Online Annexes

Industrial Policies: Handle with Care

Staff Discussion Note No. SDN/2025/002

Online Annexes I–III provide information on data sources, methodology, and complementary results referenced in the main text.

Annex 1. Data Sources and Sample Coverage

Industrial Policies Data

Data on industrial policies (IPs) are from Juhász and others (2023). The authors apply state-of-the-art machine learning tools on the description of policies in the Global Trade Alert (GTA) project to build a cross-country database of IPs. The authors focus on national-level policies and define IP as "…goal-oriented state action. The purpose is to shape the composition of economic activity." The data comprise approximately 18,000 IPs covering 109 countries during 2009–22. The data can be merged to the original GTA database to extract other policy-related characteristics, such as targeted products and sectors and instruments used and whether the policy is protectionist as evaluated by GTA experts. European Union-level policies are allocated to all member countries.

Importantly, the data cover a wide range of tariff and nontariff measures and distinguish between different instruments. The data identify seven broad categories of policy instruments: export barriers (for example, export bans and quotas); import barriers (for example tariffs and import licensing); domestic subsidies (such as state loans, loan guarantees, and production subsidies); export incentives (such as tax-based incentives and trade financing); restrictions on foreign direct investment (for example, ownership requirements and foreign direct investment screening decisions); procurement policies, and local content requirements. The Staff Discussion Note (SDN) focuses mostly on three instruments that account for the bulk of IPs—protective domestic subsidies, protective export incentives, and policies that lift import barriers (liberalizing import policies). Thus, in addition to its broad coverage, the IP database constructed by Juhász and others (2023) is useful due to its detailed information about the instruments being used. For most of the analysis in the SDN, the data are aggregated at the product/sector, country, and year level.

Time Coverage: The data cover the period 2009–22.

Country Coverage: The data cover policies for 109 countries, although the number of countries used in each exercise will vary according to the availability of other data sources.

Revealed Comparative Advantage Data

Data on revealed comparative advantage (RCA) are constructed using data from CEPII BACI (see Gaulier and Zignago 2010 for details on the data). The database reconciles data reported by almost 150 countries to the United Nations Statistics Division, collated via Comtrade. When both exporting and importing countries report to Comtrade, the database reconciles these flows into a single figure. Taking advantage of this bilateral information on each flow, the database provides a large coverage of countries and more reliable data, especially in terms of unit-values. The data are then aggregated at the HS6 product code-country level. With this information at hand, and as is common in the literature, a product's RCA for a given country is defined as the export share of the product in the country's total exports, divided by the world's export share of the product. A value greater than 1 means that the country is a globally competitive producer.

Time Coverage: Data are available for the 1995–2022 period, but the analysis focuses on the 2009–22 period.

Country Coverage: The data cover all countries with available trade and IP data (100+ countries).

Firm-Level Data

Firm-level data are from the Bureau van Dijk (BvD) Orbis global database. Orbis is the largest cross-country firm-level database. These data can be used for research focusing on linking firms' financial accounts, ownership structure, and production decisions. BvD Orbis reports data for all industries and for both private and public firms. It collects data from various sources (in particular, publicly available national company registries) and harmonizes the data into an internationally comparable format. The coverage of firms varies both by country, industry, over time, and across variables. The reason for variation in firm coverage by country is that different countries have different laws in terms of which firms are required to file their financial accounts. The data allow for constructing a panel of firms for the period 2008–21.

The dataset used in the analysis follows the cleaning steps described in Kalemli-Özcan and others (2015) and Gopinath and others (2017). The variables used in the analysis are total factor productivity, labor compensation, age, total assets, sales, operating revenue (gross output), tangible fixed assets, liabilities, earnings before interest and taxes, and cash flow. All data are transformed into constant 2010 US dollars. Total factor productivity is computed following Ackerberg, Caves, and Frazer (2015).

Time Coverage: The econometric analysis focuses on the period 2009–21 due to the time coverage of the IP data.

Country Coverage: The empirical analysis focuses on 42 countries (advanced economies and emerging market economies) with available TFP data.

Patent Data Used in Cross-Country Analysis

The SDN uses data from the International Patent and Citations across Sectors (INPACT-S) database (see Labelle and others 2024). Using patent-level data from the Worldwide Patent Statistical Database global autumn 2021 edition, the authors compute the number of patent applications from a country of origin (that is, the residence of the inventor or the owner of the technology) to an application authority at the International Patent Classification (IPC) level—4-digit IPC codes—for the period 1980–2019. The authors account for both the applicant and the inventor, respectively. Then, concordance tables developed by Lybbert and Zolas (2022) are used to transform IPC codes into industry codes—ISIC Rev 3, at 2-digit. The resulting database contains 91 patent authorities, 213 countries of origin, 40 years, and 31 ISIC codes.

INPACT-S offers several key advantages over other publicly available data sets. It provides a more comprehensive view of global patent activity by encompassing a wider array of patent authorities. Importantly, INPACT-S uniquely incorporates consistently constructed data on both cross-border and domestic patents, allowing for more robust comparative analyses. These features collectively make INPACT-S a powerful tool for studying global patenting trends and their economic implications.

Time Coverage: Although INPACT-S data span the 1980–2019 period, the econometric analysis focuses on the period 2009–19 due to the time coverage of the IP data.

Country Coverage: For the country coverage, the empirical analysis focuses on all countries with available IP and patent information for the period of analysis.

Annex 2. Empirical Frameworks

Industrial Policies and the Competitiveness of Targeted Products

Baseline Empirical Specification

The baseline regression estimates the dynamic effect of industrial policy (IP) treatment on the trade competitiveness (measured by revealed comparative advantage, RCA[1]) of country *c* and product *p* over horizons *h* ∈ [0, 4] following the local projection difference-in-differences (LP-DiD) method proposed by Dube and others (2024). This method is also used in Cugat and Manera (2024) and Ahn and others (2024). The regression specification is:

$$y_{c,p,t+h} - y_{c,p,t-1} = \beta_h Treated_{c,p,t} + \sum_{l=1}^{2} \theta_{2l}\, y_{c,p,t-l} + \theta_3 \Delta nonIP_{c,p,t} + \sum_{l=1}^{2} \theta_{4l}\, \Delta nonIP_{c,p,t-l} + \alpha_{c,p} + \delta_{c,t} + \rho_{p,t} + \varepsilon_{c,p,t}$$

The dependent variable $y_{c,p,t+h} = ln\left(RCA_{c,p,t+h} + 10^{-3}\right)$, that is, the log of revealed comparative advantage (RCA) plus a small constant.[2] The main independent variable is the IP treatment dummy $Treated_{c,p,t}$. The coefficient of interest is β_h. Additional controls include the non-IP shock ($\Delta nonIP_{c,p,t}$)[3], as well as up to two lags[4] of the dependent variable and of the non-IP shock. $\alpha_{c,p}$ is the country-product fixed effect. $\delta_{c,t}$ is the country-year fixed effect. $\rho_{p,t}$ is the product-year fixed effect. $\varepsilon_{c,p,t}$ is the idiosyncratic error term. Standard errors are clustered at the country-product level.

