Do Industrial Policies Increase Trade Competitiveness?*

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Abstract

Industrial policies (IPs) are on the rise. The most common motive for pursuing IPs is to boost strategic competitiveness of the targeted products. Leveraging a novel database of industrial policies and using the local projection difference-in-differences approach, this paper examines the *dynamics* relationship between IPs and trade competitiveness. Our results point to a nuanced picture. On average, products targeted by IPs experience a larger increase in competitiveness than non-targeted ones. However, there is substantial heterogeneity across different types of product and policy instruments. The average effect is driven by initially competitive products. Turning to policy instruments, domestic subsidies are associated with short-term improvements in trade competitiveness, whereas export incentives are linked to medium-term improvements in competitiveness. Finally, we focus on three widely discussed value chains— solar photo-voltaic, wind turbines, and electric vehicles—and present suggestive evidence that IPs can have spillover effects on non-targeted products through value chain linkages. Our findings for these three value chains suggest that IPs targeting upstream products are associated with larger improvements in the RCA of products using these upstream products relative to IPs targeting products at the same value chain stage.

Keywords: Industrial policies, trade, revealed comparative advantage, domestic subsidies, export incentives, local projection difference-in-differences

JEL codes: L52, F12, F13, O25, Q48

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1 Introduction

After falling out of fashion in the aftermath of the 1990s liberalization wave, industrial policies (IPs) have been widely used by both advanced economies (AEs) and emerging markets (EMs) in recent years, especially after 2017. This is clearly reflected in the business press, where the number of articles that mention IP grew from less than 1000 times in 1990 to more than 18000 times in 2019 (Evenett et al., 2024). While there are arguments in favor of IPs (market failures, economies of scale, and collective action problems), factors such as limited state capacity and capture by private and political actors, can hamper IPs' effectiveness. Moreover, IPs' historical track record has been mixed. As new economic and geopolitical challenges loom, a fresh assessment of IPs' potential economic impacts is warranted.

Do IPs increase competitiveness of their targeted products? This is an important question, as the most commonly stated motive for IPs is to boost strategic competitiveness,[1] constituting over 35% of IPs in 2023 (Evenett et al., 2024). However, whether products targeted by IPs fulfill this stated motive merits an empirical investigation. In this paper, we focus on one particular type of competitiveness, namely trade competitiveness. We adopt the definition in Juhász et al. (2023), who focus on national-level economic activities and define IP as goal-oriented state actions. The purpose is to shape the composition of economic activity. Specifically: industrial policy seeks to change the relative prices across sectors or direct resources towards certain selectively targeted activities (e.g.,exporting, R&D), to shift the long-run composition of economic activity" (Juhász et al., 2023).

We combine a novel database of IPs (Juhász et al., 2023) with data on trade flows (Gaulier and Zignago, 2010), resulting in a final dataset of HS6-digit products spanning 156 countries between 2009 and 2022. We use a local projection difference-in-differences (LP-DiD) approach to explore the dynamics between IPs and trade competitiveness. The richness of the data enables us to explore several dimensions of heterogeneity in the relationship between IPs and competitiveness, such as the targeted product's initial competitiveness, differences across policy instruments, and importance in the green transition. Importantly, the LP-DiD method alleviates the potential bias from using the traditional difference-in-differences estimator with two-way fixed effects (DiD-TWFE) in estimating *dynamic* and heterogeneous treatment effects under *staggered* treatment (Dube et al., 2024). For example, previously treated units may be experiencing delayed effects from their previous treatment because the effects are dynamic. In the traditional DiD-TWFE, these previously treated 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. The LP-DiD approach fits our purpose very well, as country-product

[1] Strategic competitiveness refers to "the promotion of domestic competitiveness or innovation in a strategic product or sector" (Evenett et al., 2024). These are policies aimed at enhancing the productivity of a sector that is perceived as being under-performing. Both Evenett et al. (2024) and this paper find that strategic competitiveness is the most frequent IP motive.

pairs could receive multiple IP treatments at different points in time. To the best of our knowledge, our paper is the first to employ this method to empirically investigate the *dynamic* relationship between IPs and competitiveness, both on average, as well as by product characteristics and policy instruments.

Our findings point to a nuanced relationship between IPs and trade competitiveness, as measured by the Balassa revealed comparative advantage (RCA) index. On average, products that are targeted by IPs experience a greater increase in competitiveness compared to non-targeted products. The short-term increase in competitiveness appears to be driven by an increase in the exports of products that were already in the country's export basket (intensive margin), while the medium-term increase appears to be driven by export participation of previously non-exporting products (extensive margin).

However, the average effect masks substantial heterogeneity across products and IP instruments. At the product level, we find that the positive association between IPs and competitiveness is mostly driven by products that were globally competitive prior to the introduction of the IP. As for policy instruments, we focus on the two most popular IP instruments in the data: domestic subsidies and export incentives. We show that products targeted by domestic subsidies experience a short-term improvement in trade competitiveness, with effects vanishing after a few years. By contrast, export incentives are associated with larger medium-term improvements in the trade competitiveness of targeted products compared to non-targeted ones. These findings are consistent with anecdotal evidence attributing export promotion strategies, foreign orientation (Cherif and Hasanov, 2019), and competition (Aghion et al., 2016) to IPs' success in East Asia.

One key distinction between the current IP wave compared to the wave before the 1990s is the growing share of IPs aimed at addressing climate change concerns. Motivated by this observation, we compare the relationship between IPs and the RCA of green versus non-green products. Green products are defined as HS6-digit products critical to the green transition. We compile a list of HS6-digit green products from six different sources. These sources cover products at different stages of production, from raw materials to intermediate inputs to final products. The final list contains 869 HS6-digit products. Our results highlight three noticeable differences for green versus non-green products. First, the positive association between IPs and competitiveness manifests mostly in the medium-term for green products; whereas the positive association only appears in the short term for non-green products. Second, unlike non-green products, the positive long-run gains in RCA for green products are mainly driven by products that have *not* yet established comparative advantage in the global market. Third, there is a stronger positive association between IPs (both subsidies and export incentives) and RCA when IPs target green products, particularly in the longer horizon.

Finally, we provide suggestive OLS evidence on potential cross-product spillovers of IP for three widely discussed value chains: wind turbines, photovoltaic panels, and electric vehicles. There are two main reasons to focus on these value chains. First, climate mitigation has become a common motive of IPs (Evenett et al., 2024). Second, data that map HS6-digit products to value chain stage is extremely scarce, with the exception of Rosenow and Mealy (2024), who compile a mapping between HS6-digit products and production stages for these three value chains. Our results show that, for these value chains, IPs targeting upstream products are associated with larger improvements in the RCA of products using these upstream products compared to those targeting the same value chain stage, while IPs targeting downstream products yield similar effects as those targeting products at the same value chain stage. Intuitively, upstream IPs may alleviate capacity constraints and benefit downstream products through reductions in input costs.

It should be noted that our analysis is only a partial assessment of IPs' impact on competitiveness. By design, our empirical approach compares the *relative* performance of targeted and non-targeted products. Moreover, the paper does not assess the overall welfare gains and absolute desirability of IPs. Such assessment would require a structural analysis that fully incorporates general equilibrium effects and potential retaliatory actions, as in Lashkaripour and Lugovskyy (2023) and Hodge et al. (2024). A full assessment of IPs' desirability is challenging due to the lack of information on the size of IPs, and hence their fiscal costs. Finally, although the LP-DiD approach alleviates certain bias compared to the standard two-way fixed effects estimator under staggered treatment setting, our results do not necessarily establish a fully causal relationship between IPs and trade competitiveness due to endogeneity concerns (e.g., selection bias, reverse causality, endogenous selection into the time of treatment). However, our results are informative of the expected effects of IPs on a specific outcome, namely trade competitiveness.

Related Literature. Our paper contributes to two strands of literature. First, we contribute to the growing empirical literature studying the economic impact of IPs. We contribute by offering an empirical analysis of IPs' effects from a cross-country perspective. In fact, most papers rely on country-specific case studies (Juhász et al., 2024; Cherif and Hasanov, 2019). Others leverage detailed information on state-aid in Europe to gauge the impact of subsidies on firm and labor market performance (Criscuolo et al., 2019; Brandao-Marques and Toprak, 2024). More recently, a number of studies have leveraged data stemming from the Global Trade Alert (GTA) project to study the relationship between IPs and different economic outcomes in a cross-country setting. For example, using the GTA data and following a similar large language model (LLM) as Juhász et al. (2023), Barwick et al. (2024) study the relationship between IPs and innovation in the global automobile industry. Moreover, Machado Parente et al. (2025) analyze the link between IPs and firm performance in a cross-country and cross-industry empirical setting.

Closely related to our work, Rotunno and Ruta (2024) use the GTA database to assess the impacts of domestic subsidies (both IPs and non-IPs) on trade flows. Apart from the difference in the main policy intervention of interest,[2] our paper differs from Rotunno and Ruta (2024) along three main dimensions. First, in addition to studying the average effect of IPs on targeted products, our work explores how these effects vary for green versus non-green products, and potential cross-product spillovers within the value chain. We show that IPs targeting green products exhibit different RCA dynamics than IPs targeting non-green products. This is particularly relevant, as climate mitigation is the second most important motive for the current wave of IPs. Second, methodologically, our analysis explores the dynamic relationship and uses the LP-DiD approach to tackle potential biases of standard two-way fixed effects estimator under staggered treatment. Third, the *dynamic* analysis of different policy instruments allows us to track the effect of IP by policy instrument over time. The effect of domestic subsidies materializes in the short term and fades in the longer term, whereas the positive effect takes a longer time to materialize for export incentives.

Second, our findings complement a long-standing literature on the determinants of RCA. Namely, we argue that IPs can play a significant role in shaping trade patterns across countries. While prior research has emphasized factor endowments (Romalis, 2004; Bernard et al., 2007), technological capabilities (Hausmann and Rodrik, 2003; Costinot et al., 2012), institutional quality (Levchenko, 2007; Nunn, 2007; Shapiro, 2023), and trade policies (Eaton and Kortum, 2002; Boltho, 2022) as key drivers of RCA, we provide evidence that other government interventions—such as subsidies and export incentives—can also influence a country's trade specialization patterns. Our results suggest that comparative advantage is not solely determined by underlying economic fundamentals but can be actively shaped by policy, highlighting the role of IP in shaping global trade patterns.

The rest of the paper is as follows. We present our data sources and document key stylized facts on the recent wave of IPs in Section 2. Section 3 discusses the empirical strategy. The empirical findings are in Section 4. Section 5 concludes.

2 Data and Facts

2.1 Data Sources

Our empirical analysis aims to study whether IPs increase the trade competitiveness of targeted products. To this end, we merge country-product level data on IP counts and trade competitiveness measures. Below we describe all the different data sources used in the analysis.

[2] Rotunno and Ruta (2024) focus on domestic subsidies in general, which includes both IPs and non-IPs. Roughly 70-80% of protectionist domestic subsidies are classified as IPs.

2.1.1 Data on Industrial Policies

Country-product level IP counts are from Juhász et al. (2023). The authors implement state-of-the-art machine learning algorithms to classify whether policy announcements in the Global Trade Alert (GTA) database over the period 2009-2022 qualify as IPs. The GTA is an initiative launched in 2008, which collects state policy measures and credible announcements that discriminate against foreign commercial interests (Evenett and Fritz, 2020).

In their machine learning exercise, Juhász et al. (2023) leverage the policy descriptions in the GTA. The authors focus on national-level economic activities[3] and define IP as "goal-oriented state action. The purpose is to shape the composition of economic activity. Specifically: industrial policy seeks to change the relative prices across sectors or direct resources towards certain selectively targeted activities (e.g., exporting, R&D), to shift the long-run composition of economic activity" (Juhász et al., 2023). We refer interested readers to their paper for more details on IP classification.

In addition to the policy description, the GTA database also contains other useful characteristics for each policy that are relevant for our analysis. These include the implementing jurisdiction, the HS codes of targeted products, the type of instrument used, and GTA evaluation. GTA evaluation indicates the *direction* of the policy change assessed by GTA experts. There are three categories: red, amber, and green. Policies with red GTA evaluation are protectionist, as they almost certainly discriminate against foreign commercial interests. Policies with green GTA evaluation are liberalizing. For example, an elimination of the export bans on rye and mineral fertilizers is classified as liberalizing. Policies with amber GTA evaluation are ambiguous ("likely involve discrimination against foreign commercial interests").[4] We refine our definition of IPs to incorporate the direction of policy change. Specifically, we restrict our attention on *IPs with a red GTA evaluation*, as *protectionist* IPs are those at the center of the current policy debate around IPs.

We follow the recommended reporting-lag adjustment by only keeping policies that are announced and published by GTA within the same calendar year. Such adjustment is necessary to ensure consistent comparison of policy counts across time. This is because policies are collected in the GTA on a continuous basis. This reporting lag leads to an inflated policy count in earlier years relative to more recent years, as policies in earlier years have a longer time to be detected and collected.

For each country and product in a given year, we count the number of *active* IPs: IPs that are announced but not yet removed. We choose the starting point to be the announcement year rather than

[3]Specifically, Juhász et al. (2023) exclude sub-national (e.g., province-level in China) policies.

[4]Among all the GTA policies, which include both IP and non-IP, approximately 80% are protectionist and 15% are liberalizing. More than 35% of policies are liberalizing for FDI measures, import and export barriers.

implementation year to account for the role of anticipation. We fill the missing values of active IP counts with zero if the country has ever had a strictly positive number of active IPs in at least one product during 2009-2022. Note that this is a stock variable. Therefore, to properly capture the IP shock, which is a flow variable, one needs to take the first difference. Therefore, the main empirical analysis in Sections 3 and 4 uses the year-to-year change in the number of active IPs to account for the possibility of IP removals. However, for the descriptive statistics in Section 2.2, we use a slightly different definition of IP shock — the counts of *announced* IPs. We choose this definition for ease of interpretation. Note that the two definitions of "IP shock" are equivalent if there are no policy removals at the country-product pair.[5]

Although the GTA-derived IP data has decent time and country coverage, thereby allowing for a cross-country, empirically-grounded evaluation of IP over time, there are several caveats. First, a direct comparison between advanced economies (AEs) versus emerging market and developing economies (EMDEs) may be challenging. It is possible that EMDEs have less transparent and granular policy disclosure and reporting standards, thereby resulting in an underestimated number of IPs in EMDEs relative to AEs. Second, as in the case of GTA, the IP database we use only records a subset of IPs, namely those affecting commercial interests. Third, the database only starts in 2009, and hence may underestimate the stock of IPs in countries that were active before 2009 but introduced a small number of IPs since then. This feature may be particularly relevant for some large EMDEs with a historical record of state interventions. Fourth, the IP database developed by Juhász et al. (2023) focuses on national-level economic activities, while the implementation of IPs in some countries is fairly decentralized (Goldberg et al., 2024). Furthermore, in certain countries, IPs take the form of indirect incentives, such as subsidized loans provided by banks, which may not be well reflected in the GTA. Given this, we test the robustness of our main empirical results by excluding some of the large EMDEs from the sample in Appendix F.1. Fifth, IPs in Juhász et al. (2023) are only indicator variables and not measures of intensity (e.g., value of the subsidies). By contrast, approximately a third of the policies in the New Industrial Policy Observatory (NIPO)[6] (Evenett et al., 2024) have an associated subsidy value. Reassuringly, the positive correlation between the count of IPs and the log of the subsidy value at the country-product level in 2023 (0.52) suggests that the count of IPs provides an approximation of the size of IP values.

2.1.2 Data on Trade Competitiveness

Our main metric for trade competitiveness is revealed comparative advantage (RCA), proxied by the Balassa index.[7] RCA of a product for a given country is defined as the export share of the product in

[5]Around 10% of the IPs in the 2009-2022 period were removed.

[6]The data in NIPO is described in Evenett et al. (2024). The definition of IP in NIPO is slightly different than Juhász et al. (2023). Moreover, NIPO contains additional information of the policy, such as stated motive and size of subsidy. However, its short time coverage (only since 2023) limits the scope for cross-country empirical analyses.

