTs– that theoretical and country studies identify as relevant targets for IPs due to novelty-related coordination failures and emissions externalities (Aghion et al., 2016; Barwick et al., 2025). Consistent with this rationale for effectiveness, our findings indicate that climate-motivated IPs are particularly effective at spurring domestic innovation, notably through extensive-margin effects.

Third, this paper contributes to the literature on cross-sectoral spillovers and innovation networks. We build on the model of Liu and Ma, which shows that a social planner seeking to maximize long-run growth would allocate R&D resources toward industries with high innovation centrality–industries playing a central role in the economy's innovation network–to take advantage of knowledge spillovers for future growth. Garcia-Macia and Sollaci's theoretical model also suggests that targeting sectors with high knowledge spillovers is essential for IPs to have positive welfare impacts (Garcia-Macia and Sollaci, 2024). In this paper, we empirically find that, on average, IPs lead to a temporary increase in foreign patenting that is larger in innovation-central sectors, likely as foreign firms optimize their patenting to secure access to frontier sectors supported by government policy and in which they anticipate a potential wide range of downstream innovations. In addition, we empirically estimate the externalities of IPs along the innovation network within a four-year time span. We show that IPs on downstream sectors have positive externalities on foreign patent applications in upstream ones, potentially as foreign firms expect an increased demand for complementary knowledge-providing technologies. This result is in line with Barwick et al., who suggest that targeting downstream sectors may be preferable, as consumer subsidies for electric vehicles in China generated learning-by-doing effects in the upstream battery industry.

The remainder of the paper is organized as follows. Section 2 describes the data and construction of the variables. Section 3 presents the empirical strategy. Section 4 shows the main findings and associated robustness exercises, and Section 5 concludes. Additional information, data descriptions, and robustness results are provided in the Appendix (Sections A, B, and C, respectively).

2 Data and Summary Statistics

To assess whether industrial policies (IPs) stimulate innovation, we construct a novel panel dataset at the country-year-sector level by merging information on IPs with patenting activity across 177 countries and 31 manufacturing sectors (ISIC 2-digit), covering the period 2009–2019. This Section describes the construction and composition of the dataset.

2.1 Industrial Policies

Our measure of IP builds on the dataset developed by Juhász et al., who apply a machine learning classifier to policy descriptions recorded in the Global Trade Alert (GTA) database between 2009 and 2022. The GTA, established in 2008, systematically compiles governments' policy measures and announcements that may disadvantage foreign commercial actors (Evenett and Fritz, 2020). Juhász et al. define IPs as goal-oriented state interventions intended to shift the composition of economic activity. To ensure consistency over time, we implement a reporting-lag adjustment, as recommended by Juhász et al.. This adjustment retains only policies recorded in the same calendar year as their announcement, thereby reducing artificial inflation in early-year policy counts resulting from continuous updates in the GTA database. With this classification of IPs, we build a count of IPs in place in each country, sector, and year. We use the World Integrated Trade Solutions' (WITS) concordance table to link the products targeted by IPs (HS1992 product codes) with their respective sector (ISIC Rev. 2) (WITS, 2025). Non-reported policy counts are treated as zeros if the country has never reported an IP in that sector since 2009.

To capture policy heterogeneity, we use GTA's red-amber-green classification of discriminatory intent. Our analysis focuses on protectionist IPs ("red" measures that "almost certainly discriminate against foreign commercial interests"), such as export subsidies, and liberalizing IPs ("green" measures that "liberalize towards foreign commercial interests"), such as the removal of export bans (Evenett and Fritz, 2020). Ambiguous ("amber") measures are excluded from the analysis, but they represent only 5 percent of IPs in GTA, compared to 63 percent for protectionist IPs and 32 percent for liberalizing ones. Examples of policies by category are provided in Table A.3. Figure 1A shows that the use of IPs has increased sharply since 2017 across both AEs and EMDEs, consistent with trends documented by Baquié et al. (2025),Machado-Parente et al. (2025), and Huang et al. (2025)[1].

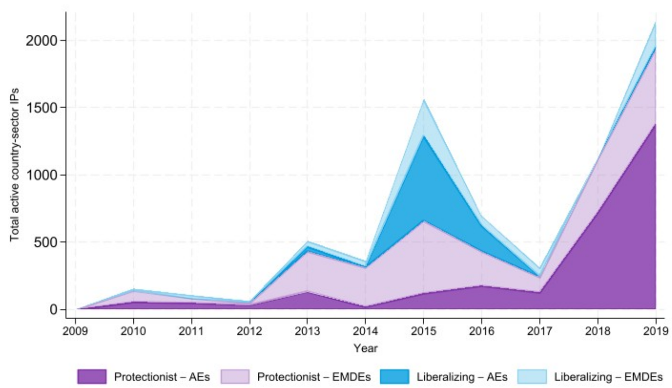
We also classify IPs by policy instrument, based on GTA instrument categories aggregated into five groups aligned with the UN MAST classification for non-tariff measures: (i) trade barriers (export/import restrictions), (ii) domestic subsidies, (iii) export incentives, (iv) local content requirements, and (v) other instruments (e.g., public procurement or FDI measures), following Goldberg et al. (2024); Evenett and Fritz (2020); Evenett et al. (2024). Figure 1B shows that, over 2009-2019, protectionist IPs were predominantly composed of

[1]Figure 1 leverages the data used for the regression analysis, as such IPs applying to several countries or sectors are double counted. Although this counting method helps to capture IPs importance, it can lead to differences in IP counts when compared to other papers that use a different sectoral definition.

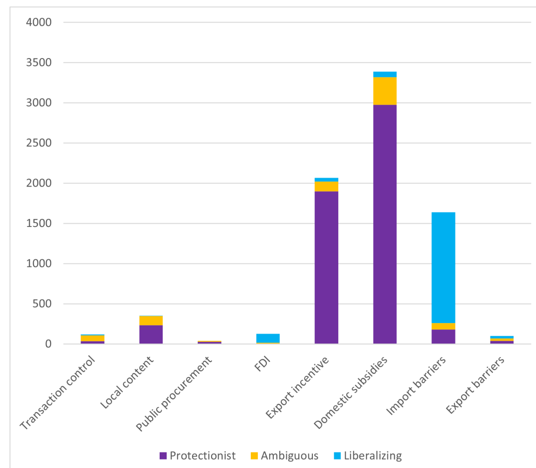
subsidies (65%) and export incentives (35%), while liberalizing IPs are primarily import liberalization measures (84%). Other IP instruments have been less implemented historically, which reduces the available variation in our dataset and the precision of the results for those instruments.

Figure 1: Distribution of the change in total active protectionist and liberalizing industrial policies, by country income group and year (left) and by instrument (right).

A. Change in total active country-sector IPs over time, in AEs and EMDEs



B. Change in active IPs between 2009 and 2019, by instrument



Notes: Panel A shows the year-to-year change in active country-sector IPs in AEs and EMDEs. IPs are counted as they are in the analysis, represented by the first difference in the stock of IP policies. An IP applying to two sectors will be counted twice. Similarly, IPs applying to several countries will be counted several times. Double counting policies in this way enables to capture their spread. Panel B shows the composition of the change in total active IPs between 2009 and 2019. In both panels, the purple color represents protectionist IPs, and the blue color represents liberalizing IPs.
Sources: GTA (2022), Juhász et al. (2025), and authors' calculations.

To study the targeting of IPs supporting LCTs, we follow a three-step classification of these policies, combining information about targeted products and IPs' description (Huang et al., 2025). First, we rely on an extensive literature review to identify products (Harmonized System (HS) codes) corresponding to LCTs (Pigato et al., 2020; OECD/Eurostat, 1999; Rosenow and Mealy, 2024; Kowalski and Legendre, 2023; Goldschlag et al., 2020; Hasna et al., 2023; Mealy and Teytelboym, 2022). We define climate-related IPs as those targeting sectors where at least 70 percent of products are LCTs. Second, we use Huang et al. (2025)'s large language model (LLM) to detect motives related to climate mitigation or environmental concerns in GTA policy descriptions (Evenett and Fritz, 2020; Evenett et al., 2024). Third, in cases where the HS-based and LLM-based methods disagree, we conduct manual validation to ensure accurate classification. This methodology is described in more depth in Huang et al. (2025).

Several data limitations are worth noting. First, although GTA enables a cross-country analysis, heterogeneity in countries' reporting standards may bias IP counts. Second, the data begins in 2009, undercounting IP stocks in countries with pre-existing IP frameworks. These two concerns are partially addressed by our methodology, which considers the effects of *changes* in the number of active IPs rather than the stock level and includes fixed effects for country and year. Third, GTA captures only policies affecting foreign commercial interests, omitting purely domestic or subnational interventions, which may have potentially important implications in strongly decentralized systems (Goldberg et al., 2024). We address this by excluding countries with a potentially large number of subnational IPs in a robustness check (see Section 4.6). Fourth, the dataset captures the presence, not the intensity, of policies. While this limitation prevents us from discussing policy magnitudes, recent analysis from the New Industrial Policy Observatory shows a positive correlation between the IP count and the total value of subsidies in 2023 (Evenett et al., 2024), providing some reassurance on the representativeness of our IP measure.

2.2 Patents

We gauge innovation activity by using patent applications across countries and sectors, building on the INPACT-S dataset developed by LaBelle et al. (2024). The authors leverage the PATSTAT database to derive flows of patent applications from one country to another in manufacturing sectors (ISIC Rev. 2) from 1980 to 2019 (LaBelle et al., 2024). To ensure accurate attribution of patents to their country of origin, LaBelle et al. apply a fractional counting method assigning patent applications to origin countries based on both the residence of the applicant (which can be the firm owning the patent) and of the inventors (the individual or team developing the technology). Regarding patent destination, when a patent is submitted to a regional patent authority (such as the European Patent Office), the INPACT-S dataset uses a weighted-dispersion method to distribute applications across individual member states, improving spatial precision in measuring patent receipt. Moreover, INPACT-S includes all patent filings, regardless of family size, capturing the complete set of innovations.