LP-DiD intends to deal with the bias of using the standard local projection with fixed effects to estimate dynamic and heterogeneous treatment effects across groups that receive the treatment at different points in time ("staggered treatment"). For example, previously treated units may be experiencing delayed effects from their previous treatment. However, these units are implicitly used as control groups for the newly treated units, leading to a biased estimate of the average effect of the control group, and consequently a biased estimated treatment effect. Since the empirical analysis estimates dynamic treatment effects and country-product pairs could receive multiple IP treatments at different points in time, LP-DiD fits the purpose of the analysis well.

The key distinction between LP-DiD and conventional local projection with ordinary least squares is the selection of a clean sample:

$$\text{clean sample} = \begin{cases} \text{first} - \text{time IP}, & D_{c,p,t} = 1 \text{ and } D_{c,p,t-j} = 0, 1 \le j \le L \\ \text{clean controls}, & D_{c,p,t-j} = 0, -h \le j \le L \end{cases}$$

where $D_{c,p,t} = \left(\Delta IP_{c,p,t} > 0\right)$ is an indicator variable taking value 1 if there is a positive IP shock. *L* refers to stabilization lag, that is, the number of periods required for the effect of IP to stabilize. The choice of *L* faces

[1] The revealed comparative advantage (RCA) of a product for a given country is defined as the export share of the product in the country's total export, divided by the world's export share of the product. As discussed in Annex 3, results are robust to using alternative measures of RCA that take into account imports.

[2] Adding a small constant 10^{-3} to the RCA allows for the inclusion of country-product pairs with zero RCA, which are prevalent in the sample. The choice is 10^{-3} in the baseline because the mean value of RCA in the sample is very small, equals to 1.29. Note that the choice of this specification can lead to biases (Chen and Roth 2024), but it is better suited to estimate dynamic impacts of industrial policies (IPs).

[3] $nonIP_{c,p,t}$ represents the number of active (that is, announced and not yet removed) policies in the Global Trade Alert that are not classified as IP in country *c*, product *p*, year *t*. This is a stock variable. The first difference is a flow variable and measures the non-IP shock.

[4] The choice of two lags follows from the rule-of-thumb proposed by Chudik and Pesaran (2015), who recommend the optimal number of lags to be $T^{1/3} = 14^{1/3} \approx 2.41$.

a bias-variance trade-off and is subject to the decision of the researcher. Intuitively, a smaller L results in a larger number of IP treatments qualifying as "first-time IP" and included in the clean sample. However, this comes at a cost of bias, as the clean sample would resemble the ordinary least squares sample. By contrast, a larger L reduces the concern for bias, but leads to a smaller number of observations in the treatment group. The baseline L is set to 5, with robustness test for L = 3 as well.

The definition of clean sample implies that the clean treatment group is restricted to first-time IP treatments up to L preceding periods. Doing so excludes country-product pairs that are treated between $t-1$ and $t-L$ in the control group at time t, where the effects of the treatment are not yet stabilized. The clean treatment group consists only of "clean controls," namely country-product pairs that are never treated between $t-L$ and $t + h$. In sum, the choice of the clean sample eliminates the inclusion of country-product pairs that may be experiencing dynamic effects from previous or later treatments, which may confound the control group during the current treatment period.

The analysis is closely related to that in Rotunno and Ruta (2024), with two main differences. The first is that this Staff Discussion Note (SDN) tracks the impact of the introduction of a new IP as defined by Juhász and others (2023). This means the SDN looks at a subset of the subsidies considered in Rotunno and Ruta (2024). The second difference is that the SDN follows the local projection difference-in-difference approach proposed by Dube and others (2024), which means that the treatment and controls groups in the SDN differs from those in Rotunno and Ruta (2024).

Heterogeneity: Targeted Products

The following regression specification explores the differential impact of IPs targeted at initially competitive versus initially noncompetitive products through the interactions of the initially competitive product indicator with the IP treatment and non-IP shocks. Initially competitive products are those with a lagged RCA greater than 1. Intuitively, a value greater than 1 implies that the country exports a relatively higher share of the product compared to the world average; thus, the country is competitive in the particular product. β_h is the estimated effect for initially uncompetitive products, whereas $\beta_h + \gamma_h$ picks up the estimated effect for initially competitive products.

$$
\begin{aligned}
y_{c,p,t+h} - y_{c,p,t-1} = \beta_h Treated_{c,p,t} &+ \gamma_h Treated_{c,p,t} \times (RCA_{c,p,t-1} \\
&> 1) + \sum_{l=1}^{2} \theta_{2l}\, y_{c,p,t-l} + \lambda_3 \Delta nonIP_{c,p,t} + \theta_3 \Delta nonIP_{c,p,t} \times (RCA_{c,p,t-1} \\
&> 1) + \sum_{l=1}^{2} \lambda_{4l}\, \Delta nonIP_{c,p,t-l} + \sum_{l=1}^{2} \theta_{4l}\, \Delta nonIP_{c,p,t-l} \times (RCA_{c,p,t-1} \\
&> 1) + \alpha_{c,p} + \delta_{c,t} + \rho_{p,t} + \varepsilon_{c,p,t}
\end{aligned}
$$

Heterogeneity: Policy Instruments

There are two modifications to the baseline specification when assessing the heterogenous effect of IP policy instruments. First, the clean sample for evaluating policy instrument i is:

$$
\text{clean sample } i = \begin{cases} \text{first} - \text{time IP } i, & D_{i,c,p,t} = 1 \; and \; D_{-i,c,p,t} = 0 \text{ and } D_{c,p,t-j} = 0, 1 \le j \le L \\ \text{clean controls}, & D_{c,p,t-j} = 0, -h \le j \le L \end{cases}
$$

In words, the treatment group to examine the effect of IP policy instrument i is restricted to country-product pairs that are treated by policy instrument i for the first time ($D_{i,c,p,t} = 1$) up to L preceding periods ($D_{c,p,t-j} = 0, 1 \le j \le L$) and not treated by any other policy instruments $-i$ at the same time ($D_{-i,c,p,t} = 0$). The control group remains the same as the clean controls in the baseline regression.