[7]For more details on the Balsa index, see https://unctadstat.unctad.org/EN/RcaRadar.html.

the country's total exports, divided by the world's export share of the product:

$$RCA_{cpt} = \frac{\frac{X_{cpt}}{\sum_p X_{cpt}}}{\frac{\sum_c X_{cpt}}{\sum_c \sum_p X_{cpt}}}$$

where c is country, p is product, t is year. X is the value of exports. RCA with a value greater than 1 implies that the country exports a relatively higher share of the product compared to the world average, suggesting that the country is competitive in the particular product. Note that the Balassa index has drawbacks, as discussed in Leromain and Orefice (2014). Thus, we also use an alternative RCA proposed by Vollrath (1991)[8] to test the robustness of results (Appendix F.4).

To calculate RCA metrics, we extract information of export value from the CEPII BACI database (Gaulier and Zignago, 2010). BACI provides bilateral trade flow data for 233 countries and 5018 products at the Harmonized System (HS) 6-digit level. Merging the RCA data with data on IP counts described in 2.1.1 gives a balanced panel of 156 countries and 5018 products for 2009-2022.

2.1.3 IP motives

We follow the machine learning algorithm in Evennett et al. (Forthcoming) to assign motive(s) to all IPs from Juhász et al. (2023) (see Appendix A for a description). The exercise leverages information on IPs' stated motives from the New Industrial Policy Observatory (NIPO) dataset, which is only available since 2023.

Since 2023, GTA experts have assigned stated motives to policy interventions, by collecting and reviewing statements from official sources or direct quotes from senior officials. One IP can be assigned more than one motive. We use the NIPO dataset as a starting point to train our machine learning algorithm. We focus on the four most common IP motives: climate mitigation, strategic competitiveness, geopolitical concerns or national security, and GVC resilience.[9]

2.1.4 Classification of Green vs. Non-Green Products

To further gain insights about the relationship between IPs and competitiveness, the paper explores potential differences among products related to the green transition ("green products") and other products ("non-green products"). Such distinction is important given that "environmental concerns" is a common justification behind the use of IPs (Evenett et al., 2024). To identify green products, we compile a list of HS 6-digit products from six different sources. These sources cover products at different stages of production, from raw materials to intermediate inputs to final products that are critical for the green

[8] Specifically, we use a RCA measure that accounts for both exports and imports, such that $RCA = \left(\frac{\frac{X_{cpt}}{\sum_p X_{cpt}}}{\frac{\sum_c X_{cpt}}{\sum_c \sum_p X_{cpt}}}\right) / \left(\frac{\frac{M_{cpt}}{\sum_p M_{cpt}}}{\frac{\sum_c M_{cpt}}{\sum_c \sum_p M_{cpt}}}\right)$, where X represents exports and M represents imports.

[9] See Evenett et al. (2024) (pp. 10-11) for definitions of each category.

transition. The final list of green products contains 869 products.

IMF Climate Change Dashboard - Low Carbon Technologies (LCT). The LCT designation is based on Pigato et al. (2020). LCT products are defined based on their contribution to reducing carbon emissions, enhancing energy efficiency, and supporting renewable energy production and use. Some examples include: products that are directly used in the generation of energy from renewable sources (e.g., solar panels, wind turbines); products that improve energy efficiency (e.g., energy-efficient lighting, HVAC systems, and insulation materials that reduce energy consumption and carbon emissions); products that reduce emissions directly (filters and scrubbers used in industrial processes) or indirectly by contributing to more efficient processes and use of resources; infrastructure/components that are essential for the deployment of renewable energy and energy efficiency technologies (parts of wind turbines or solar panel mounting systems); and products that contribute to sustainable environmental management and pollution control, which support broader environmental objectives.

IMF Climate Dashboard - Environmental Goods. Environmental goods include two types of goods: connected goods (goods that are connected to environmental protection) and adapted goods (goods that have been adapted to be more environmentally friendly or "cleaner"). Connected goods are goods whose use directly serves environmental protection purposes. Examples include septic tanks, catalytic converters for vehicles, trash bags, bins, rubbish containers. Adapted goods are those whose use is beneficial for environmental protection. Examples include biofuels, mercury-free batteries, and hybrid and electric cars.

The starting point of the classification of environmental goods is a list identified in OECD/Eurostat (1999). Over time, due to environmental, social, and technological advances, 108 product codes were added, mainly in adapted goods. These additions were made in part by consulting the Amendments to the HS Nomenclature, published every 5 years by the World Customs Organization. Examples include electric and hybrid vehicles and other cars, biodiesel, and rechargeable batteries. However, the resulting list does not necessarily cover all environmental goods. Some environmental goods have no equivalent HS commodity codes (e.g., Chlorofluorocarbon (CFC)-free products). On the other hand, some HS commodity codes include goods which may not be environmental goods (e.g., the code for wind turbines includes other engines unrelated to wind power). Appendix B compares IMF's Environmental Goods and LCT products.

Rosenow and Mealy (2024). The authors compile a list of HS 6-digit products involved in three green value chains: solar photo-voltaic (PV), wind turbines and electric vehicles (EVs). This list is based on the assessment of industry experts. Moreover, these HS products are classified in four categories, characterized by their position in the value chain: raw materials, processed materials, sub-components, and end products. In Section 4.3.1, we use this information to provide evidence for IP's role on industrial upgrading along the green value chain.

Kowalski and Legendre (2023). Critical raw materials are defined as those used intensely in green transition technologies such as li-ion batteries, fuels cells, wind energy, electric traction motors and photovoltaics. This classification is taken from Bobba et al. (2020). Table 2.1 (p. 12) of Kowalski and Legendre (2023) summarize the critical raw materials and the respective technologies in which they contribute to the green transition. Figure 2.1 (p. 13) of the paper lists "green raw materials" based on the OECD Inventory of Export Restrictions on Industrial Raw Materials. Annex B of the paper details the products in the Inventory at HS2007 code.

Goldschlag et al. (2020). The authors construct a link between CPC patent classification and HS product codes using machine learning. They proceed in three steps. First, for each HS product description, the authors generate a set of keywords to be used as search terms. Second, they data mine the title and abstracts of all patents, matching them to HS products with corresponding keywords. Third, they generate weights that represent how frequently each HS product's keywords appear in each patent classification. For example, HS code 842121 "Machine for filtering or purifying water" has a weight of 95.8 percent on CPC code Y02 "Technologies or Applications for Mitigation or Adaptation against Climate Change" and 4.2 percent on CPC code E03 "Water Supply: Sewerage". We classify green patent codes as all those with CPC code of Y02, following Hasna et al. (2023). Lastly, we define HS codes to be green if they have a weight greater than 50 percent on Y02.

Mealy and Teytelboym (2022). We replicate the dataset of Mealy and Teytelboym (2022) by gathering data from multiple sources: the WTO core list, the APEC list of environmental goods, and OECD's illustrative product list of environmental goods and customized products lists. Each product classified as green has been either endorsed by large number of WTO/APEC member countries, or its environmental benefits have been determined by OECD countries. This represents a range of environmental categories such as air pollution, wastewater management and recycling.

2.2 Descriptive Statistics

We provide descriptive statistics of *protectionist* IPs by stated motive, country income group, policy instrument, and GTA evaluation. For the rest of the paper, we use the term IP for short to refer to protectionist IP, unless when explicitly comparing IPs by GTA evaluation.

2.2.1 Evolution of IP Announcements over Time

Figure 1 plots the evolution of announced IP counts by stated motive during 2009-2022. There is a clear surge in announced IPs since 2017. The number of announced IPs increases by eight times between 2017 and 2022. We are able to assign approximately 60% of IPs to at least one stated motive.[10] For those with non-missing IP motive, about 13% have more than one motive. These IPs with multiple motives are counted as many times as the number of associated motives. Amongst IPs with stated motive(s), during the last five years of the sample (2018-2022), approximately half of the IPs are motivated by strategic competitiveness reasons, followed by climate mitigation (34%) and global value chain (GVC) resilience (16%). IPs that seek to deal with geopolitical concerns or national security are very uncommon (1%).

In Figure 2, we split the analysis of IP counts by stated motive into advanced economies (AEs) and emerging economies (EMs).[11] The classification by country income group (AE/EM) is based on the IMF's World Economic Outlook. We make four observations. First, both AEs and EMDEs have actively implemented IPs. The pervasive use of IPs predates the period of analysis, particularly in some large EMDEs with well-recognized data limitations on subsidies and other state interventions and systematically less transparent and granular policy disclosure and reporting standards (see section 2.1.1). However, in recent years, the number of IPs introduced by AEs rose substantially—from around 100 in 2017 to over 1000 in 2022. There was also a continued rise in IPs among EMDEs, adding 350 interventions between 2017 and 2022. Consequently, the share of recently implemented active IPs by AEs rose since 2017. Second, IP motives are more diverse in AEs than EMs. While AEs pursue IPs for climate mitigation, strategic competitiveness, and more recently GVC resilience, strategic competitiveness by far outweighs all other stated motives in EMs - representing 70% of all IPs with an assigned motive. Third, consistent with the patterns in Figure 1, there is a very low share of IPs with explicitly stated geopolitical/national security concerns in both AEs and EMs. Fourth, EMs, and even more so AEs, have seen an uptick in IPs for GVC resilience purpose since 2020, possibly motivated by heightened geopolitical tensions and supply chain disruptions during COVID-19.

Appendices D.1 and D.2 document the evolution of IPs over time for the global aggregate and by country income group. The surge of IPs since 2017 is clear. Before 2017, IPs accounted on average for less than 25 percent of the total count of policies in GTA. This number rose to over 35 percent during the 2017-2022 period.

[10] Figure 1 indicates around 50% of IPs without assigned stated motive, because we are double-counting on IPs with multiple stated motives. Therefore, the denominator of the fraction is higher.

[11] We leave out low-income countries (LICs) in Figure 2, because they only account for a very small fraction (1%) of all announced IPs (see Appendix D.2). However, LICs are included in the sample in the empirical analysis.

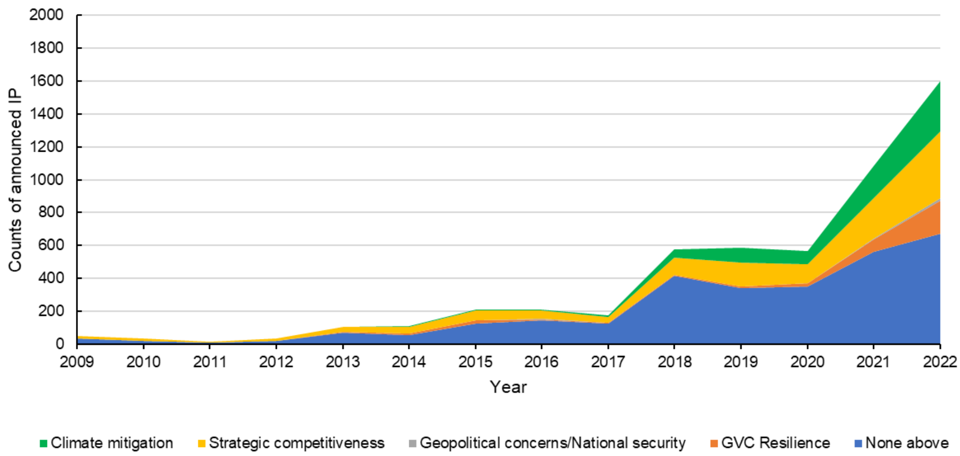
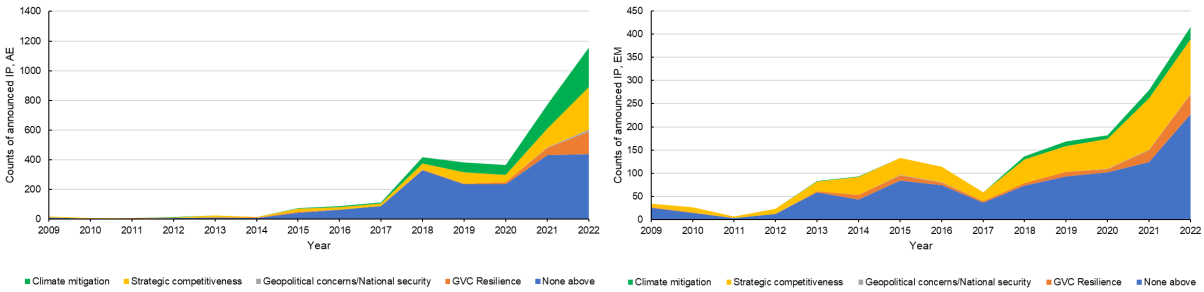


Figure 1: Evolution of Announced IP Counts by Stated Motive

Sources: GTA (2022), Juhász et al. (2023), and author's calculations.

Notes: y-axis represents the counts of announced IP over time, adjusted for reporting lags. An announced IP with n stated motives is counted n times.



(a) Advanced Economies (AEs)

(b) Emerging Economies (EMs)

Figure 2: Evolution of Announced IP Counts by Stated Motive, AE vs. EM

Sources: GTA (2022), Juhász et al. (2023), and author's calculations.

Notes: y-axis represents the counts of announced IP for AE vs. EM over time, adjusted for reporting lags. An announced IP with n stated motives is counted n times. Panel (a) uses the sample of advanced economies (AEs). Panel (b) uses the sample of emerging economies (EMs). The classification of country income group (AE/EM) is based on the IMF's World Economic Outlook.

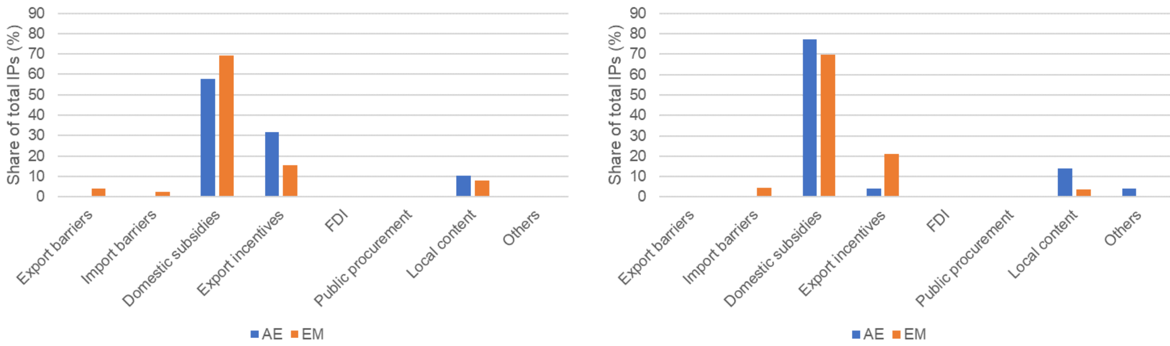
2.2.2 Breakdown by Policy Instrument

GTA assigns each policy to one of 66 policy instruments. To facilitate the empirical analysis later on, we follow Goldberg et al. (2024) and Evenett et al. (2024) by classifying the more disaggregated policy instruments into eight broad groups according to the UN MAST (Multi-Agency Support Team) Chapter classification for non-tariff measures. These eight groups are: export barriers, import barriers, domestic subsidies, export incentives, FDI measures, public procurement measures, local content measures, and others. Appendix C provides more details on the composition of the eight broad policy instrument groups.

One interesting observation is that close to 80% of domestic subsidies take the form of financial-related measures, such as state loan, financial grant, and loan guarantee. This is in contrast with the textbook formulation of domestic subsidies, which are typically modeled as a production subsidy (Lashkaripour and Lugovskyy, 2023), a specific type that in the data only accounts for 2.24% of domestic subsidies IPs. Similarly, approximately 90% of export incentives IPs are financial-related measures, such as trade finance and financial assistance in foreign market.

Figure 3 shows the share of the eight policy instruments out of total IPs by AEs and EMs in 2018-2022. Panel (a) counts each policy once, even if the policy targets multiple HS products. Panel (b) counts each policy as many times as the number of targeted HS products. First, domestic subsidies and export incentives are the most commonly used policy instruments in both AEs and EMs. Second, EMs use a more diverse set of policy instruments. Third, EMs tend to use more trade barriers, whereas AEs tend to use more local content measures.

The differences between the two panels in Figure 3 are explained by the differences in the average number of products each policy instrument targets (see Appendix D.3). There are substantial differences in the average number of targeted products between AEs and EMs. One export incentive in EMs targets on average almost 400 products, the highest number across all policy instruments and country income groups. For AEs, one local content measure is the policy instrument with the highest average number of targeted products: close to 200. These patterns are clearly reflected in the differences between the two panels in Figure 3.