In our empirical analysis, we aggregate this information into three different country-sector-year measures: domestic inventions–with the same country of invention and application–, patents received from abroad, and patents submitted abroad. The resulting dataset spans 1980–2019, covering 31 manufacturing industries and 212 countries. These indicators are then merged with our IP dataset at the country-year-sector level, resulting in data that covers 180 countries, 31 manufacturing sectors, and the period from 2009 to 2019. As shown in Figure A.1, China, the USA, Japan, Korea, and Germany have the highest yearly number of patent applications over the considered period. The three sectors receiving the most patent applications are chemistry, medical and precision equipment, and computing machinery (Figure A.2).

Even if patent applications are widely used to measure innovation in the economics literature, there are limitations to keep in mind when analyzing the results. First, differences in patenting behaviors across countries and industries—some systematically patent-intensive, others rarely patenting—could affect the comparability across sectors and countries. We partially address this concern in our analysis by including sector and country fixed effects, as well as testing the robustness of the results to the exclusion of the main trading economies, which also happen to be the main patenting economies. Second, the count of patent applications may not capture the quality of patents (Hall et al., 2001). Finally, as we will see in the rest of the paper, patent applications can sometimes stem from strategic behaviors rather than genuine inventions (Blind et al., 2006).

2.3 Innovation network

To describe the propagation of innovations in the economy, we leverage INPACT-S's patent citation data to build a directed innovation network at the sector level. Indeed, Liu and Ma show that sectors with higher innovation centrality have a greater influence on future knowledge creation across the economy. As a result, in their model, the innovation centrality vector coincides with the growth-maximizing R&D allocation along a balanced growth path.

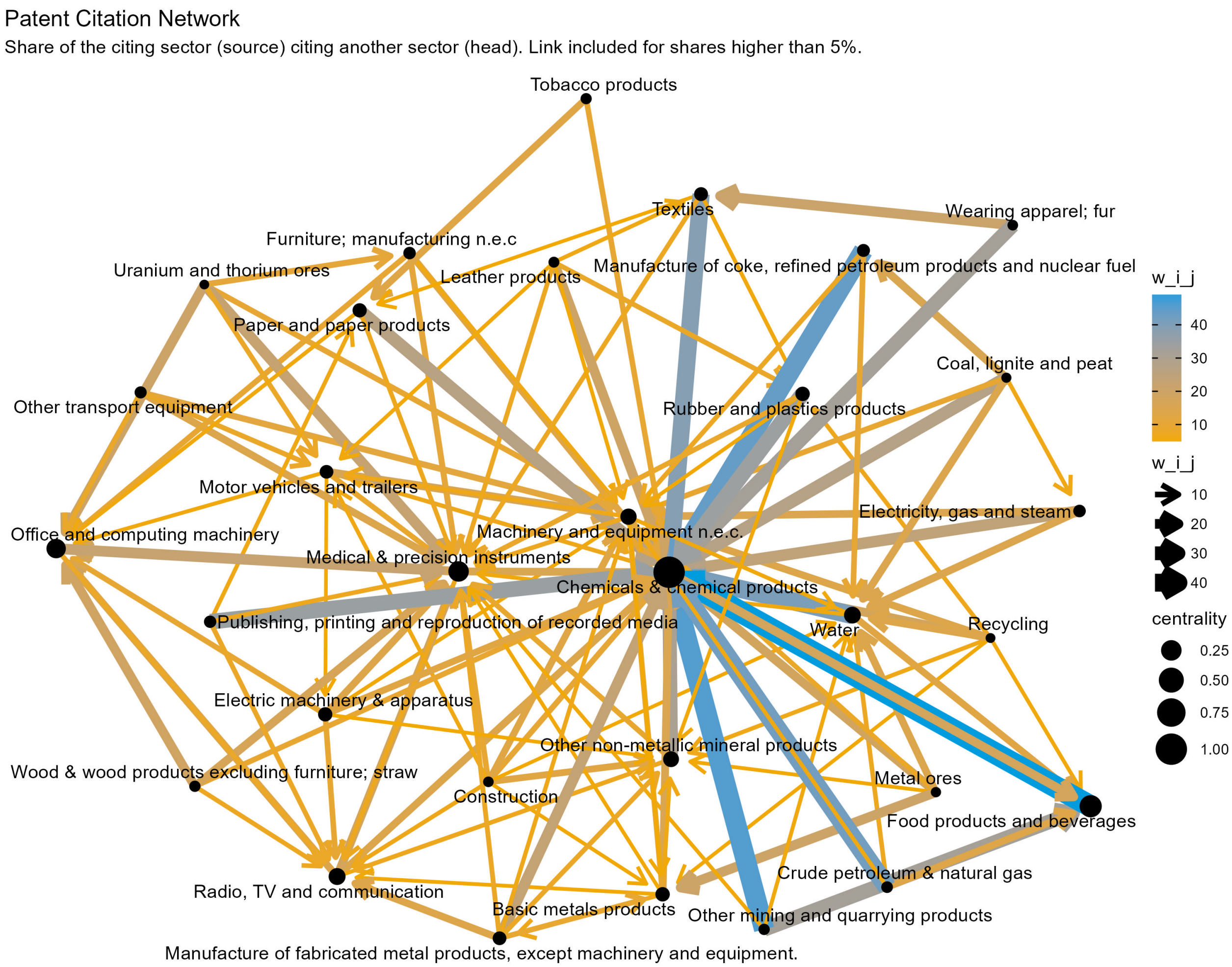
Formally, the innovation network is a matrix Ω, where the (i, j)-th element, $w_{i,j}$, is the share of sector i's citations of sector j. In other words, $w_{i,j}$ represents how sector i's innovation production benefits from sector j's existing knowledge stock. In this case, j is upstream of i, and i downstream of j. We calculate innovation networks for each country c and year t and get $w_{cts \to s'}$, the share of patent citations in sector s made to sector s'. We will leverage these values to calculate weighted averages of the number of IPs upstream and downstream of a considered sector. In addition, we calculate for each country c and year t, the network's innovation centrality, also known as eigenvector centrality and defined as the dominant eigenvector of the Ω matrix. This measure captures the relative importance of each sector in propagating innovation spillovers. We will use it to shed light on the importance of IP targeting.

The average innovation network across countries and years is represented in Figure 2. Each node represents a sector (ISIC Rev 2, 2 digits). The citing sector is the arrow's source, and the cited sector is the head of the arrow. Citation-weighted edges capture the extent to which innovation in one sector contributes to another sector as measured by $w_{cts \to s'}$. The size of the dots represents the sector's innovation centrality. According to this representation, the most innovative central sector, on average, is the chemical industry. It is widely cited in the following sectors: mining, food and beverages, petroleum, textile, and publishing.

2.4 Infant industries

We follow the definition of infant industries proposed by IMF (2025), identifying them within each country as sectors characterized by an above-average share of young and leveraged firms, as well as an above-average distance from the world productivity frontier. The measures of firm age, leverage, and distance to the frontier are derived by aggregating firm-level information from the Bureau van Dijk (BvD) Orbis global database. This large cross-country firm-level database combines data from multiple sources—in particular, publicly available national company registries—and harmonizes them into a consistent international format.

Figure 2: Average innovation network.



Notes: Each node represents a sector (ISIC Rev. 2, 2 digits), and citation-weighted edges capture the extent to which innovation in one sector contributes to another sector. The size of the dots represents the sector's innovation centrality. The citing sector is the arrow's source, and the cited sector is the head of the arrow. Only links with a citation percentage higher than 5% are represented on the graph for readability.
Source: LaBelle et al. (2024).

The dataset used in our analysis is derived from Orbis by applying the cleaning procedures described in Gopinath et al. (2017) and IMF (2025) and selecting the following variables: firm age, total assets, operating revenue (gross output), tangible and intangible fixed assets, material costs, liabilities, earnings before interest and taxes, and cash flow. All variables are expressed in constant 2010 U.S. dollars, and sectoral total factor productivity, which underlies the measure of distance to the productivity frontier, is calculated following Hsieh and Klenow (2009) and IMF (2025).

3 Methods

This Section describes our empirical strategy for estimating the effect of industrial policies (IPs) on patenting activity. We begin by presenting our main regression specification, using the combined local projection method with instrumental variable (IV) strategy to address endogeneity concerns. Then, we present methodological extensions to explore heterogeneity, assess the importance of targeting, and examine potential externalities along the innovation network.

3.1 Local projections-IV

Our baseline analysis builds on the local projection method developed by Jordà (2005) to estimate the dynamic effect of IPs at time t on patent filings over multiple horizons h. The corresponding regression equation is:

$$\begin{aligned} &\Delta_h \log\big(\text{PatentStock}_{c,s,t+h} + 10^{-6}\big) \\ = \beta_h \Delta\text{IPStock}_{c,s,t} + \theta_1 \log\big(&\text{PatentStock}_{c,s,t-1} + 10^{-6}\big) + \theta_2 \text{IPStock}_{c,s,t-1} \\ &+\theta_3 X_{c,s,t} + \lambda_{c,s} + \lambda_{c,t} + \lambda_{s,t} + \varepsilon_{c,s,t} \end{aligned} \tag{1}$$

where the dependent variable, $\Delta_h \log\big(\text{PatentStock}_{c,s,t+h} + 10^{-6}\big)$, is the change over h years in the log of the patent stock for country c and sector s, with a small constant added to retain observations with zero values. $\Delta\text{IPStock}_{c,s,t}$ is the change in either protectionist or liberalizing IP stock between t and t-1 for country c and sector s. In the absence of IP removals, this corresponds to the count of newly introduced policies. The coefficient of interest, β_h, measures the association between one additional active IP and the growth rate of the patent stock over h years. Following the local projections method, we control for the stock of patents and IPs at $t-1$. In addition, $X_{c,s,t}$ are controls including changes and past stocks of other IPs and non-IP trade policies. $\lambda_{c,s}, \lambda_{c,t}, \lambda_{s,t}$ are country-sector, country-year, and sector-year fixed effects that respectively control for global shocks to different sectors (i.e., sectoral trends), growth shocks in different countries, and sectoral differences across countries. Standard errors are clustered at the country level. This conservative level of clustering accounts for the correlation of IPs within-country and across sectors, as an IP targeting products in several sectors is counted as one for each one of them.