Second, the regression is estimated separately for each policy instrument *i* given the instrument-specific clean sample *i*. The regression specification is similar to the baseline, except that the main independent variable $Treated_{c,p,t}$ becomes $Treated_{i,c,p,t}$ (that is, treatment dummy if country-product receives a positive IP shock under the policy instrument *i*).

Green Value Chain

The green value chain is highly specialized, is niche, and requires high level of granularity. This SDN uses the data set from Rosenow and Mealy (2024), who compile a product mapping at six-digit Harmonized System code to three major green value chains: wind turbines, solar panels, and electric vehicles. Products involved in these three value chains are assigned to one of the four value chain stages: raw materials (for example, iron ore, nickel ore); processed materials (for example, nickel waste or scrap); subcomponents (for example, seats, nickel-iron electric accumulators); end products (for example, lead-acid electric accumulators (vehicle); and buses (except diesel powered). Moreover, no product is assigned to more than one green value chain.

The analysis is based on a simple ordinary least squares local projection framework:

$$
\begin{aligned}
ln\,(RCA_{c,p,t+h} + 10^{-3}) = {} & \beta_d \Delta DownGIP_{c,v(p),s(p),t} + \sum_{l=1}^{2} \theta_{1l} DownGIP_{c,v(p),s(p),t-l} + \beta_u \Delta UpGIP_{c,v(p),s(p),t} \\
& + \sum_{l=1}^{2} \theta_{2l} UpGIP_{c,v(p),s(p),t-l} + \sum_{l=1}^{2} \theta_{3l}\, ln\big(RCA_{c,p,t-l} + 10^{-3}\big) + \theta_4 \Delta NonGIP_{c,v(p),s(p),t} \\
& + \sum_{l=1}^{2} \theta_{5l} NonGIP_{c,v(p),s(p),t-l} + \theta_6 \Delta NonIP_{c,v(p),s(p),t} + \sum_{l=1}^{2} \theta_{7l} NonIP_{c,v(p),s(p),t-l} + FEs + \varepsilon_{c,p,t}
\end{aligned}
$$

$\Delta DownGIP_{c,v(p),s(p),t}$ is the first difference of active downstream green IPs for the value chain of product *p* (denoted by *v(p)*) relative to the value chain stage of product *p* (denoted by *s(p)*). This variable captures the shock to downstream green IPs for the product. Similarly, $\Delta UpGIP_{c,v(p),s(p),t}$ represents the upstream green IP shock. Additional controls include non-green IP shock ($\Delta NonGIP_{c,v(p),s(p),t}$), non-IP shock ($\Delta NonIP_{c,v(p),s(p),t}$), their two lags, as well as two lags of the dependent variable. FEs refers to a comprehensive set of fixed effects: country-product, country-year, product-year, value chain-year, and country-value chain. The outcomes of interest are β_d and β_u, which capture the effect of downstream (upstream) green IPs relative to green IPs targeting products within the same stage of the value chain.[5]

Industrial Policies and Firm-Level Economic Performance

The baseline regression analysis, which tracks the relationship between IPs and firm performance, builds on the local projection method proposed by Jordà (2005):

[5] Note that these estimated effects are relative to the effects of IPs targeting products within the same value chain ($\Delta OwnGIP_{c,v(p),s(p),t}$), because $\Delta DownGIP_{c,v(p),s(p),t} + \Delta UpGIP_{c,v(p),s(p),t} + \Delta OwnGIP_{c,v(p),s(p),t} + \Delta NonGIP_{c,v(p),s(p),t} + \Delta NonIP_{c,v(p),s(p),t} = \Delta GTA_{c,t}$ and $\Delta GTA_{c,t}$ is absorbed by the country-year fixed effect. Therefore, including all these five left-hand side variables in the equation and country-year fixed effect results in multi-collinearity issue.

$$\log Y_{ft+h} - \log Y_{ft-1} = \sum_{instr\ k} \sum_{\substack{GTA \\ eval\ e}} \beta_h^{ke} \Delta IP_{ict}^{ke} + \sum_{j=1}^{2} \sum_{instr\ k} \sum_{\substack{GTA \\ eval\ e}} \lambda_{t-j}^{ke} IP_{ict-j}^{ke} + \theta_h^{up} \Delta Upstr_{sct} + \theta_h^{dwn} \Delta Dwnstr_{sct} + \sum_{j=1}^{2} \phi_{t-j}^{up} Upstr_{sct-j} + \sum_{j=1}^{2} \phi_{t-j}^{dwn} Dwnstr_{sct-j} + \sum_{j=1}^{2} \mu_{t-j} \log Y_{ft-j} + \delta' X_{ict} + \alpha_f + \alpha_{ct} + \alpha_{it} + \varepsilon_{ft}.$$

where Y_{ft} denotes the main outcome of interest: payroll, capital, productivity measured as total factor productivity quantity, and value added of firm f in year t={2011,…,2018}.[6] The main independent variable ΔIP_{ict}^{ke} (IP_{ict}^{ke}) denotes the change in the stock (stock) of IP instrument k={subsidies, export incentives, trade barriers, local-content requirements, other instruments} of a given Global Trade Alert (GTA) evaluation e={protectionist (red), likely protectionist (amber), liberalizing (green)} in country c and NACE Rev. 24-digit industry code i between t and $t-1$.