(a) Policy Level

(b) Policy × HS product Level

Figure 3: Breakdown by Policy Instrument (2018-2022), AE vs. EM

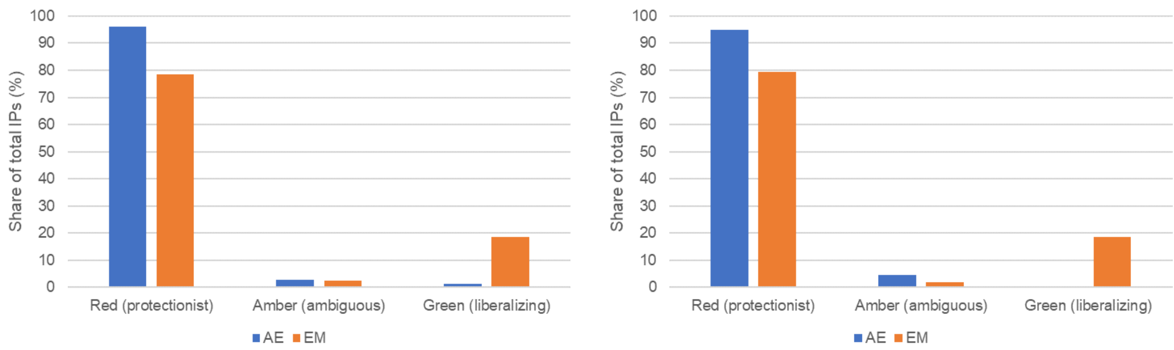
Sources: GTA (2022), Juhász et al. (2023), and author's calculations.

Notes: y-axis represents the share of policy instrument (x-axis) out of total IPs in 2018-2022, adjusted for reporting lags. Panel (a) counts each policy once, even if the policy targets multiple HS products. Panel (b) counts each policy n times if it targets n HS products. The classification of country income group (AE - blue bars/EM - orange bars) is based on the IMF's World Economic Outlook. Appendix C provides details on the categorization of policy instruments.

2.2.3 Breakdown by GTA Evaluation

Figure 4 depicts the share of GTA evaluation (i.e., red - protectionist, amber - ambiguous, green - liberalizing) out of total IPs by AEs and EMs in 2018-2022. Similar as Figure 3, Panel (a) counts each policy once, even if the policy targets multiple HS products. Panel (b) counts each policy as many times as the number of targeted HS products. The results are highly consistent across the two panels. First, the majority of IPs are protectionist: almost all IPs in AEs and close to 80% of IPs in EMs are protectionist. Second, EMs implement a larger share of liberalizing IPs - around 20%, compared to virtually zero in AEs.

Appendix D.4 presents additional facts on the breakdowns of GTA evaluation by policy instrument and country income group. Two patterns stand out. First, a large share of policies classified as import barriers and FDI is liberalizing, particularly in EMs. Second, EMs conduct a higher share of liberalizing domestic subsidies than AEs.



(a) Policy Level

(b) Policy × HS product Level

Figure 4: Breakdown by GTA Evaluation (2018-2022), AE vs. EM

Sources: GTA (2022), Juhász et al. (2023), and author's calculations.

Notes: y-axis represents the share of GTA evaluation (x-axis) out of total IPs in 2018-2022, adjusted for reporting lags. Panel (a) counts each policy once, even if the policy targets multiple HS products. Panel (b) counts each policy n times if it targets n HS products. The classification of country income group (AE - blue bars/EM - orange bars) is based on the IMF's World Economic Outlook.

3 Empirical Strategy

We now turn to describe the econometric strategy used to assess the relationship between IPs and export competitiveness. Our main empirical methodology is the LP-DiD, originally proposed by Dube et al. (2024) and used in Cugat and Manera (2024) and Ahn et al. (2024). The LP-DiD method aims at dealing with the bias arising when using the standard difference-in-differences with two-way fixed effects (DiD-TWFE) 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 because the effects are dynamic. However, under the DiD-TWFE, these previously treated 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. LP-DiD fits our purpose very well, as country-product pairs could receive multiple IP treatments at different points in time.

LP-DiD deals with the bias through an appropriate selection of a "clean sample", which creates comparable treatment and control groups. Such sample is constructed as:

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

where $D_{c,p,t}$ is an indicator variable that equals one if the first difference of the number of active IPs in country c and product p in year t, $\Delta IP_{c,p,t} = IP_{c,p,t} - IP_{c,p,t-1}$, is greater than zero. Note that $IP_{c,p,t}$ refers to the number of active IPs in a given year, which is a stock variable. Consequently, the first difference captures the IP "shock" in a given year, which is a flow variable. The treatment unit is a country-product. H denotes the maximum number of horizons of the local projection. L refers to stabilization lag, i.e., the number of periods required for the effect of IP to stabilize. The choice of L faces 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 OLS sample. By contrast, a larger L reduces the concern for bias, but leads to a smaller number of observations in the treatment group. In the paper, we set $L = 5$ as baseline and experiment with $L = 3$ for robustness (Appendix F.2).

Specifically, equation (1) 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. Intuitively, suppose that the effect of IP is positive and increases over time up to L periods. Under traditional DiD-TWFE, country-product pairs treated between $t-1$ and $t-L$ are included in the control group for the IP treatment at t. As a result, the average effect of the control group is upward biased, which implies a downward biased estimated effect. Similarly, for the clean treatment group, we only choose "clean controls", namely country-product pairs that are never treated between $t-L$ and $t+H$. Otherwise, units that are not treated at t may still be treated between periods between $t-L$ and $t-1$ or between $t+1$ and $t+H$, thereby biasing the average effect of the control group due to dynamic effects of the treatment. 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. Since we focus on protectionist IPs (i.e., IPs with red GTA evaluation), we further restrict the treated units to be those that are only treated by red IPs but not treated by green or amber IPs at t. Our final clean sample consists of approximately 30,000 observations in the treatment group and close to 10 million observations in the control group.

Another advantage of LP-DiD compared to standard DiD-TWFE is the possibility to control for differences in observed pre-trends in the dependent variable between the treatment and control groups. Hence, our baseline specification incorporates two lags of the dependent variable following the rule-of-thumb of optimal choice of lags proposed by Chudik and Pesaran (2015). We also test the robustness of our findings with three lags, thereby imposing that the treatment and control groups have the same RCA up to three periods before the shock.

Our baseline specification estimates the dynamic effect of IP treatment on the trade competitiveness of country c and product p over horizons $h \in [0, 4]$:

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

where $rca_{c,p,t+h} = \ln(RCA_{c,p,t+h} + 10^{-3})$. Adding a small constant 10^{-3} to the RCA allows us to include country-product pairs with zero RCA (i.e., export value is zero), which are prevalent in the sample.[12] As a result, the estimates capture the total effect of the IP treatment on RCA. We choose the 10^{-3} as the baseline because the mean value of RCA is 1.29 in the sample, which is very small. However, we also test the robustness of the main findings by adding 1 as the small constant instead of 10^{-3} (Appendix F.5). In Section 4.1.2, we further decompose the total effect into the extensive margin (i.e., probability to start exporting conditional on not being an exporter in the previous two years) and the intensive margin (i.e, $y_{c,p,t+h} = \ln(RCA_{c,p,t+h})$). $Treated_{c,p,t}$ is an indicator of whether or not the country-product pair receives an IP treatment at t. We control for the change in the number of non-IP counts ("non-IP shock")[13] and a set of fixed effects (i.e., country-product $\alpha_{c,p}$, country-year $\delta_{c,t}$, product-year $\rho_{p,t}$). In our baseline analysis, we control for two lags of $\ln(RCA + 10^{-3})$ and the non-IP shock. 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 $T^{1/3} = 14^{1/3} \approx 2.41$. We also test the robustness of our findings by controlling for up to three lags of $\ln(RCA + 10^{-3})$ and the non-IP shock (Appendix F.3).

One important issue we also investigate in this paper is the potential heterogeneous effect of different IP instruments in Section 4.1.4. It is possible that each country-product pair is treated by different

[12] Approximately 42% of observations in the clean sample have zero RCA.

[13] Non-IPs are GTA policies that are not classified as IPs in Juhász et al. (2023). Hence, non-protectionist IPs (i.e., IPs without amber or green GTA evaluation) are not non-IPs.

types of IP instruments in a given year. Therefore, we refine the sample selection criteria to be:

$$\text{clean sample } i = \begin{cases} \text{first-time IP } i & D_{i,c,p,t} = 1 \text{ and } D_{-i,c,p,t} = 0 \text{ and } D_{c,p,t-j} = 0, 1 \leq j \leq L \\ \text{clean controls} & D_{c,p,t-j} = 0, -H \leq j \leq L \end{cases} \tag{3}$$

where $i \in [1, 8]$ refers to one of the eight broad policy instruments we categorize in Section 2.2.2. In words, the treatment group to examine the effect of IP 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 ($D_{c,p,t-j} = 0, 1 \leq j \leq L$) *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 equation (1). Note that our clean treatment group ("first-time IP") requires that units should not be treated in any of the periods preceding L ($D_{c,p,t-j} = 0, 1 \leq j \leq L$) to avoid confounding dynamic effects from any policy instrument. Table 1 summarizes the number of treated units in the clean sample for each policy instrument. We focus on domestic subsidies and export incentives for the empirical analysis in Section 4.1.4, as these two instruments have the highest number of treated units the in final clean sample.

To explore the heterogeneous effect of different policy instruments in Section 4.1.4, we run a similar regression as in (2), 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 $Treated_{i,c,p,t}$ (i.e., treatment dummy if the country-product receives a positive IP shock under the policy instrument i).

Export barriers	Import barriers	Domestic subsidies	Export incentives	Local content
522	5585	14648	7519	1171

Table 1: Number of Clean Treated Units

4 Results

4.1 All Products

4.1.1 Average Effect

We find that, on average, products targeted by IPs experience a 5.6% higher increase in trade competitiveness than non-targeted products three years after the introduction of the IP (Figure 5). This result is consistent with recent findings that subsidies are associated with increased exports of targeted products (Rotunno and Ruta, 2024) and is consistent with a frequent motive stated by governments to pursue IPs, which is to promote strategic competitiveness (Evenett et al., 2024).[14]

[14]Strategic competitiveness refers to "the promotion of domestic competitiveness or innovation in a strategic product or sector" (Evenett et al., 2024). These are policies aimed at enhancing the productivity of a sector that is perceived as being

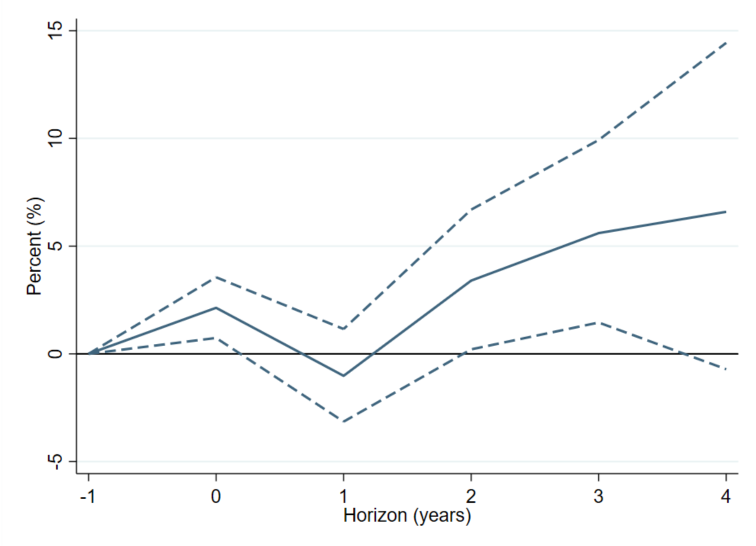


Figure 5: Effect of IP on rca, All Products

Sources: GTA (2022), Juhász et al. (2023), and author's calculations.

Notes: Solid line is the estimated percent change in $RCA + 10^{-3}$. Dashed lines are 90% confidence intervals. Standard errors are clustered at the country-product level.

4.1.2 Decomposition: Extensive Margin vs. Intensive Margin

To further explore the link between IPs and competitiveness, we decompose our trade competitiveness measure into the extensive margin (i.e., the probability to start exporting conditional on not being an exporter in the previous two years) and the intensive margin (i.e., change in $\ln(RCA)$ conditional on already being an exporter).

Specifically, the extensive margin (i.e., export participation) effect of IP is estimated according to:

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

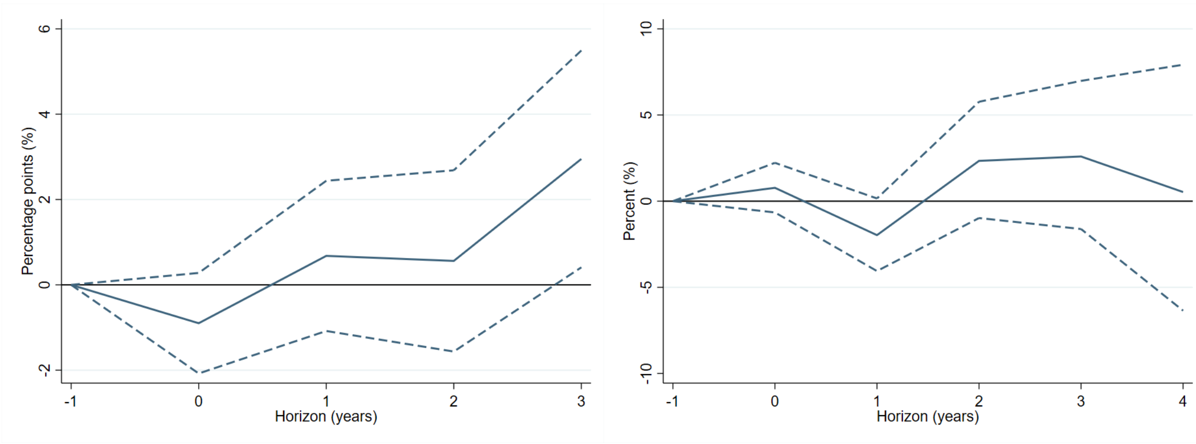
where $Export_{c,p,t+h}$ is an indicator variable that equals to 1 if country c exports a strictly positive value of product p at time $t+h$. To capture export *participation*, we restrict the sample to products that the country was not exporting in the previous two periods ($Export_{c,p,t-1} = Export_{c,p,t-2} = 0$). To estimate the intensive margin effect, we follow the same specification as in (2) by replacing $rca_{c,p,t+h}$ with $\ln RCA_{c,p,t+h}$ for $-2 \leq h \leq 4$.[15]

Figure 6 plots the dynamic effects at the extensive margin (Panel (a)) and the intensive margin (Panel

under-performing. Both Evenett et al. (2024) and this paper find that strategic competitiveness is the most frequent IP motive.

[15] We put h up to -2 because we control for two lags of $\ln RCA$ on the right-hand side.

(b)). We find that targeted products experience higher probability to start exporting compared to non-targeted products in the medium run (i.e., three years after the IP treatment). The intensive margin dynamics, though insignificant, inherits the shape of the average effect plotted in Figure 5. In Sections 4.1.3 and 4.2, we show that this insignificant effect masks significant heterogeneity by product characteristics, such as the product's initial competitiveness or importance in the green transition.



(a) Extensive Margin

(b) Intensive Margin

Figure 6: Decomposition: Extensive vs. Intensive Margin, All Products

Sources: GTA (2022), Juhász et al. (2023), and author's calculations.
Notes: Solid line is the estimated percentage points change in the probability to start exporting conditional on not exporting in the previous two periods (Panel (a)) and percent change in RCA (Panel (b)). Dashed lines are 90% confidence intervals. Standard errors are clustered at the country-product level.

4.1.3 Heterogeneity by Product Characteristic: The Role of Initial Competitiveness

Next, we test whether the relationship between IPs and RCA dynamics varies depending on the targeted product's initial competitiveness.