Although the local projection specification includes an extensive set of controls and fixed effects to capture potential omitted variables behind the decision of countries to implement IPs and past dynamics in IPs, we may still not be able to interpret OLS estimates of β_h causally. Indeed, policymakers may target sectors based on their innovation trends, introducing a reverse causality bias. For instance, if governments target sectors with increasing innovation activity, OLS estimates of β_h would be upward biased. The pre-trend estimates of our OLS estimations suggest that such targeting may indeed be happening.

To tackle this issue, we combine the local projection approach with an instrumental variable strategy, following Jordà and Taylor (2016). Our instrument for the change in protectionist IPs is constructed from the change in protectionist IPs in other sectors and politically distant countries:

$$\sum_{\substack{c' \neq c \\ s' \neq s}} \left(\frac{\text{PolDist}_{c,c',t}}{\sum_{c'' \neq c} \text{PolDist}_{c,c'',t}} \right) \Delta\text{ProtectionistIPStock}_{c',s',t}. \tag{2}$$

Political distance is measured following Bailey et al. (2017), who use voting alignment in the United Nations General Assembly for a given pair of countries and year to gauge political proximity/distance. The relevance of the instrument comes from the fact that countries adopt retaliatory IPs in response to protectionist IPs in politically distant countries. We check for relevance by reporting the first-stage KP rank Wald F-statistics throughout the paper and confirm they exceed the conventional threshold of 10. In addition, the first stage coefficients are presented in Figure A.4. As expected, the instrument performs less well for IPs not driven by retaliation—such as those with climate motives—so we estimate their effects using OLS.

The exogeneity of the instrument relies on the assumption that IPs in other sectors ($s' \neq s$) and politically distant countries ($c' \neq c$) are not related to innovation trends in sector s and country c. A potential threat arises if the change in IPs in politically distant countries is a response to the change in IP in country c. Since this is more likely for major trading nations, we test the robustness of our results to excluding the top three global traders from the sample (Section 4.6).

For liberalizing IPs, we construct a similar instrument based on the change in active liberalizing IPs in other countries and sectors. However, to improve the strength of the first stage, we add a second instrument: the change in active liberalizing IPs in the country's main trade partners (those accounting for over 90 percent of trade). The corresponding formula is:

$$\sum_{\substack{c' \neq c \\ s' \neq s}} \left(\frac{1(\text{Main Trade Partner})_{c,c',t}}{\sum_{c'' \neq c} 1(\text{Main Trade Partner})_{c,c'',t}} \right) \Delta\text{LiberalizingIPStock}_{c',s',t} \tag{3}$$

While these instruments are relevant, the exogeneity condition is slightly weaker, as liberalizing IPs from trade partners could indirectly affect innovation in country c, even in another sector s, if there are second-order cross-sectoral spillovers via trade, prices, or innovation. However, the Hansen J-statistics (Figure A.12) and robustness checks (Section 4.6) are reassuring.

Although the IV strategy enables a causal interpretation of the estimated coefficient, it identifies a local average treatment effect (LATE), focusing on IPs influenced by the instrument, in our case, retaliatory policies. This raises questions about external validity, as the targeting of retaliatory IPs may differ from more strategic interventions. This trade-off between identification and external validity is explained by Juhász and Lane (2024b). Nonetheless, if retaliatory IPs are on average less well-targeted and, in turn, less effective, our estimates would be a lower bound of the true effect (Juhász and Lane, 2024b).

3.2 Heterogeneity and targeting

To study heterogeneity, we extend Equation 1 in three ways. First, we split the sample by income level—AEs and EMDEs—to assess differences across income groups. Second, we estimate separate effects by policy instrument (e.g., export incentives, subsidies), replacing the overall IP count with instrument-specific counts and adjusting controls accordingly to account for all other policies[2].

Third, we examine the role of targeting by focusing on innovation-central sectors—defined as those with eigenvector centrality above the 80th percentile in the country's innovation network. Indeed, theory suggests that protectionist IPs targeting innovation-central industries should have a larger effect on innovation outcomes than those targeting peripheral ones (Liu and Ma, 2021; Garcia-Macia and Sollaci, 2024). We test this hypothesis by including interaction terms between IPs and a dummy for innovation-central sectors, hence comparing the effects of protectionist policies on received patent applications in innovation central and non-central sectors. The same instruments are used, but controls are expanded to account for all other policies (e.g., IPs in non-innovation central sectors, IPs in upstream and downstream sectors, other IPs, and other trade policies).

Fourth, we investigate IPs supporting the development of infant industries. Our measure of infant industry is derived from firm-level Orbis data, as described in Section 2.4. The Orbis dataset provides uneven coverage of forms across countries, sectors, and years; as a result, 31 percent of the country–sector–year observations are missing for the infant industry measure. Missing values are overall evenly distributed across sectors, though relatively niche industries–such as recycling, tobacco manufacturing, and uranium mining–account for a disproportionate share. Data gaps are also more pronounced in developing economies, which may bias the sample toward advanced countries, although emerging and developing economies remain relatively well represented. In addition, coverage is somewhat thinner in earlier years (2009–2010), limiting the accuracy of regressions for large horizons. Hence, the corresponding regression results are only presented up to horizon 3. Despite these limitations, the resulting dataset identifies infant industries for 13,820 observations. This allows us to test whether the effects of IPs on innovation are stronger in infant industries by including an interaction term between IPs and a dummy variable indicating infant-industry sectors, thereby comparing the impact of protectionist policies on patent applications across infant and non-infant industries. In addition to the controls used in the baseline regression, we also control for IPs in non-infant industry sectors. As policies targeting infant industries are most often designed for strategic purposes rather than as responses to foreign actions, our instrumental variable approach has limited power in this context with low first-stage F statistics. Therefore, we base this analysis on OLS estimates. Nonetheless, since such policies focus on promoting emerging sectors, their introduction is plausibly unrelated to prior innovation patterns, and the timing of their implementation is likely exogenous to innovation levels, supporting a causal interpretation of the results.

[2] We control for other (liberalizing or protectionist) policies involving this instrument, other IPs, and other non-trade policies.

Finally, we dig deeper into one infant industry: low-carbon technologies[3]. As mentioned in the data section, we are able to classify industrial policies targeting LCTs, therefore keeping the same number of observations and power as in the baseline regression. However, these policies are typically strategic and not retaliatory, weakening the power of our IV approach. Therefore, like with the infant industry regressions, we rely on OLS estimates for this analysis. Still, as with infant industries, since climate-related IPs often aim to develop new sectors, their targeting may be uncorrelated with past innovation trends, and their timing may be exogenous relative to innovation, which again, supports a causal interpretation.

3.3 Within country-externalities along the innovation network

To analyze spillovers within the innovation network, we construct exposure measures to upstream and downstream IPs based on citation-weighted connections between sectors. Using the above definition of weights in the directed innovation networks ($w_{cts \to s'}$) denoting the share of patent applications in sector s' that sector s is citing, we define upstream and downstream IPs as:

$$\text{IPUpstr}_{sct} = \sum_{\text{sectors } s' \neq s} w_{cts \to s'} \cdot IP_{s'ct}, \quad \text{such that} \quad \forall s, \sum_{\text{sectors } s \neq s'} w_{cts \to s'} = 1 \tag{4}$$

$$\text{IPDown}_{sct} = \sum_{\text{sectors } s \neq s'} w_{cts' \to s} \cdot IP_{s'ct}, \quad \text{such that} \quad \forall s, \sum_{\text{sectors } s \neq s'} w_{cts' \to s} = 1 \tag{5}$$

To study spillovers in the innovation network, we add these two variables counting protectionist or liberalizing IPs upstream or downstream to Equation 1. We do not instrument upstream or downstream IPs as their implementation is likely not depending on the innovation in the considered sector. The absence of pre-trends for these coefficients supports this assumption.

4 Results

This Section presents our findings on the effects of industrial policies (IPs) on patent activity. We start by examining the effects of protectionist and liberalizing IPs on patent applications, distinguishing between foreign and domestic inventors. We then explore how results vary across policy instruments, income groups, and targeting strategies, before analyzing potential externalities along the innovation network and assessing the robustness of our findings.

[3]In our dataset, sectors associated with LCTs–if 40% of their products are LCTs or if LCTs represent more than 10 percent of its products, when defining LCT products as in Huang et al. (2025) are associated with 2.4 percentage point more infant industry observations.

4.1 Protectionist industrial policies

Protectionist industrial policies are associated with a short-lived increase in patent application from foreign inventors. As illustrated in Figure 3A, the introduction of an additional protectionist industrial policy is, on average, associated with a 1.4 percent increase in the number of foreign patent applications in the targeted sector. However, this effect dissipates rapidly and becomes statistically insignificant after the second year. This reversal suggests that foreign inventors may expedite filing patent applications for innovations already in the pipeline in response to policy implementation. In other words, IPs seem to encourage front-loading applications for existing innovations rather than stimulating new ones. As such, in the considered horizons, industrial policies likely fasten the pace of technological transfers, but without fostering foreign innovation.

Turning to the link between protectionist industrial policies and patent applications by domestic inventors, our results show that, on average, this relationship is not statistically significant over the considered four-year horizon: careful targeting is crucial to unleashing these benefits. Estimates in Figure 3B are insignificant across all horizons, indicating a limited response of domestic inventors to protectionist industrial policies in the first four years of the policy intervention. The fact that foreign patent applications increase in the short-run while domestic applications do not, suggests that there may be fewer "low-hanging fruits" for domestic inventors. That is, domestic inventors are more likely to have already patented inventions in the pipeline in their country before IPs are implemented. Thus, contrary to foreign inventors, domestic ones cannot hasten the patenting of innovations in the pipeline to benefit from the industrial policy. In addition, as with foreign patent applications, protectionist industrial policies do not foster new inventions in the considered horizons. That being said, the average effects documented in Figure 3 mask heterogeneity related to policy design and implementation. As explored in Section 4.4, successful targeting is critical for IPs to foster innovation, including by domestic inventors.