The SDN constructs a measure of exposure of firm f in industry i sector s to protectionist IPs in other sectors s' in the spirit of Amiti and Konings (2007):

$$Upstr_{sct} = \sum_{sectors\ s' \neq s} io_{cs' \to s} \cdot IP_{s'ct}, \qquad \sum_{sectors\ s' \neq s} io_{cs' \to s} = 1\ \forall s.$$

where $io_{cs' \to s}$ denotes, for each country c, the share of inputs of sector s that come from sector s' obtained from the Global Trade Analysis Project. This measure captures *how many protectionist IPs are in place in the average sector upstream of that firm*. A similar measure is constructed for downstream exposure:

$$Dwnstr_{sct} = \sum_{sectors\ s' \neq s} io_{cs \to s'} \cdot IP_{s'ct}, \qquad \sum_{sectors\ s' \neq s} io_{cs \to s'} = 1\ \forall s.$$

The remaining controls included in X_{ict} are the change and two lags of the stock of other GTA policies not IPs but targeting industry i, and the change and two lags of the stock of IPs in *other industries in the same sector* of industry i, scaled down by own-sector input-output link from Global Trade Analysis Project. All regressions include firm, country-year, and industry-year fixed effects (FEs), and two lags of the dependent and independent variables in line with the rule of thumb proposed by Chudik and Pesaran (2015). Standard errors are clustered at the country-industry level.

The main coefficient of interest, β_h^{ke}, tracks the evolution of outcomes in the average firm within a country and industry after the implementation of one additional *IP*, controlling for spillovers of IPs in other sectors, unobserved country- and industry-specific shocks, and unobserved time-invariant firm characteristics.

Firm Heterogeneity

Firm heterogeneity is explored in the following regression framework:

[6] These were constructed following IMF (2024) for comparability of results on allocative efficiency.

$$\log Y_{ft+h} - \log Y_{ft-1}$$
$$= \sum_{q=1}^{3} \sum_{instr\ k} \sum_{\substack{GTA \\ eval\ e}} \beta_h^{qke} \Delta IP_{ict}^{ke} \cdot 1\{Z_{ft-1} \in Q_{qct-1}^Z\} + \sum_{q=1}^{3} \gamma^q 1\{Z_{ft-1} \in Q_{qct-1}^Z\}$$
$$+ \sum_{j=1}^{2} \sum_{instr\ k} \sum_{\substack{GTA \\ eval\ e}} \lambda_{t-j}^{ke} IP_{ict-j}^{ke} + \theta_h^{up} \Delta Upstr_{sct} + \theta_h^{dwn} \Delta Dwnstr_{sct} + \sum_{j=1}^{2} \phi_{t-j}^{up} Upstr_{sct-j}$$
$$+ \sum_{j=1}^{2} \phi_{t-j}^{dwn} Dwnstr_{sct-j} + \sum_{j=1}^{2} \mu_{t-j} \log Y_{ft-j} + \delta' X_{ict} + \alpha_f + \alpha_{ct} + \alpha_{it} + \varepsilon_{ft}.$$

where Z_{ft-1} denotes the firm characteristic (that is, age and cash flow to assets ratio) and Q_{qct-1}^Z represents tercile q of the distribution of Z among all firms in country c and year $t-1$. The coefficient of interest β_h^{qke} captures the dynamic relationship between IPs and firm outcomes *for firms in each tercile of firm characteristic* Z.

Country Heterogeneity

Country heterogeneity is explored following the regression:

$$\log Y_{ft+h} - \log Y_{ft-1}$$
$$= \sum_{\substack{GTA \\ eval\ e}} \beta_h^e \Delta IP_{ict}^e \cdot Z_{ct-1} + \sum_{\substack{GTA \\ eval\ e}} \gamma_h^e \Delta IP_{ict}^e + \sum_{j=1}^{2} \sum_{\substack{GTA \\ eval\ e}} \lambda_{t-j}^e IP_{ict-j}^e + \theta_h^{up} \Delta Upstr_{sct}$$
$$+ \theta_h^{dwn} \Delta Dwnstr_{sct} + \sum_{j=1}^{2} \phi_{t-j}^{up} Upstr_{sct-j} + \sum_{j=1}^{2} \phi_{t-j}^{dwn} Dwnstr_{sct-j} + \sum_{j=1}^{2} \mu_{t-j} \log Y_{ft-j} + \delta' X_{ict}$$
$$+ \alpha_f + \alpha_{ct} + \alpha_{it} + \varepsilon_{ft}.$$

where Z_{ct-1} represents the country characteristic from Budina and others (2023) (for example, trade openness, credit market conditions, business environment) or average schooling year by country from the United Nations (UN) Human Development Index. The coefficient of interest $\beta_h^{ke} \bar{Z} + \gamma_h^{ke}$ measures the impact of an additional IP (of a given type) *in the average firm of a country with characteristic level* $\bar{Z}$. The SDN assesses the role of country fundamentals in emerging market economies or advanced economies by further interacting all IP variables above with respective regional dummies. Confidence intervals are calculated using the delta method for a given value of $\bar{Z}$. The authors evaluate the impact of IPs at the 10th/25th and 75th /90th percentiles of the distribution of Z_{ct}.

Threats to Identification and Robustness Exercises

The baseline regressions include a rich set of FEs and lags of the dependent and independent variables to control for potential omitted variables in the decision of countries to implement IPs and to capture past dynamics in both IPs and the variables of interest. For example, industry-year FEs control for global shocks to different industries (that is, industry trends); country-year FEs control for growth shocks in different countries; and firm FEs control for firm-specific time-invariant differences across firms (for example, underlying managerial ability). Endogeneity concerns are also alleviated by visually inspecting whether outcomes of firms in industries that received IPs were catching up to outcomes of firms in industries that did not receive IPs three years prior to the implementation of the policy (that is, check for pre-trends in the same direction of estimated treatment effects).

The main independent variable counts the number of IPs that targeted each industry. In this sense, policies that affect small or large products (in how much they represent of an industry's economic activity) are counted the same. In a robustness exercise, we construct an index of IP intensity that measures the *share of trade* in each industry that is affected by IPs and re-do the firm-level analysis. The IP intensity index is:

$$IP_{ict}^{Trade} = \sum_{\text{policy } p} \sum_{\text{product } q \in ic} \frac{Trade_{qic}}{Trade_{ic}} \cdot 1\{\text{policy } p \text{ affects product } q\}.$$

To further address endogeneity concerns, the SDN implements two methodologies to complement the baseline LP specification. First, the authors implement a LP-DiD method following Dube and others (2024). The key difference is that the authors restrict the sample to two types of firms: those that were treated for the first time in three years (clean treatment), and those that were never directly exposed to IPs (clean controls). Only considering clean treatment and clean control firms alleviates concerns that the control group may be contaminated with firms that were "just treated," biasing the estimates of the treatment effect.