To gauge how the relationship between IPs and RCA varies with the product's initial competitiveness, we run the following regression:

$$\begin{aligned} rca_{c,p,t+h} - rca_{c,p,t-1} =& \beta_h Treated_{c,p,t} + \gamma_h Treated_{c,p,t} \times (RCA_{c,p,t-1} > 1) + \sum_{l=1}^{2} \theta_{2l} rca_{c,p,t-l} \\ & + \theta_3 \Delta nonIP_{c,p,t} + \lambda_3 \Delta nonIP_{c,p,t} \times (RCA_{c,p,t-1} > 1) \\ & + \sum_{l=1}^{2} \theta_{4l} \Delta nonIP_{c,p,t-l} + \sum_{l=1}^{2} \lambda_{4l} \Delta nonIP_{c,p,t-l} \times (RCA_{c,p,t-1} > 1) \\ & + \alpha_{c,p} + \delta_{c,t} + \rho_{p,t} + \varepsilon_{c,p,t} \end{aligned} \tag{5}$$

We report the coefficient estimates from (5) for $\beta_h + \gamma_h \times (RCA_{c,p,t-1} > 1)$, which captures the marginal effect of IP on RCA. Results in Figure 7 showcase the dynamic effects of IPs by initial RCA. Previously competitive products (red line) experience a large short-term boost in competitiveness after the IP shock. This positive association peaks after two years, but then declines and becomes statistically insignificant in four years, though the estimated magnitude remains as high as 9 percent. Patterns are reversed for non-competitive products (blue line). RCA initially declines and then increases gradually, albeit non-significantly over the horizon considered.

These results could reflect that initially uncompetitive products face short-term adjustment costs to become globally competitive. Therefore, for IPs to be associated with improvements in RCA in products that are initially non-competitive, the country may need a set of fundamentals in place (e.g., high levels of human capital). These findings may rationalize why countries often target products with high comparative advantage (Juhász et al., 2023), as such strategy may yield more immediate results and entail lower risk of failures (Reed, 2024). From a welfare point of view, targeting products where there is evidence of distortions and that are not too far from the global frontier may be desirable, as such IPs require small policy nudges that can limit adverse spillovers on other potentially competitive sectors or products. Alternatively, targeting low initial RCA products may be justified if there are potential dynamic gains from supporting newer products/sectors, especially products with high potential for further innovation and productivity growth. As we show in Section 4.2, green products are examples of such.

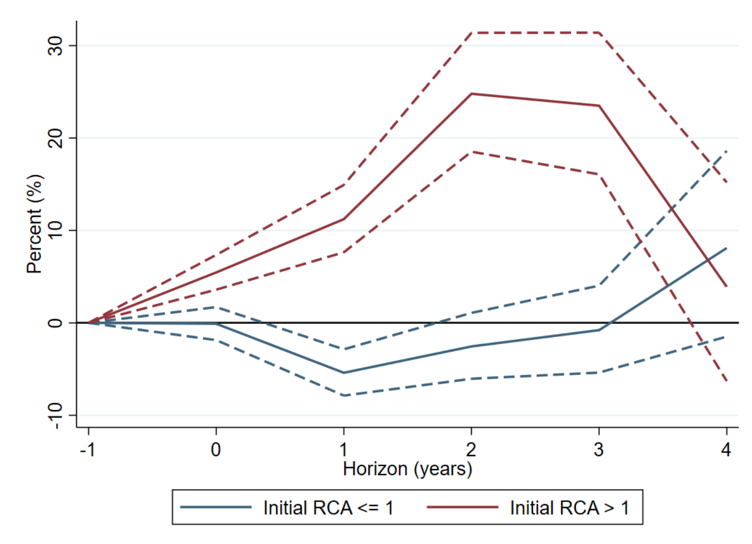


Figure 7: Effect of IP on rca, by Initial RCA

Sources: GTA (2022), Juhász et al. (2023), and author's calculations.

Notes: Solid line is the estimated percent change in $RCA + 10^{-3}$. Dashed lines are 90% confidence intervals. Red lines correspond to products with $RCA_{c,p,t-1} > 1$ (initially competitive) and blue lines correspond to products with $RCA_{c,p,t-1} \leq 1$ (initially uncompetitive). Standard errors are clustered at the country-product level.

4.1.4 Heterogeneity by Policy Instrument

Next we turn to studying how RCA dynamics relate to different IP instruments. In the main text we focus on the empirical analysis of domestic subsidies and export incentives, as these two instruments have the highest number of treated units in the final clean sample: 14658 treated units for domestic subsidies and 7519 for export incentives. Results on other policy instruments are in Appendix E.1.

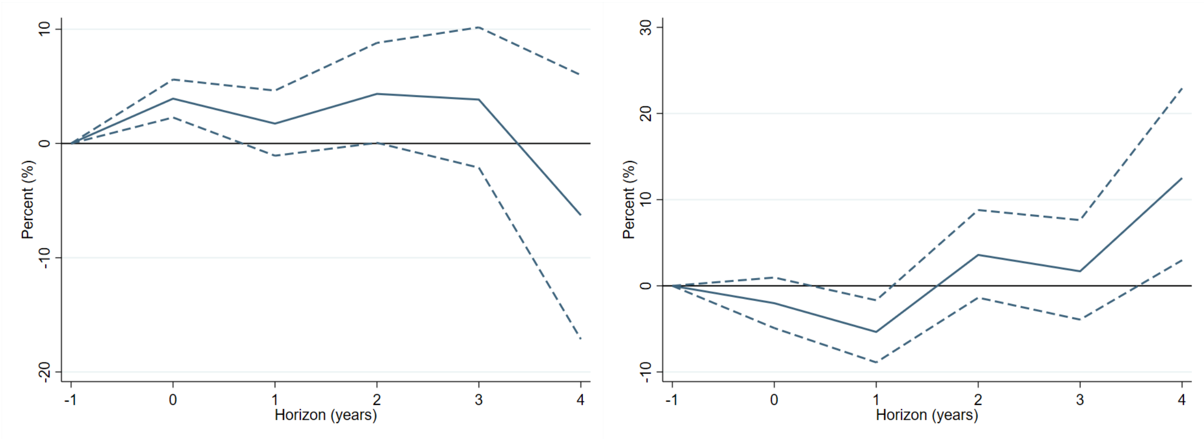
Figure 8 shows that the relationship between IPs and competitiveness varies across policy instruments. Domestic subsidies are associated with a short-term 5 percent increase in competitiveness for targeted relative to non-targeted products, which fades over time (Panel (a)). By contrast, export incentives yield an initial 1 percent decline in competitiveness, followed by longer-term improvements (Panel (b)). Thus, results point to a potential trade-off between short- and long-run benefits across instruments. The short-term boost in competitiveness from domestic subsidies may be appealing to policymakers with a short-term horizon. However, our evidence suggests that IPs focused on boosting exports may provide more sustained benefits. Indeed, the successful experience of export promotion strategies in East Asia underscores the importance of foreign orientation (Cherif and Hasanov, 2019) and competition (Aghion et al., 2016) in the design of effective IPs. Export incentives encourage firms to improve performance to compete in the global market, a strategy that could bear fruits in the medium- to long-term (e.g., Choi and Levchenko (2024) on Korea). However, the full welfare assessment of different policy instruments requires gauging their potential cross-sector, cross-country effects, which is beyond the scope of this paper. In fact, export incentives, most of which are prohibited under WTO rules, may spark retaliatory measures by other countries, which may undermine their benefits.

Appendix E.2 presents results for initially competitive vs. initially uncompetitive products by policy instrument. The results by policy instrument are similar to the ones for overall IPs, discussed in Section 4.1.3: we find a positive association for initially competitive products in the short run and for initially uncompetitive products in the longer horizon.

4.2 Green vs. Non-Green Products

One key distinction between the current IP wave compared to the wave before the 1990s is the growing share of green IPs. Motivated by this observation, we compare the relationship between IPs and RCA for green versus non-green products. Green products are defined as 6-digit HS92 products that are critical to the green transition. Section 2.1.4 provides a detailed description of the green products list.

Intuitively, there are two particular justifications for IPs targeting green products: (*i*) the novelty of green technologies, and (*ii*) emission externalities. Low carbon technologies (LCTs) are new technologies that compete with established ones. Successfully establishing LCTs requires a transition away from old



(a) Domestic Subsidies (b) Export Incentives

Figure 8: Effect of IP on rca, by Policy Instrument

Sources: GTA (2022), Juhász et al. (2023), and author's calculations.
Notes: Solid line is the estimated percent change in $RCA + 10^{-3}$ for domestic subsidies (Panel (a)) and export incentives (Panel (b)). Dashed lines are 90% confidence intervals. Standard errors are clustered at the country-product level.

technologies. Such transition is challenging because it requires upfront fixed costs and coordination by multiple agents, including consumers, producers, and public sector. For example, the introduction of electric vehicles requires the coordination of many agents, and producers need clear signals about the direction of the industry. IPs could help coordinate actions to accelerate such a transition (Aghion et al., 2016). Second, emission externality implies that LCTs' private benefits are lower than social benefits, so the provision of LCTs is lower than socially optimal. IPs can help address such under-provision, especially when other policy instruments, such as carbon pricing, are initially politically difficult to put in place.

Figure 9 shows that IPs targeting green products increase RCA by about 20 percent after 4 years (green line). By contrast, IPs targeting non-green products are associated with only a mild short-term increase in RCA, with smaller and insignificant effects in the medium term. Therefore, evidence suggests that IPs targeting green products have a more prominent impact on competitiveness in the longer horizon than those that target non-green products.

We further examine the role of initial competitiveness separately for green and non-green products. Figure 10 presents the results. Our previous findings on initial competitiveness in Section 4.1.3 are mainly driven by non-green products. In contrast, IPs are positively associated with long-run gains in RCA for *green* products that have not yet established comparative advantage in the global market. These findings underscore the distinct nature of IPs when targeting green products.

Finally, we investigate policy instrument heterogeneity by distinguishing between green and non-green products. The association between IP and RCA is generally more positive while targeting green products for both domestic subsidies and export incentives, particularly in the longer horizon. Figure 11 shows that the association between domestic subsidies and the RCA of green products is insignificant in the short term and positive in the medium term. By contrast, domestic subsidies are linked to a small temporary improvement in the RCA of non-green products, which turns negative in the medium-term. This mimics the patterns found in Figure 8 for the average product, which is likely non-green. For export incentives, while both green and non-green products experience boosts in competitiveness after the IP treatment, the effect for green products is more significant and pronounced.

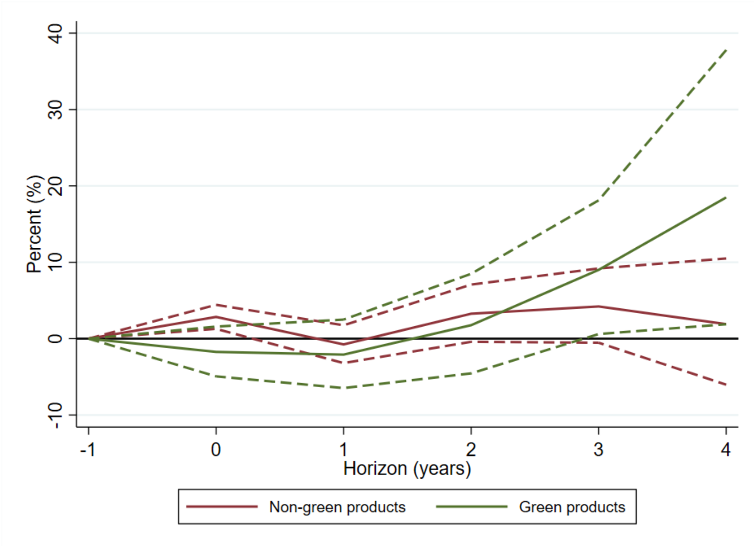


Figure 9: Effect of IP on rca, Green vs. Non-Green Products

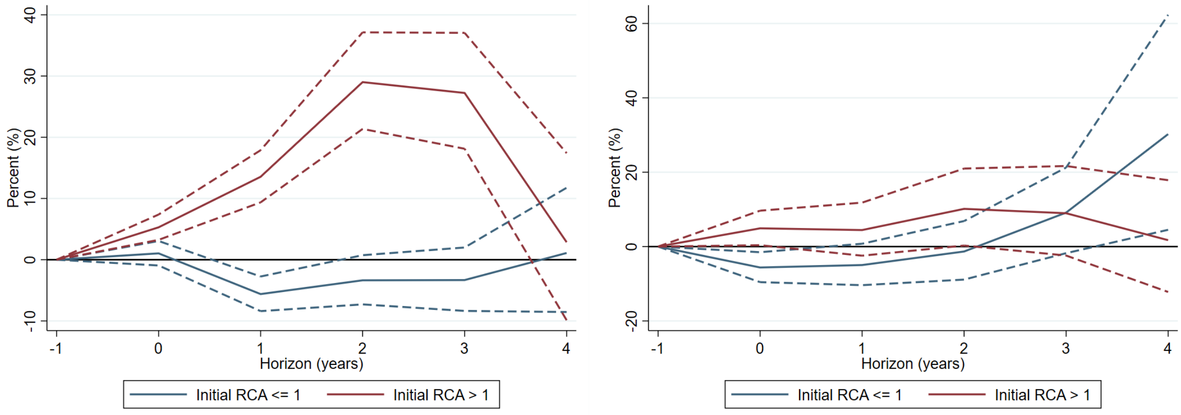
Sources: GTA (2022), Juhász et al. (2023), and author's calculations.

Notes: Solid line is the estimated percent change in $RCA + 10^{-3}$. Dashed lines are 90% confidence intervals. Red lines correspond to non-green products and green lines correspond to green products. Standard errors are clustered at the country-product level. The list of green products is described in Section 2.1.4.

4.3 Additional Results and Robustness

4.3.1 Cross-Product Spillover along The Green Value Chain

Motivated by the positive long-run association between IPs and the RCA of green products, we further examine the potential cross-product spillover along the the green value chain. Moreover, this exercise allows us to study potential spillover effects of IP on products that are not directly targeted by the policy. The key challenge is data availability: the green value chain is highly specialized, niche, and requires high level of granularity. To this end, we use the dataset from Rosenow and Mealy (2024), who compile a



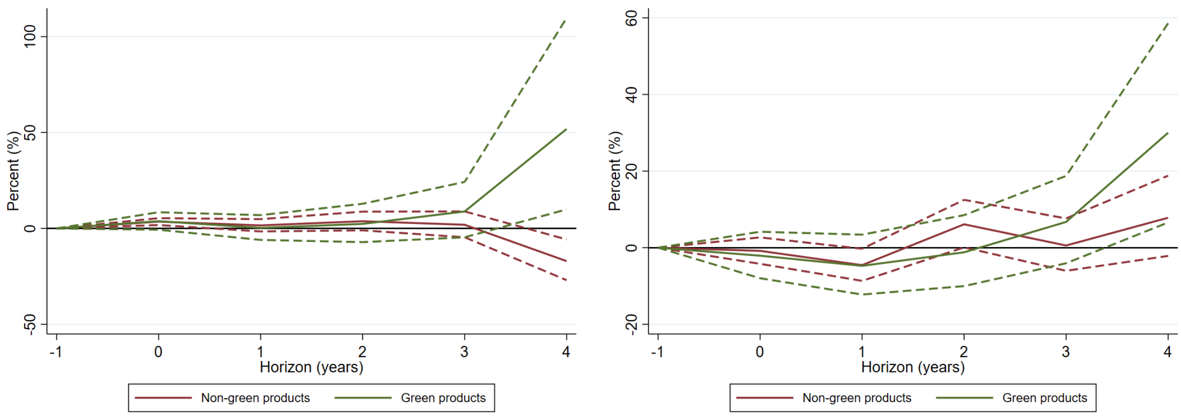
(a) Non-Green Products

(b) Green Products

Figure 10: Green vs. Non-Green Products: The Role of Initial RCA

Sources: GTA (2022), Juhász et al. (2023), and author's calculations.

Notes: Panel (a) restricts the sample to non-green products. Panel (b) restricts the sample to green products. Solid line is the estimated percent change in $RCA + 10^{-3}$. Dashed lines are 90% confidence intervals. Red lines correspond to products with $RCA_{c,p,t-1} > 1$ (initially competitive) and blue lines correspond to products with $RCA_{c,p,t-1} \leq 1$ (initially uncompetitive). Standard errors are clustered at the country-product level.



(a) Domestic Subsidies

(b) Export Incentives

Figure 11: Domestic Subsidies vs. Export Incentives: The Role of Green Products

Sources: GTA (2022), Juhász et al. (2023), and author's calculations.