Turning to heterogeneity across instruments, we find that subsidies and export incentives drive the short-term average increase in foreign patent applications following the implementation of protectionist industrial policies, with export-oriented instruments potentially yielding larger gains. Applying the local projection-IV specification to specific policy instruments, Figure 4A shows that an additional protectionist subsidy is associated with a 2 percent increase in received foreign patent applications in the first year. However, like the average effect, the effects of subsidies are short-lived. Export incentives are associated with a comparable effect in magnitude, but which materializes in the second year (Figure 4B). Note that since export incentives are less frequently implemented than subsidies, there is less variation in the IP variable. Consequently, the results are more imprecise (and statistically insignificant) and the first stage is weaker than with subsidies. Still, Appendix Figure A.16 confirms the robustness of the findings under alternative clustering assumptions, with stronger statistical significance and instrument relevance when standard errors are clustered at the country-sector level.

These findings on the effectiveness of industrial policy tools are consistent with the broader literature on the role of industrial policies in supporting East Asia's export-led

Figure 3: Protectionist industrial policies and patent applications from foreign (left) and domestic (right) inventors.

A. Foreign inventors

B. Domestic inventors

Figures/iv_lproj_ln_st_patent_received

Notes: The upper part of the Panels presents the main results. The y-axes represent the percentage change in patent applications received from abroad in percent in Panel A. In Panel B, the y-axis represents the percentage change in patent applications received from domestic inventors in percent. In both panels, the x-axis represents the considered horizon in years. Year 0 is the year of IP implementation. The percentage changes are estimated following Equation 1 with $100 \times (exp(\beta_h) - 1)$. Standard errors are clustered at the country level and the regression includes as well as sector-year, country-year and country-sector fixed effects. The dashed lines represent 90 percent confidence intervals. The histograms in the bottom parts of the Figure represent the first stage KP rank Wald F-statistic for the considered horizon. The black line delineates F=10.
Sources: LaBelle et al. (2024), GTA (2022), Juhász et al. (2025), and authors' calculations.

growth model (Cherif and Hassanov, 2019; Choi and Levchenko, 2025). According to this strand of the literature, export-oriented IPs are particularly effective in helping firms overcome domestic market limitations, facilitating the accumulation of technological capabilities and scale economies that would be difficult to attain through domestic markets alone (Reed, 2024). In line with this mechanism, recent empirical evidence also points to larger effects of export-oriented IPs on firm performance and trade competitiveness relative to subsidies (Machado-Parente et al., 2025; Huang et al., 2025).

4.2 Liberalizing industrial policies

Protectionist industrial policies are not always the most effective policy tool to boost innovation. While well-targeted protectionist measures can yield short-term gains, liberalizing policies–mainly lifting import barriers–appear to generate larger and more persistent effects. As shown in Figure 5A, lifting one additional policy is associated with a 4 percent increase in received foreign patent applications after four years. This positive effect may

Figure 4: Protectionist subsidies and export incentives and patent applications received from foreign inventors.

A. Subsidies

B. Export incentives

Figures/iv_lproj_ln_st_patent_received [illegible]

Figures/iv_lproj_ln_st_patent_received_abroad [illegible]

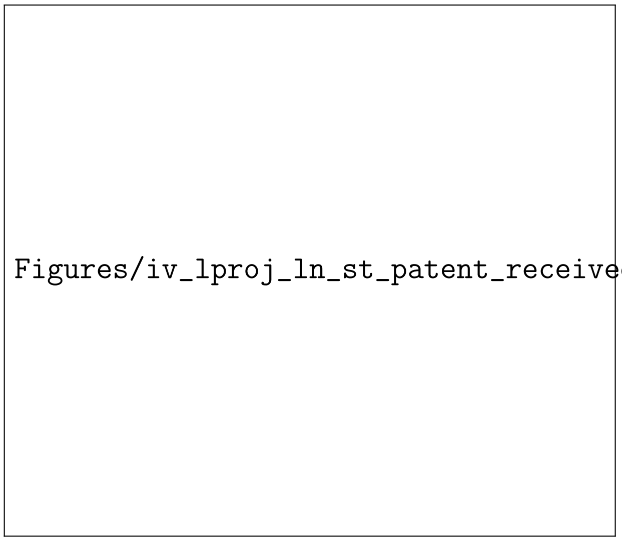
Notes: The upper part of the Panels presents the main results. Panel A estimates the effect of one additional protectionist subsidy and Panel B presents the effect of one additional export incentive. In both Panels, the y-axis represents the percentage change in patent applications received from abroad in percent and the x-axis represents the considered horizon in years. Year 0 is the year of IP implementation. The percentage changes are estimated following Equation 1 with $100 \times (exp(\beta_h) - 1)$. Standard errors are clustered at the country level and the regression includes as well as sector-year, country-year and country-sector fixed effects. The dashed lines represent 90 percent confidence intervals. The histograms in the bottom parts of the Figure represent the first stage KP rank Wald F-statistic for the considered horizon. The black line delineates F=10.
Sources: LaBelle et al. (2024), GTA (2022), Juhász et al. (2025), and authors' calculations.

reflect the removal of growth-constraining policies, or enhanced trade-driven collaboration and investment opportunities through increased competition and openness (Aghion et al., 2015; Harrison, 2024). By contrast, there is no evidence of a significant impact of liberalizing IPs on patenting by domestic inventors within the same time frame 5B, consistent with the literature indicating that innovation cycles typically span a decade or more (Alston et al., 2023; Wang et al., 2024). Similarly to the results for protectionist policies, these findings suggest that liberalization facilitates knowledge diffusion and cross-border technology adoption rather than domestic invention in the short to medium term.

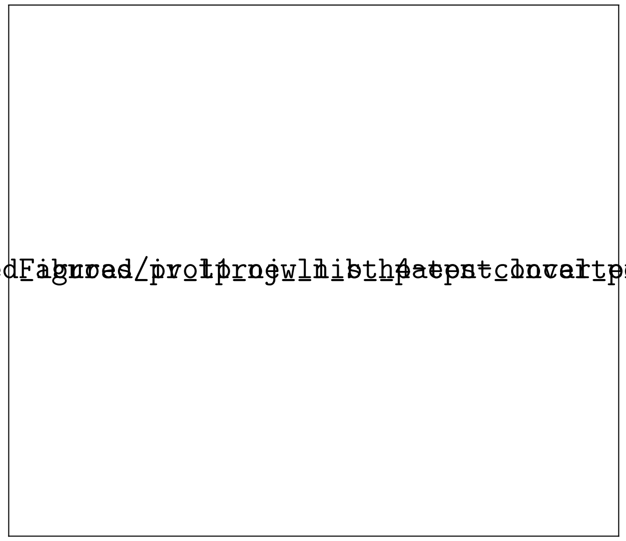
The strong response of foreign patenting to liberalizing industrial policies underscores the importance of appropriate targeting and trade flows in fostering long-term innovation. Indeed, as noted by Harrison (2024), effective industrial policy design should satisfy four criteria: (i) Correct a market failure, (ii) Consult with the private sector, (iii) Enhance competition, (iv) Conclude (for instance, by including a sunset clause). In this context, liberalizing policies may enhance medium-term technological transfers by fulfilling criteria (iii) and (iv), enhancing competition and policy credibility. These results reinforce the broader point that industrial policy effectiveness depends on a wide range of factors, including their design, the timing of their implementation and removal, but also their targeting–an issue explored further in Section 4.4.

Figure 5: Liberalizing industrial policies and patent applications from foreign (left) and domestic (right) inventors.

A. Foreign inventors



B. Domestic inventors



Notes: The upper part of the Panels presents the main results. In Panel A, the y-axis represents the percentage change in patent applications received from abroad in percent. In Panel B, the y-axis represents the percentage change in patent applications received from domestic inventors in percent. In both panels, the x-axis represents the considered horizon in years. Year 0 is the year of IP implementation. The percentage changes are estimated following Equation 1 with $100 \times (exp(\beta_h) - 1)$. Standard errors are clustered at the country level and the regression includes as well as sector-year, country-year and country-sector fixed effects. The dashed lines represent 90 percent confidence intervals. The histograms in the bottom parts of the Figure represent the first stage KP rank Wald F-statistic for the considered horizon. The black line delineates F=10.
Sources: LaBelle et al. (2024), GTA (2022), Juhász et al. (2025), and authors' calculations.

4.3 Industrial policies by country income group

The effect of industrial policies on patenting differ across AEs and EMDEs. Running the above specification separately for AEs and EMDEs sheds light on this differential effect, despite reduced statistical power and weaker first-stage relevance due to smaller sample sizes. Results show that protectionist industrial policies have no significant impact on patent applications by domestic and foreign inventors in AEs over the observed horizon (Figure A.5 in the Appendix). As shown in Figure 1A, this may partly be due to the fact that, in AEs, most protectionist industrial policies have been implemented after 2017, which prevents us from analyzing their impact beyond two years. However, protectionist industrial policies are associated with an increase in received foreign patent applications in EMDEs (Figure 6A), consistent with the interpretation that they accelerate the transfer of existing technologies rather than foster novel innovation. Nevertheless, even if industrial policies play a more catalytic role in EMDEs, AEs have been the destination of 74 percent of all patents submitted by foreign inventors between 1990 and 2019, potentially due to the integration of global value chains and the size of their markets.