Second, the authors implement a two-stage least squares instrumental variable (IV) strategy, where the change in IPs of a given type k that country c implements in industry i is instrumented with IPs of type k' implemented by trade partners $c' \neq c$ in other industries $i' \neq i$:

$$IV_{ict}^{k} = \sum_{c' \neq c} \sum_{i' \neq i} \left(\frac{\text{Total Trade}_{cc't}}{\sum_{c' \neq c} \text{Total Trade}_{cc't}} \right) \cdot \Delta IP_{i'c't}^{k'}.$$

The preferred instruments for protectionist subsidies are protectionist subsidies in other countries and industries, for liberalizing trade barriers are liberalizing trade barriers in other countries and industries, and for protectionist export incentives are total protectionist IPs in other countries and industries. This strategy further addresses endogeneity concerns that countries are targeting specific industries based on the evolution of their unobserved productivity.

Lastly, the SDN performs a battery of additional robustness checks, including (1) excluding China to address concerns of coverage of IPs in the GTA database; (2) adding firm-level controls, which restrict country coverage but enhances the comparison across firms; (3) dropping firms that experienced abnormal growth in each horizon; (4) removing countries that are over-represented in Orbis: Spain, Italy, and France; (5) reweighting regressions by the inverse of the number of firms in each country and by firm size; and (6) controlling for three lags of both dependent and independent variables to better capture past dynamics in both IPs and outcomes.

Industrial Policies and Industry-Level Economic Performance

The empirical specification for industry-level analysis follows closely the firm-level analysis. The baseline regression tracking the relationship between IPs and sectoral performance is:

$$\begin{aligned}
&\log Y_{ict+h} - \log Y_{ict-1} \\
&\quad = \sum_{instr\ k} \sum_{\substack{GTA \\ eval\ e}} \beta_h^{ke} \Delta IP_{ict}^{ke} + \sum_{j=1}^{2} \sum_{instr\ k} \sum_{\substack{GTA \\ eval\ e}} \lambda_{t-j}^{ke} IP_{ict-j}^{ke} + \sum_{\substack{GTA \\ eval\ e}} \theta_h^{up,e} \Delta Upstr_{sct}^{e} \\
&\quad + \sum_{\substack{GTA \\ eval\ e}} \theta_h^{dwn,e} \Delta Dwnstr_{sct}^{e} + \sum_{j=1}^{2} \sum_{\substack{GTA \\ eval\ e}} \phi_{t-j}^{up,e} Upstr_{sct-j}^{e} + \sum_{j=1}^{2} \sum_{\substack{GTA \\ eval\ e}} \phi_{t-j}^{dwn,e} Dwnstr_{sct-j}^{e} \\
&\quad + \sum_{j=1}^{2} \mu_{t-j} \log Y_{ict-j} + \delta' X_{ict} + \alpha_{ci} + \alpha_{ct} + \alpha_{it} + \varepsilon_{ft}.
\end{aligned}$$

The main outcomes of interest are industry value added, productivity, capital, payroll, and allocative efficiency; payroll and allocative efficiency are calculated by closely following IMF (2024). As in the firm-level analysis, the main coefficients of interest, β_h^{ke}, capture the dynamic correlations between industry performance and different types of IPs. The SDN includes a similar set of controls to those in the firm-level analysis, and standard errors are clustered at the country-industry level.

Industry Heterogeneity

To explore heterogeneity by industry characteristics, the SDN proceeds in three steps. First, it calculates median markups and median external financial dependence (EFD) across firms in each country and industry in ORBIS.[7] Second, the SDN regresses these medians on industry and country FEs. The main measure of markups and EFDs for each industry corresponds to the estimated industry FEs. Third, the authors explore heterogeneity of IPs by sectoral distortion by regressing:

$$\begin{aligned}\log Y_{ict+h} - \log Y_{ict-1} &= \sum_{\substack{GTA\\ eval\ e}} \beta_h^e \cdot \Delta IP_{ict}^e + \sum_{\substack{GTA\\ eval\ e}} \gamma_h^{e,EFD} \cdot \Delta IP_{ict}^e \cdot EFD_i + \sum_{\substack{GTA\\ eval\ e}} \gamma_h^{e,Markups} \cdot \Delta IP_{ict}^e \cdot Markups_i \\ &+ \sum_{j=1}^{2} \sum_{\substack{GTA\\ eval\ e}} \lambda_{t-j}^e IP_{ict-j}^e + \sum_{\substack{GTA\\ eval\ e}} \theta_h^{up,e} \Delta Upstr_{sct}^e + \sum_{\substack{GTA\\ eval\ e}} \theta_h^{dwn,e} \Delta Dwnstr_{sct}^e \\ &+ \sum_{j=1}^{2} \sum_{\substack{GTA\\ eval\ e}} \phi_{t-j}^{up,e} Upstr_{sct-j}^e + \sum_{j=1}^{2} \sum_{\substack{GTA\\ eval\ e}} \phi_{t-j}^{dwn,e} Dwnstr_{sct-j}^e + \sum_{j=1}^{2} \mu_{t-j} \log Y_{ict-j} + \delta' X_{ict} + \alpha_{ci} \\ &+ \alpha_{ct} + \alpha_{it} + \varepsilon_{ft}.\end{aligned}$$

The impact of IPs in high distortion industries is calculated as: $\beta_h^e IP^{(p75-p25)} + \gamma_h^{e,EFD} IP^{(p75-p25)} EFD^{p75} + \gamma_h^{e,Markups} IP^{(p75-p25)} Markups^{p75}$, where $IP^{(p75-p25)}$ denotes the difference between 75th and 25th percentiles of the distribution of IPs and $Markups^{p75}$ (EFD^{p75}) denotes the 75th percentile of the distribution of markups (EFD). The impact of IPs in low-distortion industries is estimated in a similar way, but evaluating markups and EFD at their 25th percentile. As a robustness, the SDN conducts similar comparisons using the standard deviation for each policy variable. Confidence intervals are calculated using the delta method and standard errors are clustered by country and industry.