Notes: Solid line is the estimated percent change in $RCA + 10^{-3}$ for domestic subsidies (Panel (a)) and export incentives (Panel (b)). The red lines are non-green products, the green lines are green products. Dashed lines are 90% confidence intervals. Standard errors are clustered at the country-product level.

product mapping at the 6-digit HS 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 (e.g., iron ore, nickel ore), processed materials (e.g., nickel waste or scrap), subcomponents (e.g., seats, nickel-iron electric accumulators), end products (e.g., lead-acid electric accumulators (vehicle), buses except diesel powered). Moreover, no product is assigned to more than one green value chain.

We estimate the following local projection framework:

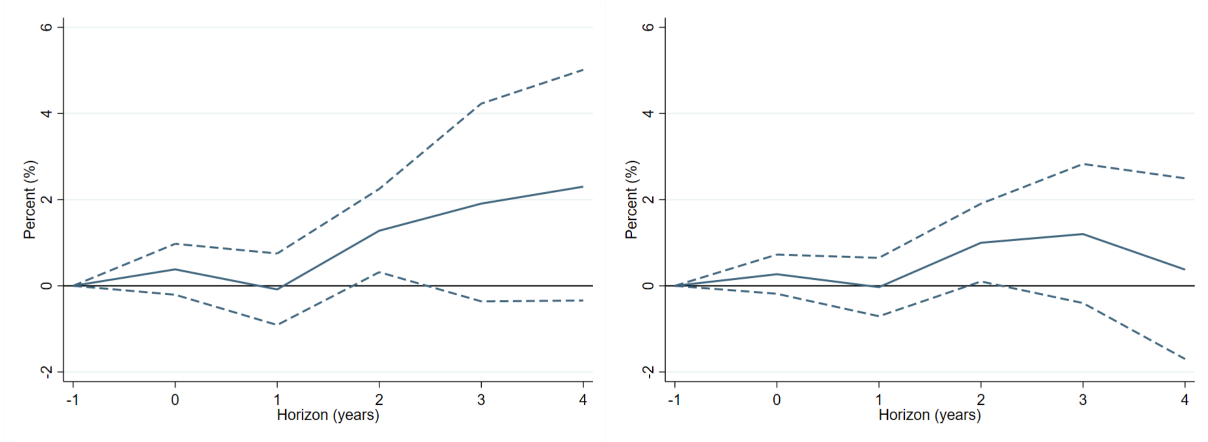
$$
\begin{aligned}
rca_{c,p,t+h} = & \beta_d \Delta DownIP_{c,v(p),s(p),t} + \sum_{l=1}^{2} \theta_{1l} \Delta DownIP_{c,v(p),s(p),t-l} \\
& + \beta_u \Delta UpIP_{c,v(p),s(p),t} + \sum_{l=1}^{2} \theta_{2l} \Delta UpIP_{c,v(p),s(p),t-l} \\
& + \sum_{l=1}^{2} \theta_{3l} rca_{c,p,t-l} \\
& + \theta_4 \Delta NonIP_{c,v(p),s(p),t} + \sum_{l=1}^{2} \theta_{5l} \Delta NonIP_{c,v(p),s(p),t-l} \\
& + FEs + \varepsilon_{c,p,t}
\end{aligned} \tag{6}
$$

$\Delta DownIP_{c,v(p),s(p),t}$ is the first difference of active downstream 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 IPs for the product. Similarly, $\Delta UpIP_{c,v(p),s(p),t}$ represents the upstream IP shock. Additional controls include 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, product-year, and country-value chain-year. The outcomes of interest are β_d and β_u, which capture the effect of downstream (upstream) IPs relative to IPs targeting products within the same stage of the value chain.[16]

Figure 12 reports the estimated effect for IPs targeting more upstream products and more downstream products in the three major green value chains.[17] IPs targeting more upstream products are associated with stronger improvements in RCA relative to those targeting products at the same stage of the value chain, while IPs targeting more downstream products have similar effects as IPs targeting products within the same value chain stage. Intuitively, upstream IPs may alleviate capacity constraints and benefit downstream products through reductions in input costs. This finding is consistent with empirical evidence considering generic IO production networks, such as Lane (Forthcoming) for the case of Korea, as well as firm-level evidence in Baquie et al. (2025) for 42 countries from Orbis.

[16]Note that these estimated effects are relative to the effects of IPs targeting products within the same value chain stage ($\Delta OwnIP_{c,v(p),s(p),t}$), because $\Delta DownIP_{c,v(p),s(p),t} + \Delta UpIP_{c,v(p),s(p),t} + \Delta OwnIP_{c,v(p),s(p),t} = \Delta IP_{c,v(p),t}$ and $\Delta IP_{c,v(p),t}$ is absorbed by the country-value chain-year fixed effect. Therefore, including all of $\Delta DownIP_{c,v(p),s(p),t}$, $\Delta UpIP_{c,v(p),s(p),t}$, $OwnIP_{c,v(p),s(p),t}$ and country-value chain-year fixed effect results in the issue of multi-collinearity.

[17]Note that the composition of instruments varies across different stages of the value chain. While domestic subsidies account for the majority of IPs in all stages of production, they are more prevalent in the initial stages of the value chain (raw materials, over 70%, compared to more downstream stages (between 40 and 60%). This means that some of the differences in impact may be in part attributable to composition effects.



(a) Upstream IP

(b) Downstream IP

Figure 12: Relative Effect of Upstream/Downstream IPs along the Green Value Chain

Sources: GTA (2022), Juhász et al. (2023), and author's calculations.

Notes: Solid line is the estimated percent change in $RCA + 10^{-3}$ for upstream IPs (Panel (a)) and downstream IPs (Panel (b)) relative to the estimated percent change in $RCA + 10^{-3}$ for IPs targeting products at the same value chain stage. Dashed lines are 90% confidence intervals. Standard errors are clustered at the country-product level.

4.3.2 Robustness

We perform robust checks of the empirical findings under seven alternative scenarios. First, we drop China from our main sample. For reasons outlined in Section 2.1.1, IPs in China are not well represented by the GTA. We show that our empirical results are robust to the exclusion of the particular subset of IPs in China. Second, we change the number of stabilization lags from 5 years to 3 years to construct the clean sample. As elaborated in Section 3, the choice of L faces a bias-variance trade-off. 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 OLS sample. Third, we additionally control for the third lag of $\ln(RCA + 10^{-3})$ and the non-IP shock. Fourth, we use an alternative RCA measure which also accounts for imports. Fifth, we use $\ln(RCA + 1)$ in place of $\ln(RCA + 10^{-3})$ as our main dependent variable. Sixth, we exclude units that are treated in 2020 due to the concern that IPs announced during 2020 are intended to address Covid-specific problems. Finally, we conduct our analysis using all subsidies in the GTA database to assuage concerns related to the classification of IPs. Appendix F contains all the results. Generally speaking, the results are robust to the main findings. The only exception is export incentives, for which the medium-term positive effect is less pronounced in certain exercises. This may be due to the relatively low number of export incentives IPs in the data.

5 Conclusion

Industrial policies are back, raising the stakes for analyses assessing their economic implications. The most commonly stated motive of IPs is to gain competitiveness. Against this backdrop, this paper empirically evaluates the extent to which products targeted by IPs achieve improvements in trade competitiveness using a large dataset covering 156 countries and 5018 products in 2009-2022. Our results point to a nuanced picture. On average, this paper documents a positive link between IPs and improvements in the competitiveness of targeted products, but effects are heterogeneous across products and policy instruments. At the product level, our analysis suggests that the positive link between IPs and a product's RCA is mostly driven by products that were previously competitive. Other product characteristics, such as whether the product is related to the green transition, affect the timing of the effects. For example, green products experience larger medium-term improvements in RCA following the introduction of IPs compared to non-green products. The timing of effects is also affected by the choice of instruments. Domestic subsidies are associated with short-term improvements in the competitiveness of targeted products, while export incentives are associated with medium-term improvements. We also find suggestive evidence that IPs can affect the performance of other products along the value chain, pointing to cross-product spillovers.

Hence, IPs should be handled with care. The nuanced effects points to limited use case. Furthermore, our analysis provides a partial picture of the potential implications of IPs, as it does not fully account for general equilibrium effects, such as potential cross-sectoral reallocations, the retaliatory measures by other countries, and fiscal costs. Thus, countries must carefully weigh the costs and benefits of IPs in general equilibrium, ensure the consistency of IPs with international rules, and prioritize multilateral policy cooperation. Moreover, IPs can entail significant fiscal costs, amplifying debt sustainability concerns. Incorporating the general equilibrium channels in the analysis of IPs is a fruitful avenue for future research.

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Online Appendix

A Classifying IP Motives: An LLM Ensemble Approach

This section describes the large language model (LLM) approach used in Evennett et al. (Forthcoming), which we leverage to assign a stated motive to the IPs in Juhász et al. (2023). Policy descriptions from the Global Trade Alert (GTA) and New Industrial Policy Observatory (NIPO) contain rich information about the intentions behind policy actions. However, accurately attributing these motives is no trivial task. While traditional Natural Language Processing techniques such as bag-of-words have seen many successful applications in economics, recent advances in Large Language Models (LLMs) brought unprecedented possibilities to make such classifications with greater flexibility and accuracy. For example, a green industrial policy that subsidizes coal production conditional on meeting high environmental standards would likely be missed by traditional bag-of-words approaches, as the term "coal" typically carries a strong signal for non-green policies on its own. In contrast, LLMs excel at natural language understanding beyond mere word frequencies, offering contextual comprehension of policy texts.

However, while unsupervised training (pre-training) on vast corpora of text endows LLMs with impressive general language processing capabilities, they are not inherently experts on industrial policies. To address this, we adopt the pretrain-finetune paradigm to fully leverage the power of LLMs for our specific classification task. To be clear, all GTA policies include text descriptions, but only a subset of those in NIPO contain human annotations regarding their motives. This annotated subset forms our training and validation dataset. We choose RoBERTa-Large as our base model, as it is widely regarded as the go-to model for such classification tasks. Introduced by Liu et al. (2019) at Meta AI, RoBERTa (Robustly Optimized BERT Approach) is an improved and more thoroughly trained version of BERT (Bidirectional Encoder Representations from Transformers), which was the original groundbreaking Language Model Liu et al. (2019). We follow best practices outlined in Sun et al. (2020); Mosbach et al. (2021) for fine-tuning.

Last but not the least, as recent work such as McCoy et al. (2020) has pointed out, LLM performance can be unstable due to randomization during training. To address this issue, we employ an ensemble approach: we train RoBERTa-Large ten times, each time with a randomly initialized classification head and a randomized batch order during training, and calculate the average probability to determine the final classification. This process is designed to enhance the robustness of our predictions. Below are details about our algorithm.

A.1 Algorithm in Detail

Step 0 - Model Construction. For each motive, we finetune RoBERTa-Large by augmenting it with a custom classification head. RoBERTa-Large generates 1,024-dimensional vector representations for each input token. We use the 1,024-dimensional hidden state corresponding to the `[CLS]` token as input to our classification head. The classification head consists of a fully connected layer (1,024 $\times$ 1,024), a `ReLU` activation function, a dropout layer (dropout rate: 0.1), and a final classification layer (1,024 $\times$ 2). A `softmax` function is applied at the output to generate probability distributions over the target classes. With 355 million parameters, RoBERTa-Large remains manageable on a single RTX 8000 GPU. As a result, we perform full finetuning, allowing all model weights—including both RoBERTa's pre-trained weights and the classification head's weights—to be updated during training.

Step 1 - Text Preprocessing. While LLMs require significantly less preprocessing than traditional NLP workflows, some basic cleaning steps are necessary to enhance their performance. We remove all non-Unicode characters and redundant escape sequences and replace non-English characters with their English counterparts whenever possible. These preprocessing steps are important because, without them, LLMs may cluster unrecognized characters into the `[UNK]` token during tokenization, reducing the information-to-signal ratio in the processed text. Additionally, we truncate input text at 512 tokens, as this is the maximum context length for RoBERTa-Large. As shown in Figure B.1, the vast majority of policy texts fall below this threshold, resulting in minimal information loss. After cleaning and trunca-

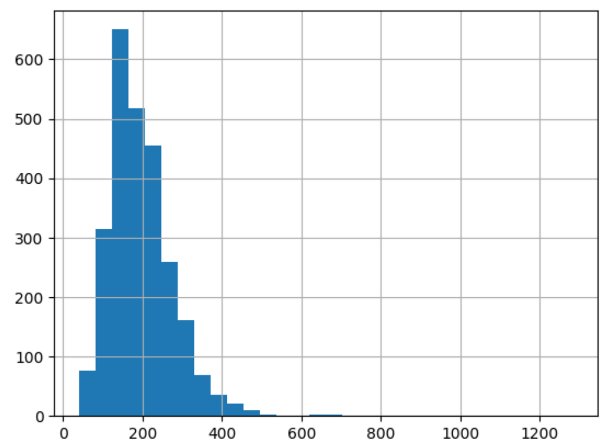


Figure B.1: Histogram of Policy Description Length

tion, we randomly split our labeled dataset into training and testing sets. We use a class-stratified 80% sample for training and reserve the remaining 20% for testing. This train/test split is performed once and remains fixed throughout our ensemble process. The test dataset is withheld until the entire algorithm is complete, at which point we evaluate its performance.

Step 2 - Finetuning Finetuning is a supervised learning technique that adjusts an LLM's responses to specialize it for a specific task. Mathematically, this involves updating the neural network's weights—the parameters that transform input text into outputs through various layers of the model. The goal of fine-tuning is to optimize these weights to minimize the loss function for the target dataset. Since our task is classification, we use cross-entropy loss, which is defined as:

$$L = -\sum_{i=1}^{N} w_i \cdot y_i \log(\hat{y}_i)$$

where y_i is the true label, $\hat{y}_i$ is the predicted probability for class i, w_i is the class weight, and N is the number of classes. To account for label imbalance, we incorporate class weights w_i, ensuring that the model does not overly favor majority classes. To improve generalization and stability, we follow the best practices from Mosbach et al. (2021), deliberately training with a combination of a small learning rate with bias correction and a large number of iterations. We use the AdamW optimizer with a learning rate of 1×10^{-5} and train the model for 8 epochs. We apply a weight decay of 0.01 and use a linear learning rate scheduler with warm-up, setting the warm-up proportion to 10% of the total training steps.

Since the model's results can vary depending on various factors even with the same inputs, this step is repeated ten times to improve the accuracy of the model's predictions, which produces ten finetuned models for each stated motive.

Step 3 - Ensemble and Production We apply our algorithm on all IPs from Juhász et al. (2023). To recap, for each policy, we feed policy title and description to each of the ten finetuned models, and then obtain final prediction which yields ten sets of probabilities for policies corresponding to each stated motive. We then compute the weighted average of the probabilities and classify the policy as having the stated motive if the weighted probability exceeded 60%.

A.2 Validation

To assess the effectiveness of our ensemble model, we compare its performance against several alternative approaches commonly used in text classification:

Term Frequency-Inverse Document Frequency (TF-IDF). TF-IDF is a traditional Bag-of-Words method for text representation that assigns weights to words based on their importance in a document relative to a corpus. We use TF-IDF features as inputs to a logistic regression classifier.

In-Context Learning. Large language models (LLMs) can perform classification tasks without fine-tuning by leveraging a few labeled examples in their prompt (few-shot learning). Given a small set of demonstration examples, the LLM generates predictions based on its pre-trained knowledge. We evaluate three different models for in-context learning: **Llama3-8b-instruct** (Llama Team, 2024), **Qwen2-8b-instruct** (Yang et al., 2024), and **GPT-3.5 Turbo** by OpenAI. These models were selected based on their strong performance, accessibility, and relative computational efficiency.

Finetuning Instruction-Following LLMs. In addition to finetuning RoBERTa-Large, we finetune instruction-following models using Low-Rank Adaptation (LoRA) (Hu et al., 2021). LoRA is a parameter-efficient finetuning technique that reduces the computational cost of adapting large language models while maintaining their expressive capacity. Instead of updating all model weights, LoRA introduces small low-rank matrices that are trained alongside the frozen original model weights, significantly reducing memory and computational requirements.