Liberalizing industrial policies promote cross-border technological diffusion, particularly from AEs to other countries. In EMDEs, liberalizing policies are not significantly associated with increased patenting activity (Figure A.6 in the Appendix). This may be partly related to the low variation in liberalizing IPs in EMDEs, as most of them have been implemented in AEs around 2015, as shown in Figure 1A. In AEs, the effect on received foreign patent applications follows a similar trajectory to the aggregate results in Figure 3B, though large standard errors—due to smaller sample size—limit statistical significance. However, a clearer pattern emerges when examining patent applications submitted abroad: liberalizing IPs significantly increase outward patenting by inventors based in AEs (Figure 6B). This result suggests that the observed rise in received foreign patenting following liberalization is primarily driven by AEs' inventors. Between 1990 and 2021, AEs accounted for 96% percent of patent filled abroad. These findings suggest that firms in AEs respond to trade liberalization by increasing cross-border patenting, likely to leverage new market opportunities and adapt to heightened competitive pressures.

4.4 Targeting

Although *on average*, industrial policies (IPs) do not increase patenting by domestic inventors within the targeted sector over the considered horizon, appropriately targeted policies may yield different outcomes. A relevant policy question is, therefore: which sectors should be prioritized? The literature provides guidance on targeting strategies, emphasizing the need to address distortions, enhance competition, engage the private sector in their design, and avoid permanent support (Harrison, 2024). While this section only focus on maximizing innovation and does not provide normative recommendations, it presents empirical evidence that well-targeted IPs can support innovation. Informed by the literature and recent policy efforts, we focus on three specific sectors: innovation-central industries, infant industries, and LCTs as an example of an infant industry.

Innovation-central industries: Our empirical results align with Liu and Ma and Garcia-Macia and Sollaci's theoretical models, as they confirm that the positive effects of industrial policies on foreign patenting are larger in innovation-central industries. Figure 7 shows that one additional protectionist IP targeting an innovation-central industry is associated with a 3.7 percent increase in received foreign patent applications, nearly double the average effect. Similarly, one additional liberalizing industrial policy applied to an innovation-central industry is associated with a 10.6 percent significant increase in received foreign patent applications after 4 years. In contrast, IPs applied to non-central industries show no statistically

Figure 6: Industrial policies and patent applications, by country income group.

A. Protectionist IPs and patent applications received from abroad in EMDEs.

B. Liberalizing IPs and patent applications submitted abroad in AEs.

Figures/iv_lproj_ln_st_patent_received_abroad_pr

Figures/iv_lproj_h4_AE_patent_submitted_abroad.pdf

Notes: The upper part of the Panels presents the main results. In Panel A, the y-axis represents the percentage change in patent applications received from abroad in percent. Sample is limited to EMDEs. In Panel B, the y-axis represents the percentage change in patent applications from domestic inventors submitted abroad in percent. Sample is restricted to AEs. In both panels, the x-axis represents the considered horizon in years. Year 0 is the year of IP implementation. The percentage changes are estimated following Equation 1 with $100 \times (exp(\beta_h) - 1)$. Standard errors are clustered at the country level and the regression includes as well as sector-year, country-year and country-sector fixed effects. The dashed lines represent 90 percent confidence intervals. The histograms in the bottom parts of the Figure represent the first stage KP rank Wald F-statistic for the considered horizon. The black line delineates F=10.
Sources: LaBelle et al. (2024), GTA (2022), Juhász et al. (2025), and authors' calculations.

significant impact. If anything, liberalizing IPs temporarily decrease received patent applications, potentially as non-central firms in the innovation network adjust to a more competitive environment. As such, the average results presented in Figures 3 and 5 mask meaningful heterogeneity: large and significant effects in innovation-central industries and insignificant effects in non-central ones. This finding implies that, for industrial policies to be conducive to technological transfers, policymakers may need to prioritize industries that are central in the country's innovation network.

Infant industries: Industrial policies (IPs) targeting infant industries appear more effective at fostering domestic innovation in the medium run than the average IP. As shown in Figure 8A, these policies are followed by a statistically significant increase in patenting by domestic inventors after two years, reaching about a one percent increase after two years. IPs applied to non-infant industries are less strongly associated with domestic innovation, and IV estimates

Figure 7: Protectionist (left) and liberalizing (right) industrial policies and received patent applications from foreign inventors, by centrality of the targeted sector (color)

A. Protectionist IPs and patent applications received from foreign inventors, by innovation centrality of the targeted industry.

B. Liberalizing IPs and patent applications received from foreign inventors, by innovation centrality of the targeted industry.

Figures/iv_lproj_ln_st_patent_received

Notes: The y-axis represents the percentage change in patent applications received from abroad in percent. The x-axis represents the considered horizon in years. The purple and light blue curves show the effect of IPs targeting innovation-central sectors and gray and dark blue curves the effects of policies targeting non-central industries. Industries are innovation central if their eigenvalue centrality in their country's innovation network is above the 80th percentile of the country's innovation centrality distribution, as explained in Section 2.3. Year 0 is the year of IP implementation. The percentage changes are estimated following Equation 1 with $100 \times (exp(\beta_h) - 1)$. The regression controls for IPs implemented in upstream and downstream sectors as well as sector-year, country-year and country-sector fixed effects. The instrumented variable is the one of interest. Standard errors are clustered at the country level. The dashed lines represent 90 percent confidence intervals.
Sources: LaBelle et al. (2024), GTA (2022), Juhász et al. (2025), and authors' calculations.

in Figure 3B shows that the small and temporary increase in the OLS specification stems from endogeneity and the targeting of sectors with upward trending innovation[4]. We further discuss the difference between OLS and IV results for the average IP in Section 4.6.

These results are consistent with evidence showing that targeted support for young, financially constrained, and high potential for learning-by-doing can generate positive innovation responses (Aghion et al., 2015; Mazzucato, 2011). Different mechanisms may be at play. For instance, Akcigit and Goldschlag (2023) find that inventors in large incumbent firms receive

[4] As detailed in Section 3.2, OLS estimates are used to study infant-industry IPs because these policies are strategic rather than retaliatory, limiting the strength of our instrument. The absence of upward pre-trends for infant industries in Figure8 supports the plausibility of a causal interpretation or of an lower bound estimation.

higher wages but tend to be less productive, suggesting limited innovation gains if dominant firms capture IPs' gains. Moreover, Machado-Parente et al. (2025) and Baquié et al. (2025) show that IPs have stronger effects on younger and smaller firms, likely by alleviating financial frictions (Brandão-Marques and Toprak, 2024).

Finally, IPs targeting infant-industries do not increase foreign patent applications, as presented in Figure 8B. Since these industries are nascent, there are likely fewer immediate technological opportunities and foreign inventors likely have fewer pre-existing innovations in the pipeline. Therefore, foreign inventors may not be able to secure access to the IP-impacted markets following policy implementation, limiting their short-term patenting response compared to the average IP.

Figure 8: Protectionist industrial policies targeting infant (purple) or non-infant industries (grey) and patent applications submitted by domestic or foreign inventors using OLS.

A. Domestic inventors. B. Foreign inventors.

Figures/lproj_ln_st_local_pat_infant_prot_new-eps-converted-to.pdf Figures/lproj_ln_st_pat_abroad_infant_prot_n

Notes: The y-axis represents the percentage change in patent applications submitted by domestic inventors (left) or foreign inventors (right) in percent. The x-axis represents the considered horizon in years. The purple line shows the effect of IPs targeting infant industries and the grey one the effect of IPs targeting non-infant industries. Definitions are explained in Sections 2.1 and 2.4. Year 0 is the year of IP implementation. The percentage changes are estimated following Equation 1 with $100 \times (exp(\beta_h) - 1)$. The regression controls for non-protectionist IPs and non-IP trade policies as well as sector-year, country-year and country-sector fixed effects. Standard errors are clustered at the country level. The dashed lines represent 90 percent confidence intervals.
Sources: LaBelle et al. (2024), GTA (2022), Juhász et al. (2025), and authors' calculations.

Low-carbon technologies: Climate-related IPs are found to be more effective in fostering domestic innovation than the average IP. As shown in Figure 9A, protectionist IPs with climate objectives are associated with a gradual and statistically significant increase in patenting by domestic inventors, reaching over 0.7 percent three years after implementation. Figure A.8 in the Appendix indicates that the coefficients on the extensive margin are significant, suggesting that climate-related IPs foster the development of new innovation ecosystems in sectors previously unpatented. By contrast, the average IP has a muted effect on domestic innovation as shown by Figure 3B's IV estimates that tackle the selection bias of non-climate-related IPs targeting sectors already experiencing innovation gains [5].

These findings align with sector-specific analyses. For instance, Barwick et al. (2024) show that a 10 percent increase in financial incentives to electric vehicle (EV) producers results in a 4 percent rise in sector-specific patent applications. Likewise, Hasna et al. (2023) document a positive association between environmental subsidies and green patenting activity. Sector-specific characteristics of LCT industries–such as high learning-by-doing potential, increasing returns to scale, and a high share of new entrants–may explain the larger effect of climate-related IPs compared to the others (Bartelme et al., 2019; Garcia-Macia and Sollaci, 2024).

Our results suggest that the difference between climate-related and non-climate-related IPs is insignificant when it comes to technology transfers. Both policies facilitate technological transfers to the same extent. This is shown by the overlap of the two curves in Figure 9B and Figure A.7 of the Appendix. The delay in the increase in received patent applications for climate-related IPs is consistent with fewer low-hanging fruits due to the novelty of the LCT sector and inventors having fewer pre-existing innovations in the pipeline.

4.5 Within-country externalities along the innovation network

Next, we turn to studying how IPs affect patent applications in sectors different than the targeted sector. In particular, we exploit information about patent citations to assess how IPs in sectors citing the considered sector (downstream) or IPs in sectors cited by the considered sector (upstream) impact innovation in the considered sector.

Our results show that foreign patent applications increase significantly in a given sector two years after the introduction of industrial policies in downstream sectors (Figure 10A). A potential explanation is that foreign inventors anticipate future demand for complementary technologies, as innovations tend to flow from upstream to downstream sectors (Liu and Ma, 2021). On the contrary, the introduction of IPs in upstream sectors is associated with a decline in foreign patenting in the considered sector. This may reflect an expected price drop in the upstream sector, which could decrease the need for innovation in the considered sector and, consequently, reduce incentives to patent technology. These results also align with Aghion et al. (2025)'s theoretical findings, showing that, in the context of the green transition, prioritizing downstream support is more effective and mis-targeting upstream sectors can delay progress.