Threats to Identification and Robustness Exercises

Similar to firm-level specifications, the rich set of FEs and lags of the dependent and independent variables partially addresses potential omitted variables and capture past dynamics in both IPs and the variables of interest. To further address endogeneity concerns, the SDN also implements the LP-DiD and local projection instrumental variables as robustness checks (with the same methodologies and instruments as in the firm-level robustness checks). To address concerns of GTA coverage across countries and under-reporting of IPs in emerging market and developing economies, the SDN also performs two robustness exercises, one which exclude China from the sample and another that uses all GTA subsidies as the variable of interest. Note that recent studies exploit the subnational design of policies (Criscuolo and others 2019), or high-frequency changes in financial variables (Brandao-Marques and Toprak 2024), to construct exogenous variation in IPs. These strategies, however, are unfeasible in the context of this SDN to the features of the data.

[7] The authors calculate long-term averages of markups and external financial dependence for each firm to control for yearly fluctuations. Markups are calculated following Díez and others (2021).

Industrial Policies and Industry-Level Patenting

Baseline Specification

The specifications used in the SDN build on the local projection method proposed by Jordà (2005). This method captures the dynamic association between industrial policies at time t and patent filing by foreign inventors over multiple horizons. Its specification would then be as follows:

$$\begin{aligned}\log\left(10^{-6}+PatentStock_{c,s,t+h}\right)-\ \log\left(10^{-6}+PatentStock_{c,s,t-1}\right)\\ =\beta_h^1\Delta LiberalizingIPStock_{c,s,t}+\beta_h^2\Delta ProtectionistIPStock_{c,s,t}+\beta_h^3\Delta AnnouncedIPStock_{c,s,t}\\ +\theta_1\log\left(10^{-4}+PatentStock_{c,s,t-1}\right)+\theta_2 LiberalizingIPStock_{c,s,t-1}\\ +\theta_3 ProtectionistIPStock_{c,s,t-1}+\theta_4\Delta AnnouncedIPStock_{c,s,t}+\theta_5\Delta NonIP_{c,p,t}\\ +\theta_6 NonIP_{c,p,t-1}+\lambda_{c,s}+\lambda_{c,t}+\lambda_{s,t}+\varepsilon_{c,s,t}\end{aligned}$$

where $PatentStock_{c,s,t}$ is the patent stock in country c, sector s, and year t. The stock measure is built by aggregating patent applications after 1980. This measure distinguishes between patents submitted by local inventors and foreign ones. $\Delta LiberalizingIPStock_{c,s,t}$ is the change in liberalizing industrial policies in this country, sector, and year, and similarly $\Delta ProtectionistIPStock_{c,s,t}$, and $\Delta AnnouncedIPStock_{c,s,t}$ refer to protectionist and announced industrial policies. $\Delta NonIP_{c,p,t}$ is the change in trade policies that are not industrial policies, as recorded by the GTA database. In agreement with the local projection method, the specification also includes lags of the dependent and independent variables. The specification also includes country-sector, country-year, and sector-year fixed effects, respectively $\lambda_{c,s}$, $\lambda_{c,t}$, and $\lambda_{s,t}$. $\varepsilon_{c,s,t}$ is the error term. Standard errors are clustered at the country level. In this specification, the coefficient of interest is β_h^2 when analyzing the effect of an additional industrial policy on patent filing. It is β_h^1 when considering the effect of liberalizing an additional industrial policy.

Controls for trade policies other than industrial policies and FEs partially address omitted variable bias. However, this specification does not tackle the potential endogeneity of industrial policies due to their targeting and timing. For instance, if IPs disproportionately target innovative sectors, there would be a positive correlation between the change in industrial policy and the change in patent stock, which could bias the estimates upward. The authors investigate potential endogeneity due to targeting and timing by examining pre-trends for horizons –3 to –1. They test whether they are significantly different from zero, which could indicate that the targeting of industrial policy is correlated with sectoral patent filing.

Application to Climate-Related Protectionist Industrial Policies

The SDN builds on the previous specification to assess the effect of climate-related and non-climate-related IPs on patent filings by local inventors (Figure 2.1.1, panel 2 of the SDN). The regression is similar but distinguishes climate-related IPs from non-climate-related ones:

$$\begin{aligned}\log\left(10^{-6} + PatentStock_{c,s,t+h}\right) - \log\left(10^{-6} + PatentStock_{c,s,t-1}\right) \\ = \beta_h^{1,\mathrm{g}} \Delta \mathrm{Green} LiberalizingIPStock_{c,s,t} + \beta_h^{1,\mathrm{ng}} \Delta \mathrm{Nongreen} LiberalizingIPStock_{c,s,t} \\ + \beta_h^{2,\mathrm{g}} \Delta \mathrm{Green} ProtectionistIPStock_{c,s,t} + \beta_h^{2,\mathrm{ng}} \Delta \mathrm{Nongreen} ProtectionistIPStock_{c,s,t} \\ + \beta_h^{3} \Delta AnnouncedIPStock_{c,s,t} + \theta_1 \log\left(10^{-4} + PatentStock_{c,s,t-1}\right) \\ + \theta_{2,\mathrm{g}} GreenLiberalizingIPStock_{c,s,t-1} + \theta_{2,\mathrm{ng}} NongreenLiberalizingIPStock_{c,s,t-1} \\ + \theta_{3,\mathrm{g}} GreenProtectionistIPStock_{c,s,t-1} + \theta_{3,\mathrm{ng}} NongreenProtectionistIPStock_{c,s,t-1} \\ + \theta_4 \Delta AnnouncedIPStock_{c,s,t} + \theta_5 \Delta NonIP_{c,p,t} + \theta_6 NonIP_{c,p,t-1} + \lambda_{c,s} + \lambda_{c,t} + \lambda_{s,t} + \varepsilon_{c,s,t}\end{aligned}$$

Here, $GreenLiberalizingIPStock_{c,s,t-1}$ refers to climate-related liberalizing industrial policies, and $NongreenLiberalizingIPStock_{c,s,t-1}$ to non-climate related ones. $\mathrm{Green}ProtectionistIPStock_{c,s,t}$ and $NongreenProtectionistIPStock_{c,s,t-1}$ refers to the climate and non-climate-related protectionist IPs. As the note focuses on protectionist IPs, the coefficients of interest are $\beta_h^{2,\mathrm{g}}$ and $\beta_h^{2,\mathrm{ng}}$. Results are reported for horizons 1 and 4 in Box Figure 1, panel 2. Pre-trends (horizons –1 to –3) are not significantly different from zero at the 90 percent significance level. This result indicates no significant pre-trends, hence, no evidence that the timing of climate-related industrial policies is correlated to sectoral trends in patent filing.