For both in-context learning and finetuning, we structure our prompts as follows:

> Classify the following policy as Green Industrial Policy or not. Green industrial policies are policies that are aimed to or likely to provide climate change mitigation or facilitate the transition to a low-carbon economy. You are only allowed to choose one of the following categories: True, False.
>
> {DEMONSTRATION POLICY 1} {DEMONSTRATION LABEL 1}
>
> {DEMONSTRATION POLICY 2} {DEMONSTRATION LABEL 2}
>
> {DEMONSTRATION POLICY 3} {DEMONSTRATION LABEL 3}
>
> ...
>
> {INPUT POLICY}

where {DEMONSTRATION POLICY i}, {DEMONSTRATION LABEL i} are replaced with three randomly chosen examples from the training dataset, and {INPUT POLICY} is replaced with the policy text to classify.

Evaluation Metrics To compare performance across methods, we use two standard metrics: **accuracy** and **macro-F1 score**. **Accuracy** measures the proportion of correctly classified instances out of the total number of instances. It is formally defined as:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{7}$$

where:

- TP (True Positives): correctly classified positive instances
- TN (True Negatives): correctly classified negative instances
- FP (False Positives): incorrectly classified negative instances as positive

- FN (False Negatives): incorrectly classified positive instances as negative

While accuracy is an intuitive measure, it can be misleading in imbalanced datasets, where a model predicting only the majority class would still achieve high accuracy.

F1 Score is the harmonic mean of precision and recall, balancing the tradeoff between them:

$$F1 = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{8}$$

where:

$$\text{Precision} = \frac{TP}{TP + FP}, \quad \text{Recall} = \frac{TP}{TP + FN} \tag{9}$$

Precision measures how many of the predicted positive instances are actually positive, while recall measures how many actual positive instances were correctly identified. For our binary classification tasks, we use the **macro-F1 score**, which averages the F1 scores across both classes:

$$\text{Macro-F1} = \frac{1}{2}\left(F1_{\text{positive class}} + F1_{\text{negative class}}\right) \tag{10}$$

Unlike accuracy, the macro-F1 score gives equal weight to both classes, making it a more reliable measure when dealing with class imbalances. Table B.1 presents the accuracy and macro-F1 scores for different methods applied to the classification of climate change mitigation motives.

Table B.1: Performance Comparison of Different Approaches on Motive: Climate Change Mitigation

Approach	**Accuracy**	**Macro-F1**
Bag-of-Words		
TF-IDF+logistic	0.88	0.81
In-Context Learning (Fewshot)		
Llama3-8b-instruct	0.87	0.75
Qwen2-8b-instruct	0.88	0.82
GPT-3.5 Turbo	0.87	0.81
Finetuning		
Llama3-8b-instruct	0.91	0.85
Qwen2-8b-instruct	0.88	0.80
GPT-3.5-Turbo	0.94	0.90
RoBERTa-Large	0.94	0.90
Ensemble RoBERTa-Large	**0.97**	**0.94**

As shown in Table B.1, our LLM ensemble approach achieves the highest accuracy and macro-F1 score, outperforming both traditional Bag-of-Words methods and finetuning approaches. While finetuned models, particularly GPT-3.5-Turbo, show significant performance gains over in-context learning, our ensemble method further improves classification performance. Notably, despite the higher computational cost associated with finetuning instruction-following LLMs, our ensemble approach demonstrates superior effectiveness, suggesting that combining multiple finetuned models can enhance performance and generalization.

Table B.2: Performance of Our LLM Ensemble Approach on Other Motives

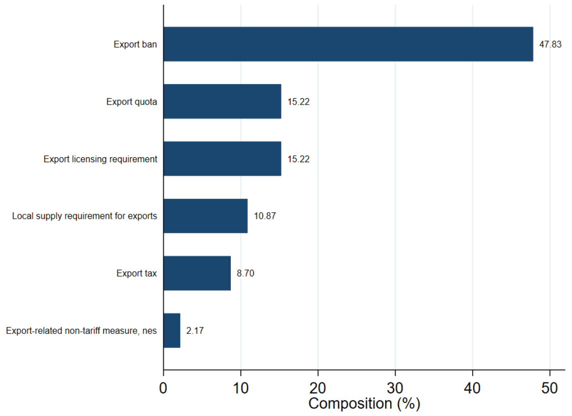
Motive	**Accuracy**	**Macro-F1**
Strategic Competitiveness	0.92	0.90
Geopolitical Concerns	0.95	0.88
GVC Resillence	0.96	0.90

B Comparing IMF's Environmental Goods and LCT Products

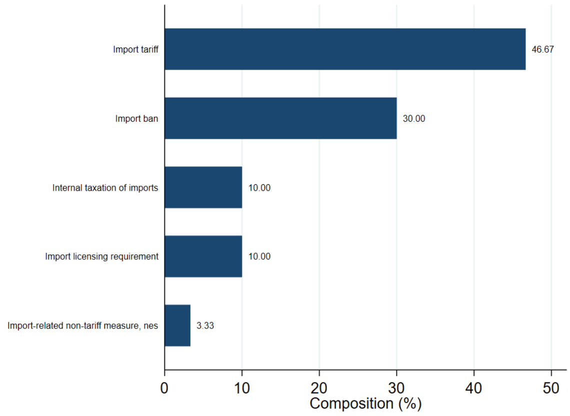
	Environmental Goods as defined for the IMF Climate Change Indicators Dashboard	**Low Carbon Technology Products** as defined for the IMF Climate Change Indicators Dashboard
Definition	Environmental goods include both goods connected to environmental protection—such as goods related to pollution management and resource management—and adapted goods—which are goods that have been specifically modified to be more "environmentally friendly" or "cleaner."	Low carbon technology products produce less pollution than their traditional energy counterparts and will play a vital role in the transition to a low carbon economy.
Number of HS codes	222	124
Types of goods covered, according to Broad Economic Categories (BEC)	Food and beverages Industrial supplies, primary Industrial supplies, processed Fuels and lubricants Capital goods Transport equipment Consumer goods	Industrial supplies, processed Capital goods Transport equipment Consumer goods

Figure B.2: Environmental Goods vs. LCT Products

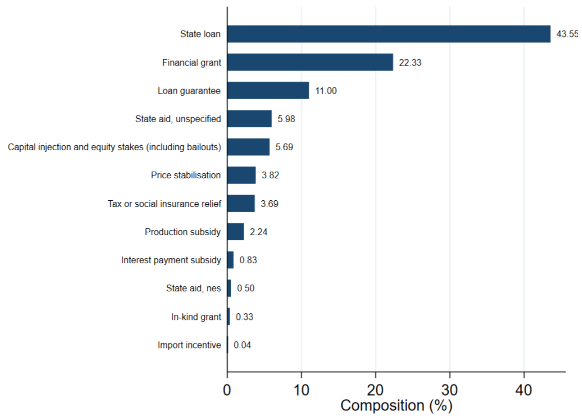
C Classification of Policy Instruments



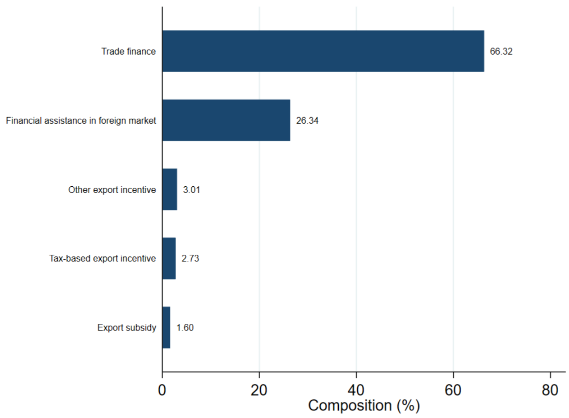
(a) Export Barriers



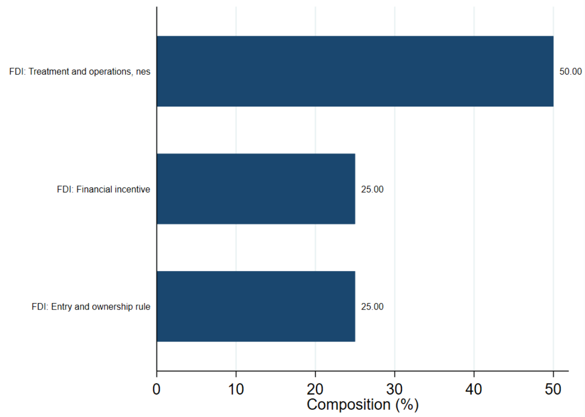
(b) Import Barriers



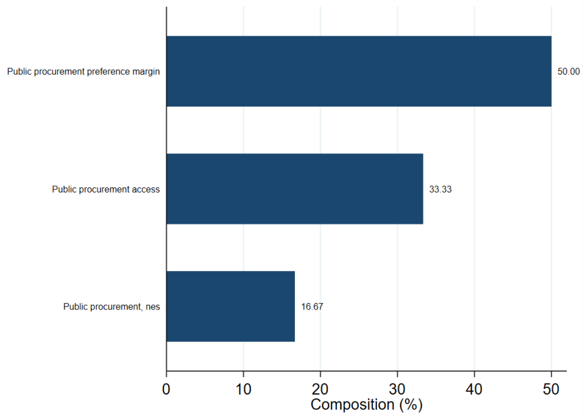
(c) Domestic Subsidies



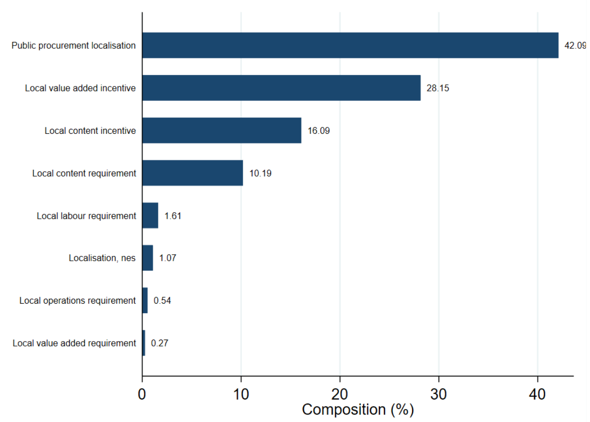
(d) Export Incentives



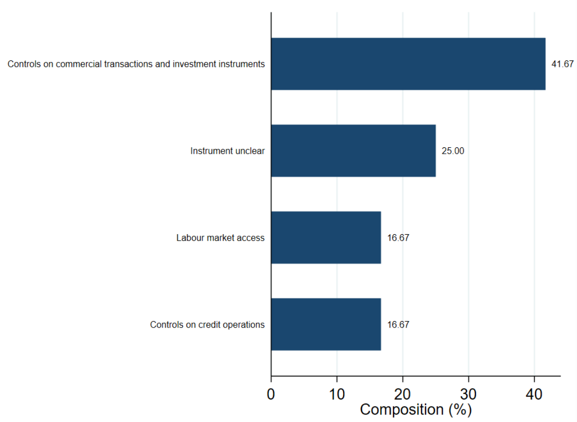
(a) FDI Measures



(b) Public Procurement Measures



(c) Local Content Measures



(d) Others

Figure B.2: Composition of Broad Policy Instruments (2018-2022)

Sources: GTA (2022), Juhász et al. (2023), and author's calculations.

Notes: y-axis represents the share of disaggregated policy instrument out of each broad group in 2018-2022, adjusted for reporting lags.

D Additional Descriptive Statistics

D.1 Evolution of Announced IPs over Time

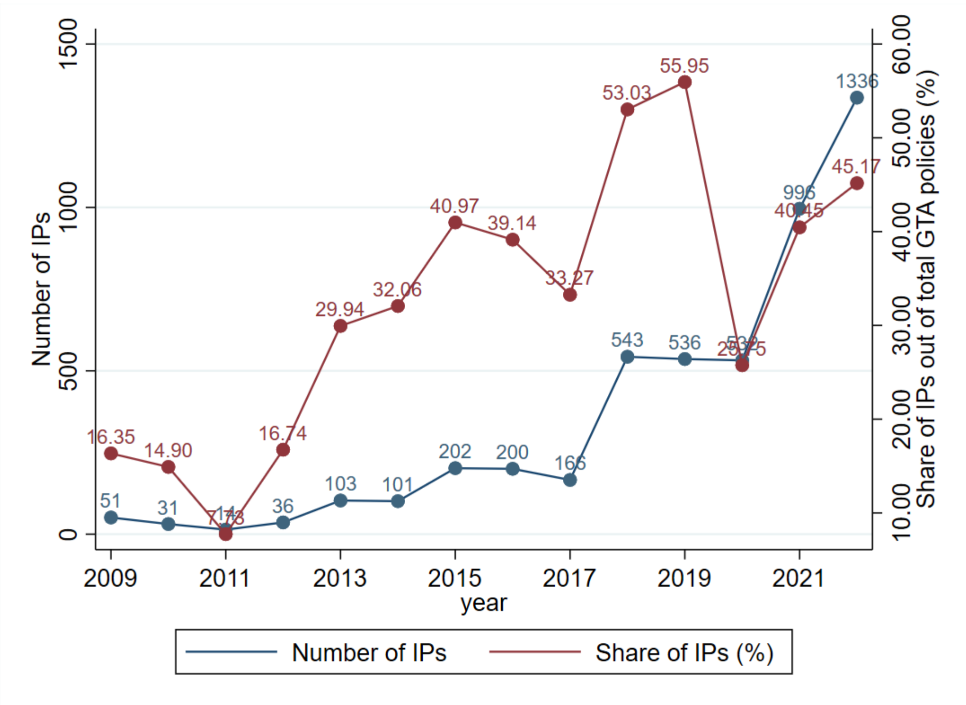


Figure B.3: Evolution of Announced IPs over Time

Sources: GTA (2022), Juhász et al. (2023), and author's calculations.

Notes: y-axis represents the counts of announced IP over time, adjusted for reporting lags.

D.2 Evolution of Announced IPs over Time by Country Income Group

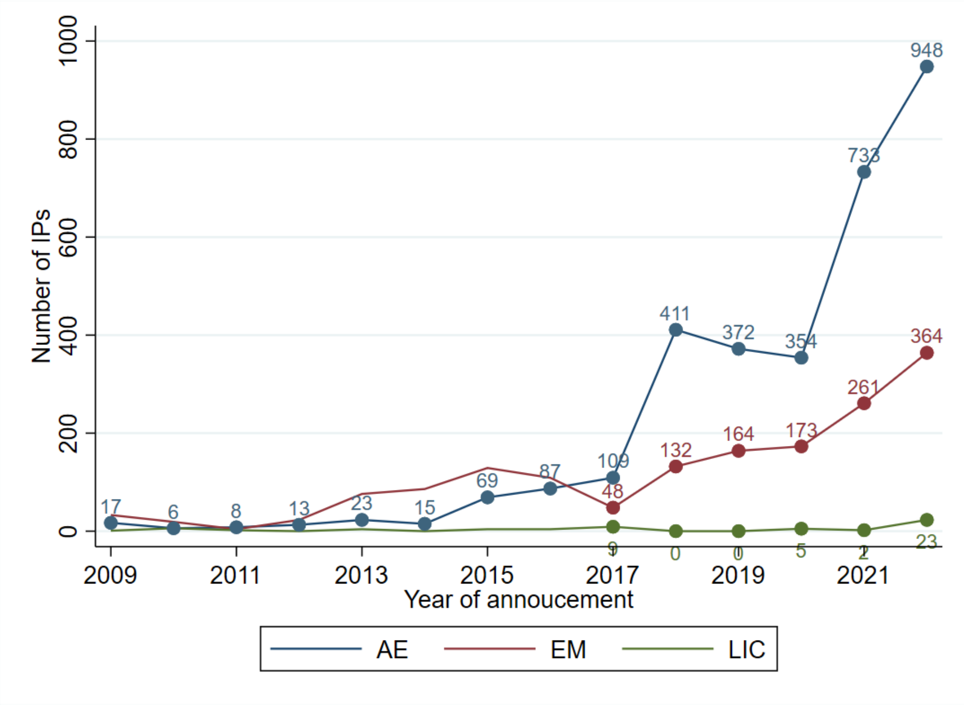


Figure B.4: Evolution of Announced IPs over Time: AE vs. EM vs. LIC

Sources: GTA (2022), Juhász et al. (2023), and author's calculations.