Figure 10B shows no statistically significant effect of liberalizing IPs in upstream or downstream sectors on foreign patenting in considered sector. As discussed above, liberalizing IPs are more likely to generate cross-border collaboration and competitive pressures that

[5] As explained in Section 3.2, our analysis of LCT-targeting IPs relies on OLS estimation of local projections because our proposed instrument is weak due to climate-related IPs not being often implemented as a retaliatory response. While this limits causal inference due to potential endogeneity—particularly the concern that LCTs may be targeted precisely because they show innovation promise—the absence of pre-trends in Figure 9 supports the plausibility of a causal interpretation.

Figure 9: Protectionist climate-related industrial policies and patent applications submitted by domestic or foreign inventor using OLS.

A. Domestic inventors. B. Foreign inventors.

Figures/lproj_ln_st_patent_local_green

Figures/lproj_ln_st_patent_received_abroad_green_

Notes: The y-axis represents the percentage change in patent applications submitted by domestic inventors (left) or foreign inventors (right) in percent. The x-axis represents the considered horizon in years. The green line shows the effect of climate-related IPs and the brown one the effect of non-climate related IPs. Definitions are explained in Section 2.1. Year 0 is the year of IP implementation. The percentage changes are estimated following Equation 1 with $100 \times (exp(\beta_h) - 1)$. The regression controls for non-protectionist IPs and non-IP trade policies as well as sector-year, country-year and country-sector fixed effects. Standard errors are clustered at the country level. The dashed lines represent 90 percent confidence intervals.
Sources: LaBelle et al. (2024), GTA (2022), Juhász et al. (2025), and authors' calculations.

unfold over longer time horizons. As a result, any second-order cross-sector spillovers would likely materialize beyond the four-year window considered in this analysis. Similarly, the response of domestic inventors to upstream or downstream IPs is statistically insignificant (Figure A.10), reinforcing the earlier finding that, on average, IPs do not spur domestic innovation in the short to medium term without effective targeting.

4.6 Robustness

We conduct a series of robustness checks to validate the above results. These tests address potential concerns related to instrument validity, sample composition, inference methods, policy heterogeneity, network definitions, and estimation strategies.

Hansen J-test: Since liberalizing IPs are instrumented with two instrumental variables, we test for over-identifying restrictions with the Hansen J-test. As shown in Figures A.11 and A.12, we cannot reject the null hypothesis across all horizons that the over-identifying

Figure 10: Industrial policies by targeted sector (considered, upstream, downstream) and received patent applications from foreign inventors.

A. Protectionist IPs. B. Liberalizing IPs.

Figures/iv_lproj_ln_st_patent_received Figures/iv_lproj_ln_st_patent_received_abroad_prot

Notes: The y-axis represents the percentage change in patent applications submitted by foreign inventors (right) in percent. The x-axis represents the considered horizon in years. The purple line shows the effect of IPs in the considered sector, the blue line in a sector upstream of the considered one, and the grey line in a sector downstream of the considered one. Definitions are explained in Section 2.1. IPs in the targeted sector are instrumented by the instrumental variable as explained in Section 3.3. IPs upstream and downstream are considered exogenous to patent applications in the considered sector and not instrumented. The absence of pre-trends supports this assumption. The Year 0 is the year of IP implementation. The percentage changes are estimated following Equation 1 with $100 \times (exp(\beta_h) - 1)$. The regression controls for non-protectionist or non-liberalizing IPs and non-IP trade policies, as well as sector-year, country-year, and country-sector fixed effects. Standard errors are clustered at the country level. The dashed lines represent 90 percent confidence intervals.
Sources: LaBelle et al. (2024), GTA (2022), Juhász et al. (2025), and authors' calculations.

restrictions are valid.

Excluding major trading economies: The absence of pre-trends when using the IV strategy supports the idea that IPs implemented at the same time as IPs in other sectors and politically distant countries are not targeted based on promising innovation trends. However, the instrument could capture reverse causality if the considered country is a major trading economy implementing an IP, to which other countries react with IPs in other sectors. This would weaken the exogeneity argument of the instrument. To address this concern, we exclude the three largest trading economies—China, the United States, and Germany—from the estimation. Results remain robust (Figure A.13), mitigating concerns about the validity of the IV strategy. The results also tackle potential concern related to possible measurement biases related to the underreporting of sub-national IPs in the GTA database and the over-reporting of patents in countries with aggressive patenting incentives (e.g., China).

Clustering standard errors at the country-sector level: The baseline specification clusters standard errors at the country level to account for potential cross-sectoral spillovers. We test robustness to a less conservative (more granular) clustering at the country-sector level. As shown in Figure A.14, results remain consistent; the first-stage F-statistics improve and overall IV results are unchanged.

All trade policies: Broadening the set of trade policies with which countries can respond to IPs in other countries and sectors does not change the results. Figure A.15 shows that results are stable, with the magnitude and shape of the effects of protectionist and liberalizing trade policies on received patent applications largely unchanged. If anything, estimates are smaller—possibly reflecting the fact that retaliatory IPs drive the main results.

Policy instrument: Figure A.16 shows that results for subsidies and export incentives are unchanged when clustering the standard errors at the country-sector level. However, the first stage F-statistics are above 10 under this less conservative assumption. In addition, Figure A.17 presents alternative results when using the same policy tool in other sectors and countries as an instrumental variable while controlling for other types of trade policy tools. The shape of the results is similar, but the magnitude is slightly smaller and insignificant for export incentives, likely due to the lower variation in retaliatory export incentives compared to retaliatory IPs.

Centrality: Figure 7's results on the targeting of innovation-central sectors rely on the eigenvector centrality definition described in Section 2.3. Although this is the measure that Liu and Ma find to be relevant for the socially optimal allocation of innovation resources in their theoretical model, other measures could better capture innovation spillovers in the network. We test the sensitivity of results on innovation-central sectors to alternative definitions of network centrality. First, we test the robustness of the results to varying the threshold. Changing the cutoff from the 80th percentile to the median (Figure A.18) yields similar results, although estimates for non-central sectors are less precise. Second, we replace the eigenvector centrality measure with the PageRank centrality one (Figure A.19), accounting for the extent of patent citations including indirect influence through citation chains[6]. Results are also unchanged. Together, these findings suggest the main results are not sensitive to the centrality metric or the threshold used.

[6] This measure was initially used by web searching engines to measure the relative importance of webpages depending on links referring to them.

OLS: Figure A.20 presents the OLS estimation of Equation 1, providing a benchmark for interpreting the IV results shown in Figure 3. Indeed, as explained in Section 3.1, the OLS results shed light on the average association between innovation and IPs, no matter targeting, even if estimates cannot be causally interpreted. The comparison between OLS and IV results supports the above point on the importance of targeting to unleash domestic innovation. An additional protectionist IP correlates with a 0.18 percentage point increase in domestic patent applications after one year. However, the presence of an upward pre-trend suggests selection bias with industrial policies disproportionately targeting sectors with upward-trending innovation.Therefore, the OLS estimation suggests that targeting "promising" sectors is important for IPs to be associated with a boost in domestic innovation, as shown in Section 4.4. For foreign patents, OLS and IV estimates align in magnitude and timing, but the pre-trends are also pronounced in the OLS results, especially for protectionist IPs–again indicating possible selection effects–. A decomposition into extensive and intensive margin shows that the pre-trend results from an increasing pre-trend on the extensive margin (i.e., entry of new patenting sectors) and a decreasing pre-trend on the intensive margin. These findings reinforce the rationale for the IV method. While OLS captures the average association, IV better identifies causal effects by addressing endogenous targeting, as supported by the absence of pre-trends in the IV specification.

5 Conclusion

We find that industrial policies can foster patent applications when well designed. Protectionist IPs are associated with only temporary increases in received foreign patents, with export-oriented policies outperforming subsidies. This temporary effect could stem from foreign inventors securing access to the market targeted by the industrial policy for innovations already in the pipeline. In contrast, liberalizing measures, such as lifting trade barriers, produce more persistent and broader technological transfers. However, protectionist IPs have no significant effect on domestic patenting on average, nor do liberalizing IPs, suggesting that, on average, new innovation by domestic firms takes more than four years to materialize and that targeting promising sector is essential to unleash innovation.

Indeed, we also find that targeting is an important dimension for IPs to boost patent applications. For instance, IPs focused on innovation-central exhibit larger gains in terms of received foreign patent applications. Turning to domestic innovation, we show that targeting infant industries, such as low-carbon technologies, is effective to boost domestic patent applications in the medium term. This is consistent with evidence that targeted support can relax financing constraints and accelerate innovation in early-stage, high-potential sectors (Aghion et al., 2015; Criscuolo et al., 2019; Mazzucato, 2011). In addition to the direct impact on the targeted sector, we show that interventions in downstream industries (from a patent citation point of view) lead to higher patent application in upstream sectors, in line with recent evidence (Philippe Aghion et al., 2015; Barwick et al., 2025).

We also show that the effect of IPs also varies by country income group. Protectionist IPs disproportionately facilitate the receipt of patent applications in EMDEs, as foreign inventors may try to secure access to markets impacted by IPs. However, as mentioned earlier, further research may be necessary to determine whether patent applications in EMDEs actually translate into increased productivity. Machado-Parente et al. (2025)'s results suggest that this may not be the case in the short run, as they find that firms benefit more from IPs in countries with better fundamentals, such as governance or financial market development. At the same time, liberalizing IPs encourage cross-country patenting from AEs, potentially as firms access lower-cost or higher-quality imported inputs that facilitate innovation or as heightened product market competition incentivizes them to engage more actively in patenting (Goldberg et al., 2009; Amiti and Konings, 2007; Bloom et al., 2011).