Instrumental Variable Strategy

To further address the endogeneity concern related to the timing and targeting of industrial policies, the authors use an instrumental variable strategy for the SDN's main results on the effect of IPs on patent filing (Figure 7 and Figure 8, panel 4).

This method instruments the change in protectionist IPs by the change in protectionist IPs in other sectors and countries, weighted political distance as measured by UN vote patterns. The corresponding first-stage regression is as follows:

$$\Delta ProtectionistIPStock_{c,s,t} = \theta \sum_{c' \neq c, s' \neq s} \left(\frac{Pol\,Dist_{c,c',t}}{\sum_{c' \neq c} Pol\,Dist_{c,c',t}}\right) \Delta IPProtectionistStock_{c',s',t} + \lambda_{c,s} + \lambda_{c,t} + \lambda_{s,t} + \varepsilon_{c,s,t}$$

The instrument is relevant: the associated *F*-statistic is above 10 for all horizons when using country-sector clustered standard errors, and for all horizons except 4 and 5 when using country clustered standard errors. The relevance of the instrument is explained by tit-for-tat dynamics: protectionist IPs are implemented in other sectors following their implementation in politically distant countries. The exogeneity comes from the fact that industrial policies in other sectors and politically distant countries do not influence patent filing in the considered country and sector. The Hansen *J*-test also does not reject exogeneity.

The change in liberalizing industrial policies is instrumented by two instruments, both counting the changes in liberalizing IPs in other sectors and countries, but using two different weights. As before, the first weight is the political distance, which is measured by UN vote patterns and captures tit-for-tat dynamics. The second weight is a set of dummy variables identifying the country's main trade partners, representing more than 90 percent of the country's trade. The first-stage regression is as follows:

$$\Delta LiberalizingIPStock_{c,s,t} = \theta^1 \sum_{c' \neq c, s' \neq s} \left(\frac{Pol\,Dist_{c,c',t}}{\sum_{c' \neq c} Pol\,Dist_{c,c',t}}\right) \Delta LiberalizingIPStock_{c',s',t} + \theta^2 \sum_{c' \neq c, s' \neq s} \left(\frac{1(Main\,Trade\,Partner)_{c,c',t}}{\sum_{c' \neq c} 1(Main\,Trade\,Partner)_{c,c',t}}\right) \Delta IPLiberalisingStock_{c',s',t} + \lambda_{c,s} + \lambda_{c,t} + \lambda_{s,t} + \varepsilon_{c,s,t}$$

Instruments: $\sum_{c'\neq c,s'\neq s}\left(\frac{Pol\,Dist_{c,c',t}}{\sum_{c'\neq c}Pol\,Dist_{c,c',t}}\right)\Delta LiberalizingIPStock_{c',s',t}$ and $\sum_{c'\neq c,s'\neq s}\left(\frac{1(Main\,Trade\,Partner)_{c,c',t}}{\sum_{c'\neq c}1(Main\,Trade\,Partner)_{c,c',t}}\right)\Delta IPLiberalisingStock_{c',s',t}$

Again, instruments are relevant: the associated *F*-statistic is above 10 for all horizons when using country-sector and country-clustered standard errors. The exogeneity argument is similar to the above one and supported by the Hansen *J*-test.

Comparing IPs and Structural Reforms

The comparison between IPs and other structural reforms implements a different specification than the analysis of industry economic performance, as the rich set of fixed effects does not allow for the estimation of the average impact of structural reforms, which vary by country-year and are consequently absorbed by α_{ct}. The SDN follows Rajan and Zingales (1998) and contrasts the *relative impact* of IPs versus structural policies across industries with different levels of distortions:

$$\begin{aligned}\log Y_{ict+h} - \log Y_{ict-1} &= \psi^{EFD,FD}\cdot EFD_i\cdot FD_{ct-1} + \psi^{Mkp,GOV}\cdot Markup_i\cdot GOV_{ct-1} + \psi^{EFD,IP}\cdot EFD_i\cdot \Delta IP^{Red}_{ict} + \psi^{Mkp,IP}\\ &\cdot Mkp_i\cdot \Delta \mathrm{IP}^{Red}_{ict} + \sum_{\substack{GTA\\ eval\ e}}\beta^e_h \Delta IP^e_{ict} + \sum_{j=1}^{2}\sum_{\substack{GTA\\ eval\ e}}\lambda^e_{t-j} IP^e_{ict-j} + \sum_{\substack{GTA\\ eval\ e}}\theta^{up,e}_h \Delta Upstr^e_{sct}\\ &+ \sum_{\substack{GTA\\ eval\ e}}\theta^{dwn,e}_h \Delta Dwnstr^e_{sct} + \sum_{j=1}^{2}\sum_{\substack{GTA\\ eval\ e}}\phi^{up,e}_{t-j} Upstr^e_{sct-j} + \sum_{j=1}^{2}\sum_{\substack{GTA\\ eval\ e}}\phi^{dwn,e}_{t-j} Dwnstr^e_{sct-j}\\ &+ \sum_{j=1}^{2}\mu_{t-j}\log Y_{ict-j} + \delta' X_{ict} + \alpha_{ci} + \alpha_{ct} + \alpha_{it} + \varepsilon_{ft}.\end{aligned}$$

The first four terms in the right-hand side of the equation contain the main coefficients of interest, ψ. They assess how industry performance relates to structural policies (FD_{ct} financial development; GOV_{ct} governance index) and protectionist IPs in industries with different distortions (EFD_i median EFD; Mkp_i median markups). Note that the country-year fixed effects make sure the authors compare countries with similar levels of structural policies, and the industry-year fixed effects guarantee the comparison of industries with similar levels of distortions. To compare financial development policies to IPs, the authors plot $\psi^{EFD,FD}\cdot EFD^{(p75-p25)}\cdot FD^{(p75-p25)}$ versus $\psi^{EFD,IP}\cdot EFD^{(p75-p25)}\cdot \mathrm{IP}^{(p75-p25)}$ for all horizons, where p75-p25 denote the difference between the 75th and the 25th percentile of the distribution of a variable. Similarly, the authors compare governance and IPs by plotting $\psi^{Mkp,GOV}\cdot Markup^{(p75-p25)}\cdot Gov^{(p75-p25)}$ versus $\psi^{Mkp,IP}\cdot Markup^{(p75-p25)}\cdot IP^{(p75-p25)}$. Coefficient intervals are calculated using the delta method and standard errors are clustered at the country-industry level.