Notes: y-axis represents the counts of announced IP over time, adjusted for reporting lags. The classification of country income group (AE/EM/LIC) is based on the IMF's World Economic Outlook.

D.3 Average Number of Targeted Products by Policy Instrument

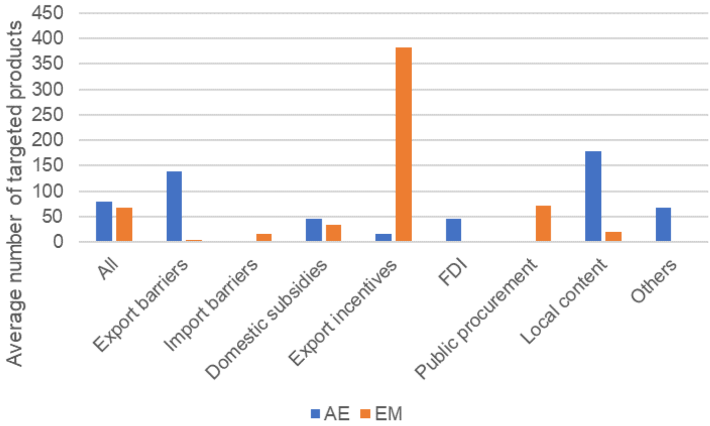


Figure B.5: Average Number of Targeted Products by Policy Instrument (2018-2022), AE vs. EM

Sources: GTA (2022), Juhász et al. (2023), and author's calculations.

Notes: y-axis represents the average number of targeted products by overall and by policy instrument (x-axis) in 2018-2022, adjusted for reporting lags. The classification of country income group (AE - blue bars/EM - orange bars) is based on the IMF's World Economic Outlook.

D.4 Breakdown by Policy Instrument and GTA Evaluation

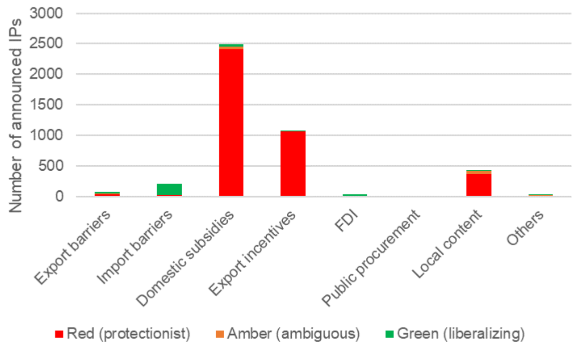
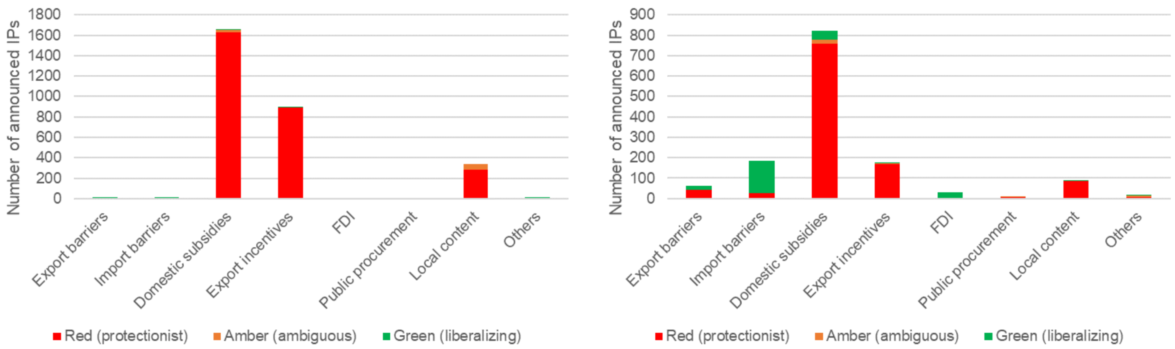


Figure B.6: Counts of Announced IPs by Policy Instrument and GTA Evaluation (2018-2022), All Countries

Sources: GTA (2022), Juhász et al. (2023), and author's calculations.
Notes: y-axis represents the number of announced IPs by policy instrument (x-axis) in 2018-2022 for all countries, adjusted for reporting lags. Each bar comprises three colors. Each color represents a GTA evaluation: red (protectionist), orange (ambiguous), green (liberalizing).

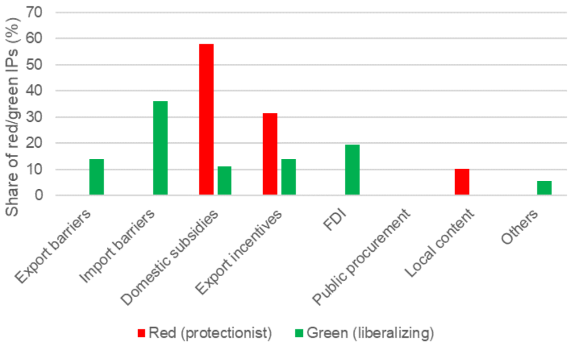


(a) AE

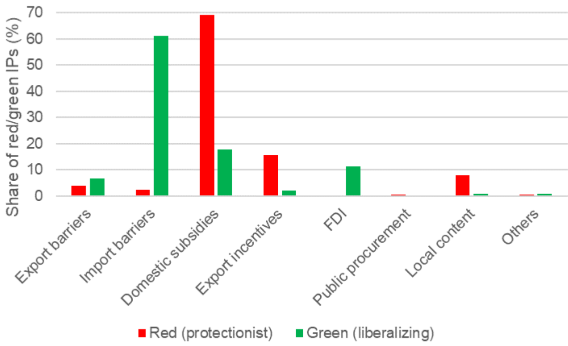
(b) EM

Figure B.7: Counts of Announced IPs by Policy Instrument and GTA Evaluation (2018-2022), AE vs. EM

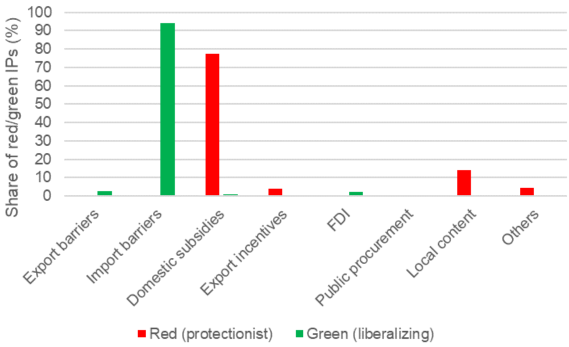
Sources: GTA (2022), Juhász et al. (2023), and author's calculations.
Notes: y-axis represents the the number of announced IPs by policy instrument (x-axis) for AE vs. EM in 2018-2022, adjusted for reporting lags. Panel (a) uses the sample of AEs. Panel (b) uses the sample of EMs. The classification of country income group (AE/EM) is based on the IMF's World Economic Outlook. Each bar comprises three colors. Each color represents a GTA evaluation: red (protectionist), orange (ambiguous), green (liberalizing).



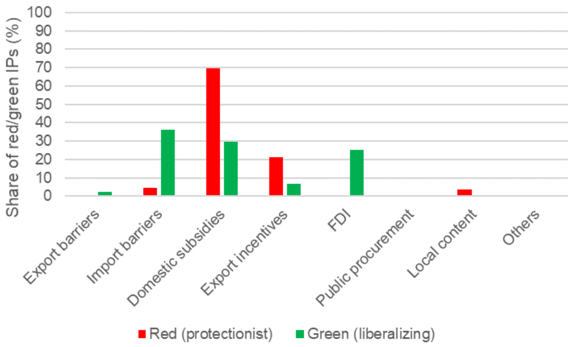
(a) AE, Policy Level



(b) EM, Policy Level



(c) AE, Policy $\times$ HS Product Level



(d) EM, Policy $\times$ HS Product Level

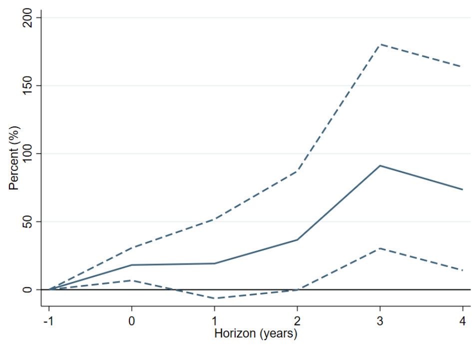
Figure B.8: Breakdown by Policy Instrument and GTA Evaluation (2018-2022), AE vs. EM

Sources: GTA (2022), Juhász et al. (2023), and author's calculations.

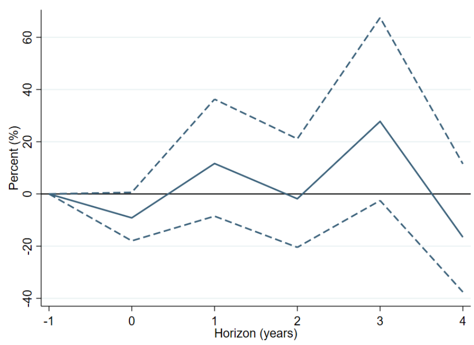
Notes: y-axis represents the share of of the eight policy instruments (x-axis) out of total protectionist (red bars) or liberalizing (green bars) IPs for AE vs. EM in 2018-2022, adjusted for reporting lags. Panels (a) and (c) use the sample of AEs. Panels (b) and (d) use the sample of EMs. Panels (a) and (b) count each policy once, even if the policy targets multiple HS products. Panel (c) and (d) count each policy n times if it targets n HS products. The classification of country income group (AE/EM) is based on the IMF's World Economic Outlook.

E Additional Results

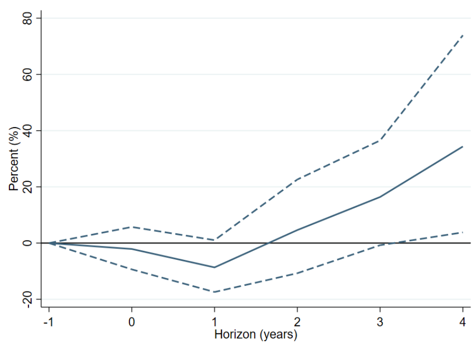
E.1 Other Policy Instruments



(a) Export barriers



(b) Import barriers



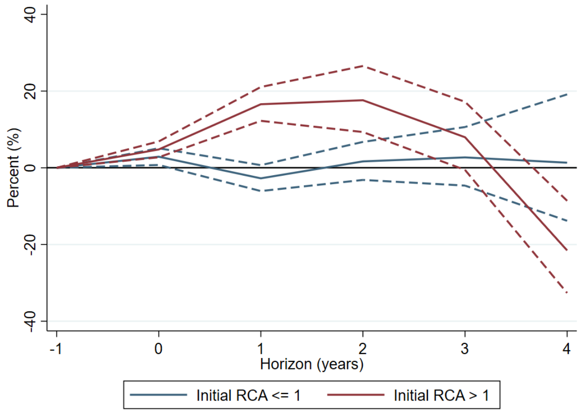
(c) Local content measures

Figure B.9: Effect of IP on $\ln(RCA + 10^{-3})$, Other Policy Instruments

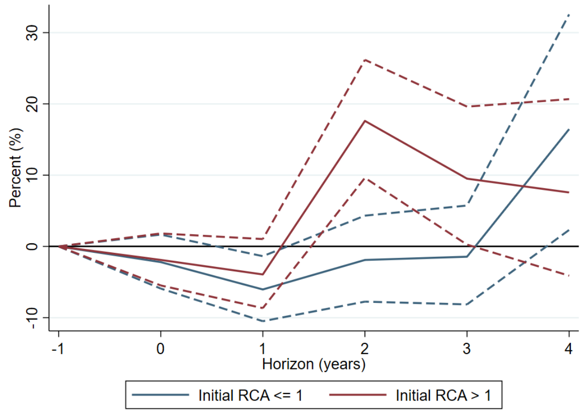
Sources: GTA (2022), Juhász et al. (2023), and author's calculations.

Notes: Solid line is the estimated percent change in $RCA + 10^{-3}$ for export barriers (Panel (a)), import barriers (Panel (b)), and local content measures (Panel (c)). Dashed lines are 90% confidence intervals. Standard errors are clustered at the country-product level.

E.2 Domestic Subsidies vs. Export Incentives: The Role of Initial RCA



(a) Domestic Subsidies



(b) Export Incentives

Figure B.10: Domestic Subsidies vs. Export Incentives: The Role of Initial RCA

Sources: GTA (2022), Juhász et al. (2023), and author's calculations.

Notes: Solid line is the estimated percent change in $RCA + 10^{-3}$ for domestic subsidies (Panel (a)) and export incentives (Panel (b)). Red lines correspond to products with $RCA_{c,p,t-1} > 1$ (initially competitive) and blue lines correspond to products with $RCA_{c,p,t-1} \leq 1$ (initially uncompetitive). Dashed lines are 90% confidence intervals. Standard errors are clustered at the country-product level.

F Robustness

F.1 Excluding China

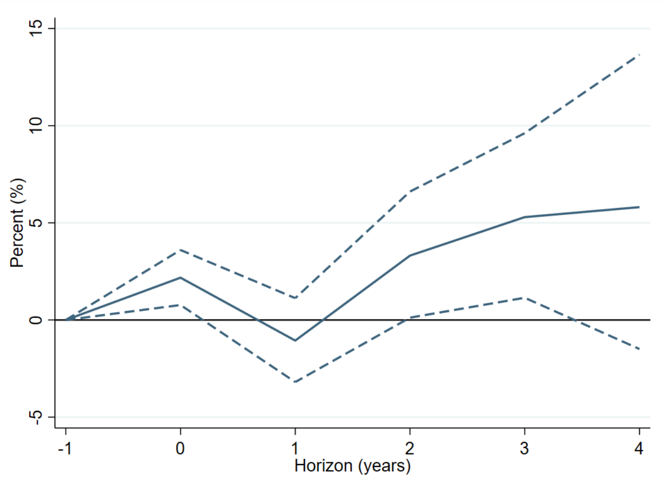


Figure B.11: Effect of IP on $\ln(RCA + 10^{-3})$, All Products, No China

Sources: GTA (2022), Juhász et al. (2023), and author's calculations.

Notes: The sample excludes China. Solid line is the estimated percent change in $RCA + 10^{-3}$. Dashed lines are 90% confidence intervals. Standard errors are clustered at the country-product level.

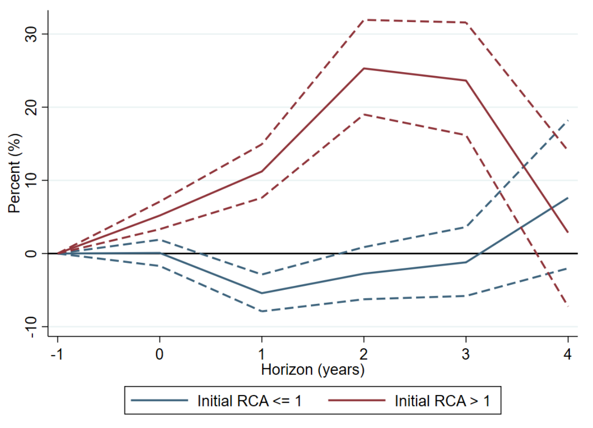


Figure B.12: Effect of IP on $\ln(RCA + 10^{-3})$, by Initial RCA, No China

Sources: GTA (2022), Juhász et al. (2023), and author's calculations.

Notes: The sample excludes China. Solid line is the estimated percent change in $RCA + 10^{-3}$. Dashed lines are 90% confidence intervals. Red lines correspond to products with $RCA_{c,p,t-1} > 1$ (initially competitive) and blue lines correspond to products with $RCA_{c,p,t-1} \leq 1$ (initially uncompetitive). Standard errors are clustered at the country-product level.