Thus, while IPs have the potential to boost innovation, their effectiveness in shaping innovation depends on their targeting and implementation. Our results suggest that supporting infant industries, or prioritizing measures that facilitate technological diffusion along the innovation network or downstream sectors could yield higher benefits. They also indicate that IPs increase technology diffusion to EMDEs, although more evidence is needed to assess whether it translates into technological development and productivity increase.

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Supporting material

A Additional Data Description

Figure A.1: Cross-country distribution of the average yearly number of patent applications received or submitted

Figures/patent_applications_country-eps-converted-to.pdf

Source: LaBelle et al. (2024).

Figure A.2: Cross-sectoral distribution of the average number of patent applications received or submitted

Figures/patent_applications_sector-eps-converted-to.pdf

Source: LaBelle et al. (2024).

Figure A.3: Examples of protectionist and liberalizing policies recorded in GTA, by instrument

	Liberalizing (Opening trade)	Ambiguous (Announcements)	Protectionist (Restricting trade)
Transaction control	"facilitating the acquisition and sale of US dollars and other currencies by Venezuelan importers [...] this facilitated process applies to imports of raw materials, consumer and capital goods"	"Anti-circumvention investigation on imports of certain woven or stitched glass fibre fabrics from Morocco"	"Executive Order bans new investment from the XX in the energy sector of YY"
Local content	"waived its Buy America requirements in response to a request from the Colorado Department of Transportation"	"2021 second supplementary budget, in which they increased the Win-Win Discount on Fisheries Products Plan by KRW 20 billion (USD 17 billion)"	"Pakistan's Automotive Development Policy 2016-21. The below incentives for new and existing manufacturers as well tariff amendments for importers were announced in this policy."
Public procurement	"public procurement of supplies required for the containment of the pandemic will be exempt from the applicability of the Public Procurement Order."	"Decree No. XX [...] to develop and approve in the criteria and procedures for the priority of locally-produced integrated circuits over ones that originate from foreign countries"	"Congress included a Buy American requirement in the 'American Recovery and Reinvestment Act of 2009'
FDI	"authorise the Luxembourgian company XX to acquire XX% of the capital of the Spanish company XX"	"On 28 February 2015, the Indian Finance Minister presented the Budget for year 2015-16. The trade and investment implications of the budget are listed below."	"issued a notification banning foreign direct investment in manufacturing of cigars, cheroots, cigarillos and cigarettes, of tobacco or of tobacco substitutes."
Export incentive	"Regulation XX, ending its last export subsidy" "Reduced the duty-free allowance for Status Holders to export promotional products."	"German XX-Bank announced it would provide an export credit worth XX million USD creating a wind farm in Uruguay."	"German Export Credit Agency XXt granted an export credit guarantee that supports XX's expansion of an existing hot strip plant in Turkey.
Domestic subsidies	"Tightening the criteria that EV manufacturers' products must satisfy in order to qualify for subsidies" "New version of a policy originally from 2009 where certain **imports** would be granted interest subsidies."	"the European Commission adopted a new Temporary Crisis and Transition Framework for streamlining support measures related to the transition to a net-zero economy."	"Decision (EU) XX establishes the list of sectors and subsectors […] that are granted 100% free allowances to prevent them from relocating their production".
Import barriers	"Disposition XX amending the list of products subject to non-automatic import licenses.[...] XX products were removed from the list of goods"	On June 30, 2010 the European Commission initiated an anti-dumping investigation on imports of XX"	"introducing an import licensing regime for steel products exceeding XX tonnes."
Export barriers	"elimination of the export bans on rye and mineral fertilizers"	"The department of Health announced signing a contract with XX for the purchase of COVID-19 vaccines […] (that) may lead to delays of vaccine orders from other counties due to the executive order which prioritizes American citizens in vaccine shipments"	"A ban has been imposed on the transport and export of logs."

Source: GTA (2022).

B Additional Results

Figure A.4: First stage coefficients: Change in protectionist or liberalizing IP stocks as a function of the respective instrumental variables

Figures/IV_first_stages_both-eps-converted-to.pdf

Notes: The y-axis gives the coefficient point estimate. The x-axis represents each instrumental variable. The purple and blue coefficients correspond to the first stages of the changes in protectionist IP stock and blue IP stock, respectively. The instrumental variables are described in Section 3. Their labels are as follows. $\Delta ProIPStock$ refers to the change in protectionist IP stock in the other countries and sectors, and $\Delta LibIPStock$ in liberalizing IP stock. "Pol Dist" refers to Political-distance weights and "Trade Part" to weights by a dummy variable if the considered country is one of the 90th percentile largest trade partners.
Sources: LaBelle et al. (2024), GTA (2022), Juhász et al. (2025), and authors' calculations.

Figure A.5: Industrial policies and patent applications in AEs.

A. Protectionist industrial policies and patent applications patented by foreign inventors.

Figures/iv_lproj_ln_st_patent_received

B. Protectionist industrial policies and patent applications patented by domestic inventors.

C. Liberalizing industrial policies and patent applications patented by foreign inventors.

Figures/iv_lproj_ln_st_patent_received

D. Liberalizing industrial policies and patent applications patented by domestic inventors.

Notes: The upper part of the Panels presents the main results. In each panel, the y-axis represents the percentage change in patent applications in percent. Sample is limited to AEs. In Panels A and B, IPs are protectionist, and in Panels C and D, they are liberalizing. The x-axis represents the considered horizon in years. Year 0 is the year of IP implementation. The percentage changes are estimated following Equation 1 with $100 \times (exp(\beta_h) - 1)$. Standard errors are clustered at the country level. The dashed lines represent 90 percent confidence intervals. The histograms in the bottom parts of the Figure represent the first stage KP rank Wald F-statistic for the considered horizon. The black line delineates F=10.
Sources: LaBelle et al. (2024), GTA (2022), Juhász et al. (2025), and authors' calculations.

Figure A.6: Industrial policies and patent applications in EMDEs.

A. Protectionist industrial policies and patent applications patented by foreign inventors.

Figures/iv_lproj_ln_st_patent_received

B. Protectionist industrial policies and patent applications patented by domestic inventors.

C. Liberalizing industrial policies and patent applications patented by foreign inventors.

Figures/iv_lproj_ln_st_patent_received

D. Liberalizing industrial policies and patent applications patented by domestic inventors.

Notes: The upper part of the Panels presents the main results. In each panel, the y-axis represents the percentage change in patent applications in percent. Sample is limited to EMDEs. In Panels A and B, IPs are protectionist, and in Panels C and D, they are liberalizing. The x-axis represents the considered horizon in years. Year 0 is the year of IP implementation. The percentage changes are estimated following Equation 1 with $100 \times (exp(\beta_h) - 1)$. Standard errors are clustered at the country level. The dashed lines represent 90 percent confidence intervals. The histograms in the bottom parts of the Figure represent the first stage KP rank Wald F-statistic for the considered horizon. The black line delineates F=10.
Sources: LaBelle et al. (2024), GTA (2022), Juhász et al. (2025), and authors' calculations.

Figure A.7: Protectionist climate-related industrial policies and received patent applications submitted abroad by domestic inventors.

Figures/lproj_ln_st_patent_submitted_abroad_green_prot_new-eps-converted-to.pdf

Notes:

Figure A.8: Protectionist climate-related industrial policies and probability that at least one patent application is submitted by a domestic or foreign inventor (extensive margin).

A. Domestic inventors. B. Foreign inventors.

Figures/lproj_ln_st_patent_local_green_

Figures/lproj_ln_st_patent_received_abroad_green_

Notes: The y-axis represents the probability that at least one patent application is submitted by a domestic inventor (left) or foreign inventor (right) in percent. The x-axis represents the considered horizon in years. The green line show the effect of climate-related IPs and the brown one the effect of non-climate related IPs. Definitions are explained in Section 2.1. Year 0 is the year of IP implementation. The percentage changes are estimated following Equation 1 with $100 \times \beta_h$. The regression controls for non-protectionist IPs and non-IP trade policies as well as sector-year, country-year and country-sector fixed effects. Standard errors are clustered at the country level. The dashed lines represent 90 percent confidence intervals.
Sources: LaBelle et al. (2024), GTA (2022), Juhász et al. (2025), and authors' calculations.

Figure A.9: Protectionist climate-related industrial policies and patent applications submitted by domestic or foreign inventors for already-patented sectors (intensive margin).

A. Domestic inventors.

B. Foreign inventors.

Figures/lproj_ln_st_patent_local_green_

Figures/lproj_ln_st_patent_received_abroad_green_

Notes: The y-axis represents the percentage change in patent applications submitted by domestic inventors (left) or foreign inventors (right) in already-patented sectors, expressed in percent. The x-axis represents the considered horizon in years. The green line show the effect of climate-related IPs and the brown one the effect of non-climate related IPs. Definitions are explained in Section 2.1. Year 0 is the year of IP implementation. The percentage changes are estimated following Equation 1 with $100 \times (exp(\beta_h))$. The regression controls for non-protectionist IPs and non-IP trade policies as well as sector-year, country-year and country-sector fixed effects. Standard errors are clustered at the country level. The dashed lines represent 90 percent confidence intervals.
Sources: LaBelle et al. (2024), GTA (2022), Juhász et al. (2025), and authors' calculations.

Figure A.10: Industrial policies by targeted sector (considered, upstream, downstream) and received patent applications from domestic inventors.

A. Protectionist IPs. B. Liberalizing IPs.

Figures/iv_lproj_ln_st_patent_local_pr

Notes: The y-axis represents the percentage change in patent applications submitted by domestic inventors (right) in percent. The x-axis represents the considered horizon in years. The purple line shows the effect of IPs in the considered sector, the blue line in a sector upstream of the considered one, and the grey line in a sector downstream of the considered one. Definitions are explained in Section 2.1. IPs in the targeted sector is instrumented by the instrumental variable as explained in Section 3.3. IPs upstream and downstream are considered exogenous to patent applications in the considered sector and not instrumented. The absence of pre-trends supports this assumption. The Year 0 is the year of IP implementation. The percentage changes are estimated following Equation 1 with $100 \times (exp(\beta_h) - 1)$. The regression controls for non-protectionist or non-liberalizing IPs and non-IP trade policies, as well as sector-year, country-year, and country-sector fixed effects. Standard errors are clustered at the country level. The dashed lines represent 90 percent confidence intervals.
Sources: LaBelle et al. (2024), GTA (2022), Juhász et al. (2025), and authors' calculations.