Annex 3. Additional Results

This annex summarizes additional evidence cited in the main text of the Staff Discussion Note, presented in Table 3.1. In particular, it focuses on extensions to the main analysis and robustness exercises.

Table 3.1. Robustness Exercises		
1. Exercise Description	2. Additional Details	3. Comparison to Baseline
Industrial Policies and Export Competitiveness		

Assessing the impact of all Global Trade Alert (GTA) subsidies	Run a regression that tracks the impact on an additional subsidy (whether it is classified as industrial policy [IP] or not) on value added.	Results are comparable to those found for subsidies classified as IPs.
Using alternative RCA measures	Run regressions using a revealed comparative advantage (RCA) measure that controls for imports (Vollrath 1991).	Results are robust to the use of this alternative RCA measure.
Industrial Policies at the Firm level		
IP trade intensity index	Construct IP trade intensity index based on the share of each industry's total trade that is affected by IPs. This robustness check restricts the analysis to IPs with non-missing Harmonized System (HS) codes.	Within the sample of IPs with non-missing HS codes, using baseline measure or the IP trade intensity index does not significantly change the results. Within the broader sample, the relationship between each instrument and firms' value added, capital, and total factor productivity (TFP) is broadly the same.
IV strategy	Implement two-stage least squares strategy where the authors instrument the count of IPs in a country-sector with the count of IPs that trading partners implemented in other industries. There are strong first stages for average firm analysis. Domestic subsidies on capital by firm financial constraints has a first-stage *F*-statistic of 8.6. Export incentives on TFP by firm age has first-stage *F*-statistic of 3.7.	Results for average firm: The behavior of value added, TFP, and capital in response to protectionist export incentives and liberalizing trade restrictions is broadly consistent with the baseline results. Protectionist subsidies lose significance on all outcomes at all horizons in the IV specification, although coefficients for capital are still positive. Firm heterogeneity: The direction of coefficients is broadly aligned with Baseline although with much larger magnitudes.
Local projections difference-in-differences (LP-DiD) strategy	Restrict sample to clean treatment (firms that received IPs for the first time in three years) and clean control (firms that did not receive IPs for the span of six consecutive years). Replace main independent variable for a dummy that equals one if IPs were implemented.	Results for average firm: The behavior of value added, TFP, and capital in response to each IP instrument is broadly consistent with Baseline, except for the impact of domestic subsidies on capital stock which becomes positive but insignificant. Firm heterogeneity: Domestic subsidies on capital by firm financial constraints remains broadly aligned with Baseline. Export incentives now increase TFP of both young and old firms in similar magnitudes, but there is evidence that targeted young firms were underperforming targeted old firms, suggesting stronger relative impact of export incentives on young firms.
Sensitivity of results to sample restrictions	(1) Drop observations from China. (2) Remove Spain, Italy, and France, one at a time, given large share of observations in the regression sample from these countries. (3) Winsorize sample at 1 and 99 percentiles of $(\log Y_{ft+h} - \log Y_{ft-1})$ for each horizon *h*.	Results broadly in line with Baseline.
Adding firm-level controls; additional lags; remove input-output exposure controls	(1) Control for total assets, leverage ratio, and cash flow to assets ratio. Reduces the sample of countries, as some emerging market developing economies do not report this information. (2) Include three lags of dependent and independent variables to test sensitivity of the rule of thumb of Chudik and Pesaran (2015). (3) Remove controls for input-output exposure.	Results broadly in line with Baseline.

Changing the weighting scheme	Weight regressions by: (1) the inverse of the number of firms in the sample for each country; (2) firms sales in the previous year.	Results broadly in line with Baseline.
Assessing the impact of all GTA subsidies	Run a regression that tracks the impact on an additional subsidy (whether it is classified as IP or not) on value added.	Results are comparable to those found for subsidies classified as IPs.
Industrial Policies at the Sectoral Level		
IV strategy	Same as firm-level robustness exercise. All first stages are strong.	Domestic subsidies on value added is still positive, but only significantly positive at the last horizon. Domestic subsidies on advanced economies (AEs) remains broadly consistent with Baseline. Export incentives on value added now becomes positive but insignificant throughout all horizons. Export incentives on AEs becomes positive at larger magnitude but insignificant starting in horizon 1.
LP-DiD strategy	Same as firm-level robustness exercise.	Domestic subsidies on VA is negative upon impact and positive with larger magnitude in the medium term. Domestic subsidies on AE is positive but insignificant. Export incentives on VA have same shape as Baseline but less significance. Positive impact of export incentives on AE now materializes in the first horizon and goes to zero in the medium term.
Excluding China	Same as firm-level robustness exercise.	Results broadly in line with Baseline.
Different specifications for the comparison with structural policies	Include all structural policies (Financial Development, Governance, Regulatory Burden of Doing Business) interacted with their respective distortions in a single equation or doing one at a time in separate regressions.	Comparison between IPs and structural policies are aligned with Baseline.
Economic Effect of Industrial Policies on Patent Filing		
Decomposition of protectionist IPs by type	Subsidies and export incentives definitions taken from GTA's classification. The specification is similar to the IV strategy described above with the instrumental variable considering the use of the same type of IP in other countries and sectors. Results are robust to using the same instruments as the ones described above.	Subsidies and export incentives drive the positive effect of protectionist IPs on patent filing by foreign inventors. An additional protectionist subsidy is associated with a 2.0 percent increase in the number of received foreign patent applications in the first year but does not last beyond the second year. Export incentives are associated with a temporary effect of the same size that only materializes in the second year.

Source: Authors' calculations.

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