C Robustness checks

Figure A.11: Hansen J-test: Liberalizing industrial policies and received patent applications.

Notes: The The y-axis represents the p=value of the Hansen J-test in the regressions of received patent applications on liberalizing IPs presented in Figure 5A. The x-axis represents the considered horizon in years. Year 0 is the year of IP implementation. Standard errors are clustered at the country level and the regression includes as well as sector-year, country-year and country-sector fixed effects. The black line delineates p=0.05.
Sources: LaBelle et al. (2024), GTA (2022), Juhász et al. (2025), and authors' calculations.

Figure A.12: Hansen J-test: Liberalizing industrial policies and domestic patent applications.

Notes: The The y-axis represents the p=value of the Hansen J-test in the regressions of received patent applications on liberalizing IPs presented in Figure 5B. The x-axis represents the considered horizon in years. Year 0 is the year of IP implementation. Standard errors are clustered at the country level and the regression includes as well as sector-year, country-year and country-sector fixed effects. The black line delineates p=0.05.
Sources: LaBelle et al. (2024), GTA (2022), Juhász et al. (2025), and authors' calculations.

Figure A.13: Robustness of the main results when excluding the USA, China, and Germany.

A. Protectionist

B. Liberalizing

Figures/iv_lproj_ln_st_patent_received

Notes: The upper part of the Panels presents the main results. In both panels, the y-axes represent the percentage change in patent applications received from abroad in percent. The x-axis represents the considered horizon in years. Year 0 is the year of IP implementation. The percentage changes are estimated following Equation 1 with $100 \times (exp(\beta_h) - 1)$. The sample excludes the USA, China, and Germany. Standard errors are clustered at the country level and the regression includes as well as sector-year, country-year and country-sector fixed effects. The dashed lines represent 90 percent confidence intervals. The histograms in the bottom parts of the Figure represent the first stage KP rank Wald F-statistic for the considered horizon. The black line delineates F=10.
Sources: LaBelle et al. (2024), GTA (2022), Juhász et al. (2025), and authors' calculations.

Figure A.14: Robustness of the main results when clustering standard errors at the country-sector level.

A. Protectionist

Figures/iv_lproj_ln_st_patent_received

B. Liberalizing

Figures/iv_lproj_ln_st_patent_received_abroad_pro

Notes: The upper part of the Panels presents the main results. In both panels, the y-axes represent the percentage change in patent applications received from abroad in percent. The x-axis represents the considered horizon in years. Year 0 is the year of IP implementation. The percentage changes are estimated following Equation 1 with $100 \times (exp(\beta_h) - 1)$. Standard errors are clustered at the country-sector level and the regression includes as well as sector-year, country-year and country-sector fixed effects. The dashed lines represent 90 percent confidence intervals. The histograms in the bottom parts of the Figure represent the first stage KP rank Wald F-statistic for the considered horizon. The black line delineates F=10.
Sources: LaBelle et al. (2024), GTA (2022), Juhász et al. (2025), and authors' calculations.

Figure A.15: Robustness of the main results to using all trade policies.

A. Protectionist

B. Liberalizing

Figures/iv_lproj_ln_st_patent_received

Figures/iv_lproj_ln_st_patent_received_abroad

Notes: The upper part of the Panels presents the main results. In both panels, the y-axes represent the percentage change in patent applications received from abroad in percent. The x-axis represents the considered horizon in years. Year 0 is the year of trade policy implementation. The percentage changes are estimated following Equation 1 with $100 \times (exp(\beta_h) - 1)$. Standard errors are clustered at the country level and the regression includes as well as sector-year, country-year and country-sector fixed effects. The dashed lines represent 90 percent confidence intervals. The histograms in the bottom parts of the Figure represent the first stage KP rank Wald F-statistic for the considered horizon. The black line delineates F=10.
Sources: LaBelle et al. (2024), GTA (2022), Juhász et al. (2025), and authors' calculations.

Figure A.16: Protectionist subsidies and export incentives and patent applications received from foreign inventors with country-sector clustering.

A. Subsidies

B. Export incentives

Figures/iv_lproj_ln_st_patent_received

Figures/iv_lproj_ln_st_patent_received_abroad

Notes: The upper part of the Panels presents the main results. Panel A estimates the effect of one additional protectionist subsidy and Panel B presents the effect of one additional export incentive. In both Panels, the y-axis represents the percentage change in patent applications received from abroad in percent and the x-axis represents the considered horizon in years. Year 0 is the year of IP implementation. The percentage changes are estimated following Equation 1 with $100 \times (exp(\beta_h) - 1)$. Standard errors are clustered at the country-sector level and the regression includes as well as sector-year, country-year and country-sector fixed effects. The dashed lines represent 90 percent confidence intervals. The histograms in the bottom parts of the Figure represent the first stage KP rank Wald F-statistic for the considered horizon. The black line delineates F=10.
Sources: LaBelle et al. (2024), GTA (2022), Juhász et al. (2025), and authors' calculations.

Figure A.17: Protectionist subsidies and export incentives and patent applications received from foreign inventors when instrumented by same policy tool.

A. Subsidies B. Export incentives

Figures/iv_lproj_ln_st_patent_received

Notes: The upper part of the Panels presents the main results. Panel A estimates the effect of one additional protectionist subsidy and Panel B presents the effect of one additional export incentive. In both Panels, the y-axis represents the percentage change in patent applications received from abroad in percent and the x-axis represents the considered horizon in years. Year 0 is the year of IP implementation. The percentage changes are estimated following Equation 1, but the instrument is the same policy tool in other countries and sectors. The formula uses $100 \times (exp(\beta_h) - 1)$. Standard errors are clustered at the country level and the regression includes as well as sector-year, country-year and country-sector fixed effects. The dashed lines represent 90 percent confidence intervals. The histograms in the bottom parts of the Figure represent the first stage KP rank Wald F-statistic for the considered horizon. The black line delineates F=10.
Sources: LaBelle et al. (2024), GTA (2022), Juhász et al. (2025), and authors' calculations.

Figure A.18: Protectionist (left) and liberalizing (right) industrial policies and received patent applications from foreign inventors, by centrality of the targeted sector (color) defined with the country's median

A. Protectionist IPs and patent applications received from foreign inventors, by innovation centrality of the targeted industry.

B. Liberalizing IPs and patent applications received from foreign inventors, by innovation centrality of the targeted industry.

Figures/iv_lproj_ln_st_patent_received

Notes: The y-axis represents the percentage change in patent applications received from abroad in percent. The x-axis represents the considered horizon in years. The purple and light blue curves show the effect of IPs targeting innovation-central sectors and gray and dark blue curves the effects of policies targeting non-central industries. Industries are innovation central if their PageRank centrality in their country's innovation network is above the 80th percentile of the country's innovation centrality distribution, as explained in Section 2.3. Year 0 is the year of IP implementation. The percentage changes are estimated following Equation 1 with $100 \times (exp(\beta_h) - 1)$. The regression controls for IPs implemented in upstream and downstream sectors as well as sector-year, country-year and country-sector fixed effects. The instrumented variable is the one of interest. Standard errors are clustered at the country level. The dashed lines represent 90 percent confidence intervals.
Sources: LaBelle et al. (2024), GTA (2022), Juhász et al. (2025), and authors' calculations.

Figure A.19: Protectionist (left) and liberalizing (right) industrial policies and received patent applications from foreign inventors, by centrality of the targeted sector (color) measured with PageRank centrality

A. Protectionist IPs and patent applications received from foreign inventors, by innovation centrality of the targeted industry.

Figures/iv_lproj_ln_st_patent_received

B. Liberalizing IPs and patent applications received from foreign inventors, by innovation centrality of the targeted industry.

Notes: The y-axis represents the percentage change in patent applications received from abroad in percent. The x-axis represents the considered horizon in years. The purple and light blue curves show the effect of IPs targeting innovation-central sectors and gray and dark blue curves the effects of policies targeting non-central industries. Industries are innovation central if their eigenvalue centrality in their country's innovation network is above the 80th percentile of the country's innovation centrality distribution, as explained in Section 2.3. Year 0 is the year of IP implementation. The percentage changes are estimated following Equation 1 with $100 \times (exp(\beta_h) - 1)$. The regression controls for IPs implemented in upstream and downstream sectors as well as sector-year, country-year and country-sector fixed effects. The instrumented variable is the one of interest. Standard errors are clustered at the country level. The dashed lines represent 90 percent confidence intervals.
Sources: LaBelle et al. (2024), GTA (2022), Juhász et al. (2025), and authors' calculations.

Figure A.20: Protectionist (purple) and liberalizing (blue) industrial policies and patent applications from foreign (left) and domestic (right) inventors estimated with OLS.

A. Domestic inventors

B. Foreign inventors

Figures/lproj_ln_st_patent_local_prot1

Figures/lproj_ln_st_patent_received_abroad_prot1_

Notes: The upper part of the Panels presents the main results. The y-axes represent the percentage change in patent applications received from abroad in percent in Panel A. In Panel B, the y-axis represents the percentage change in patent applications received from domestic inventors in percent. In both panels, the x-axis represents the considered horizon in years. Year 0 is the year of IP implementation. The purple lines shows the correlation with protectionist IPs and the blue lines the correlation with liberalizing IPs. The second stage forms are estimated with OLS. Standard errors are clustered at the country level and the regression includes as well as sector-year, country-year and country-sector fixed effects. The dashed lines represent 90 percent confidence intervals. The histograms in the bottom parts of the Figure represent the first stage KP rank Wald F-statistic for the considered horizon. The black line delineates F=10.
Sources: LaBelle et al. (2024), GTA (2022), Juhász et al. (2025), and authors' calculations.