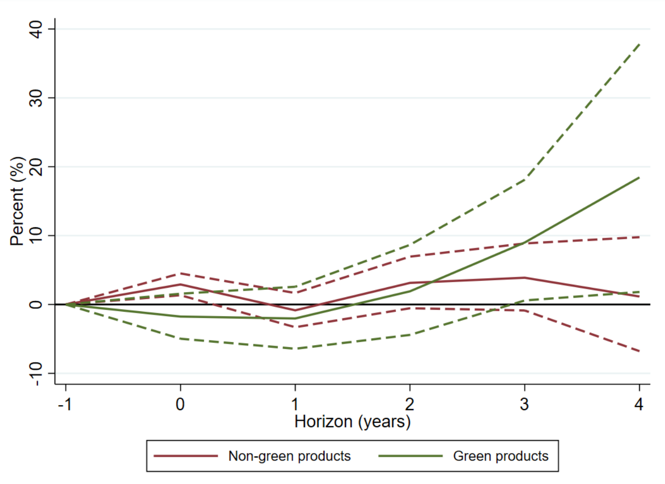
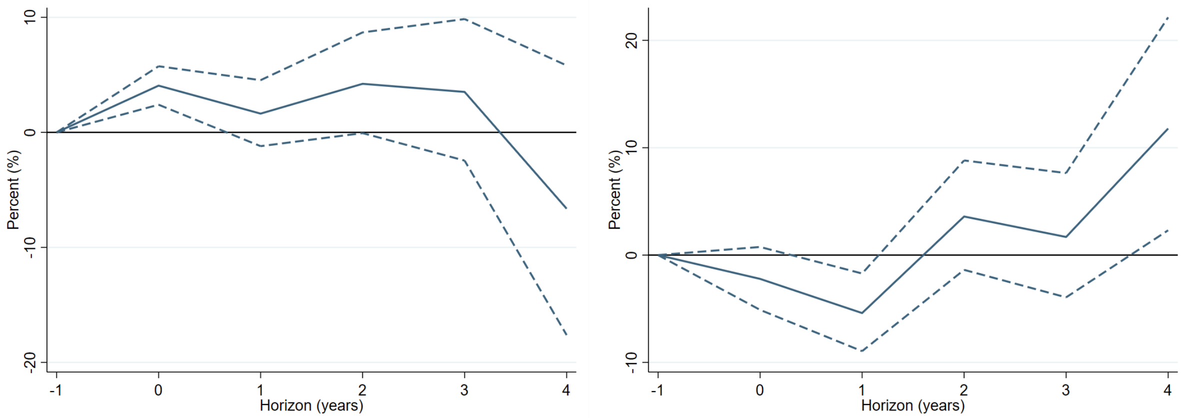


Figure B.13: Effect of IP on $\ln(RCA + 10^{-3})$, Green vs. Non-Green Products, No China

Sources: GTA (2022), Juhász et al. (2023), and author's calculations.

Notes: The sample excludes China. Solid line is the estimated percent change in $RCA + 10^{-3}$. Dashed lines are 90% confidence intervals. Red lines correspond to non-green products and green lines correspond to green products. Standard errors are clustered at the country-product level. The list of green products is described in Section 2.1.4.



(a) Domestic Subsidies

(b) Export Incentives

Figure B.14: Effect of IP on $\ln(RCA + 10^{-3})$, by Policy Instrument, no China

Sources: GTA (2022), Juhász et al. (2023), and author's calculations.

Notes: The sample excludes China. Solid line is the estimated percent change in $RCA + 10^{-3}$ for domestic subsidies (Panel (a)) and export incentives (Panel (b)). Dashed lines are 90% confidence intervals. Standard errors are clustered at the country-product level.

F.2 Alternative Number of Stabilization Lags ($L = 3$)

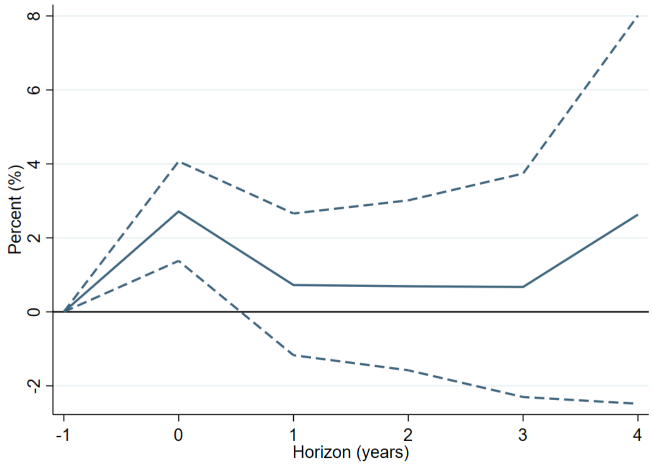


Figure B.15: Effect of IP on $\ln(RCA + 10^{-3})$, All Products, $L = 3$

Sources: GTA (2022), Juhász et al. (2023), and author's calculations.

Notes: The number of stabilization lag L to construct the clean sample is 3. Solid line is the estimated percent change in $RCA + 10^{-3}$. Dashed lines are 90% confidence intervals. Standard errors are clustered at the country-product level.

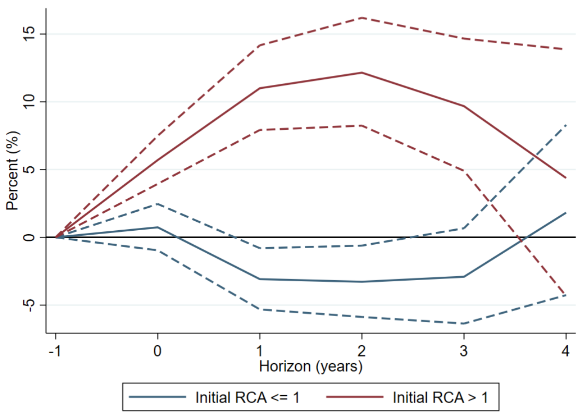


Figure B.16: Effect of IP on $\ln(RCA + 10^{-3})$, by Initial RCA, $L = 3$

Sources: GTA (2022), Juhász et al. (2023), and author's calculations.

Notes: The number of stabilization lag L to construct the clean sample is 3. Solid line is the estimated percent change in $RCA + 10^{-3}$. Dashed lines are 90% confidence intervals. Red lines correspond to products with $RCA_{c,p,t-1} > 1$ (initially competitive) and blue lines correspond to products with $RCA_{c,p,t-1} \leq 1$ (initially uncompetitive). Standard errors are clustered at the country-product level.

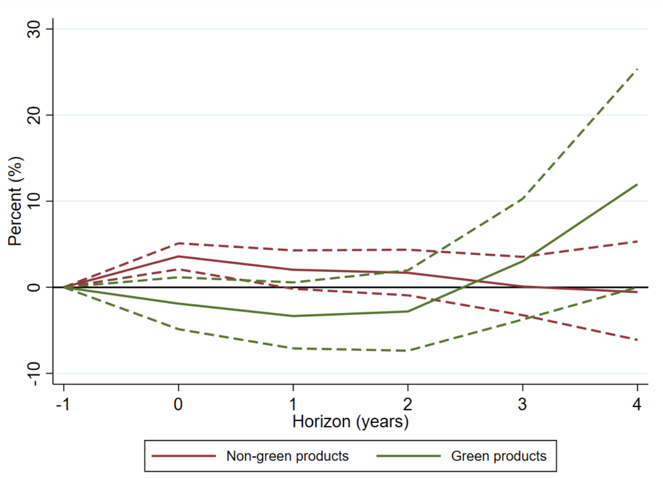
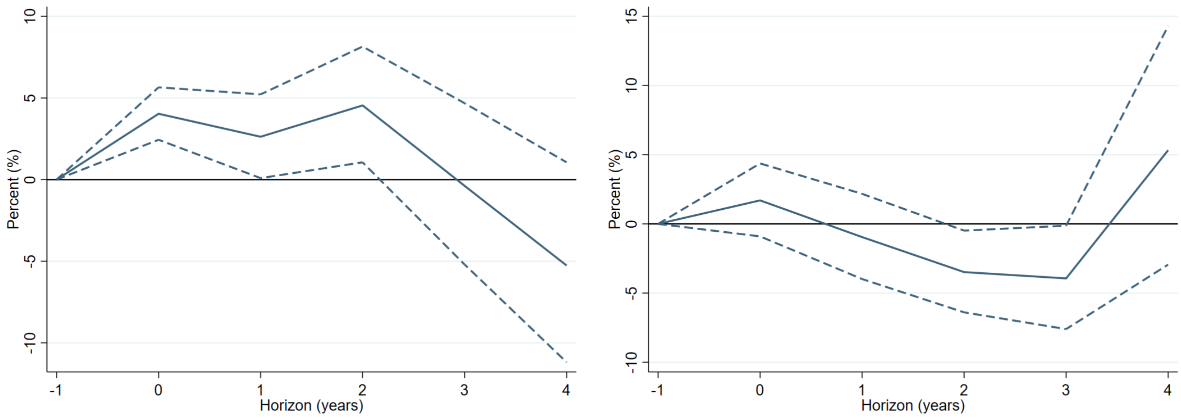


Figure B.17: Effect of IP on $\ln(RCA + 10^{-3})$, Green vs. Non-Green Products, $L = 3$

Sources: GTA (2022), Juhász et al. (2023), and author's calculations.

Notes: The number of stabilization lag L to construct the clean sample is 3. Solid line is the estimated percent change in $RCA + 10^{-3}$. Dashed lines are 90% confidence intervals. Red lines correspond to non-green products and green lines correspond to green products. Standard errors are clustered at the country-product level. The list of green products is described in Section 2.1.4.



(a) Domestic Subsidies

(b) Export Incentives

Figure B.18: Effect of IP on $\ln(RCA + 10^{-3})$, by Policy Instrument, $L = 3$

Sources: GTA (2022), Juhász et al. (2023), and author's calculations.

Notes: The number of stabilization lag L to construct the clean sample is 3. Solid line is the estimated percent change in $RCA+10^{-3}$ for domestic subsidies (Panel (a)) and export incentives (Panel (b)). Dashed lines are 90% confidence intervals. Standard errors are clustered at the country-product level.

F.3 Controlling for the Third Lag

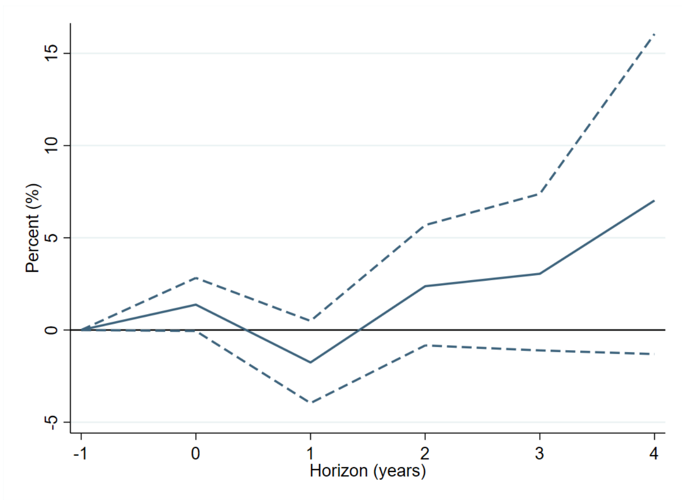


Figure B.19: Effect of IP on $\ln(RCA + 10^{-3})$, All Products, Control for the Third Lag

Sources: GTA (2022), Juhász et al. (2023), and author's calculations.

Notes: The regressions additionally control for the third lag of $\ln(RCA + 10^{-3})$ and $\Delta NonIP$. Solid line is the estimated percent change in $RCA + 10^{-3}$. Dashed lines are 90% confidence intervals. Standard errors are clustered at the country-product level.

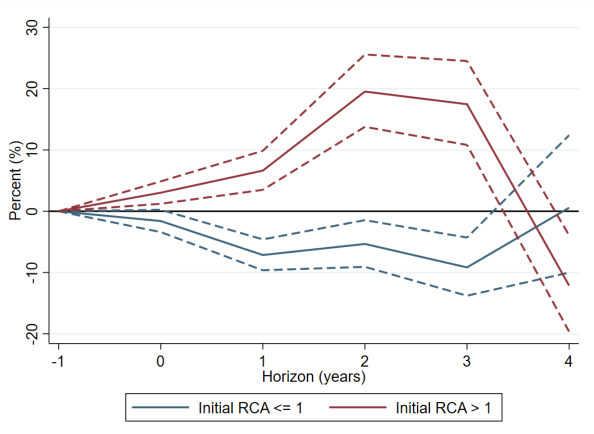


Figure B.20: Effect of IP on $\ln(RCA + 10^{-3})$, by Initial RCA, Control for the Third Lag

Sources: GTA (2022), Juhász et al. (2023), and author's calculations.

Notes: The regressions additionally control for the third lag of $\ln(RCA + 10^{-3})$ and $\Delta NonIP$. Solid line is the estimated percent change in $RCA + 10^{-3}$. Dashed lines are 90% confidence intervals. Red lines correspond to products with $RCA_{c,p,t-1} > 1$ (initially competitive) and blue lines correspond to products with $RCA_{c,p,t-1} \leq 1$ (initially uncompetitive). Standard errors are clustered at the country-product level.

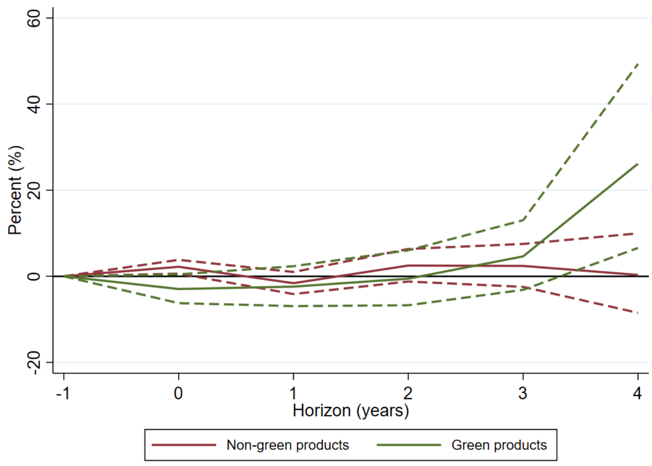
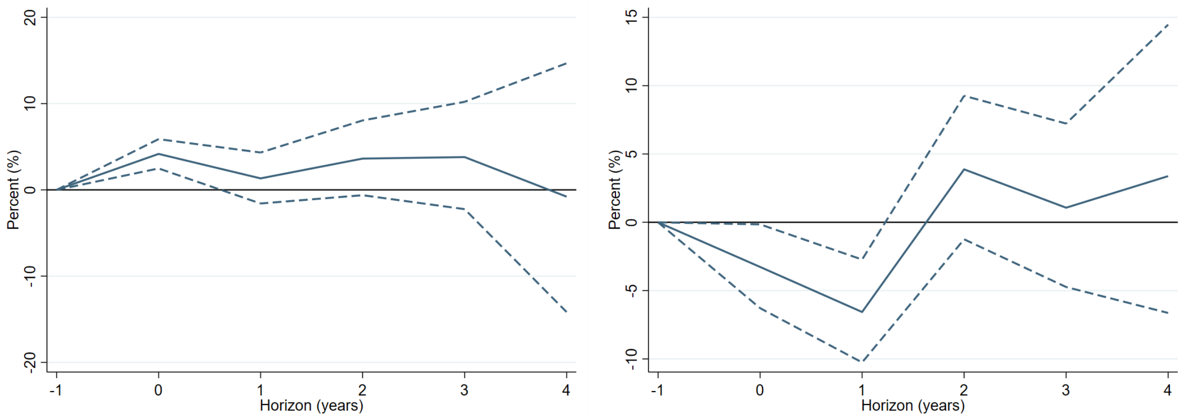


Figure B.21: Effect of IP on $\ln(RCA + 10^{-3})$, Green vs. Non-Green Products, Control for the Third Lag

Sources: GTA (2022), Juhász et al. (2023), and author's calculations.
Notes: The regressions additionally control for the third lag of $\ln(RCA + 10^{-3})$ and $\Delta NonIP$. Solid line is the estimated percent change in $RCA + 10^{-3}$. Dashed lines are 90% confidence intervals. Red lines correspond to non-green products and green lines correspond to green products. Standard errors are clustered at the country-product level. The list of green products is described in Section 2.1.4.



(a) Domestic Subsidies

(b) Export Incentives

Figure B.22: Effect of IP on $\ln(RCA + 10^{-3})$, by Policy Instrument, Control for the Third Lag

Sources: GTA (2022), Juhász et al. (2023), and author's calculations.
Notes: The regressions additionally control for the third lag of $\ln(RCA + 10^{-3})$ and $\Delta NonIP$. Solid line is the estimated percent change in $RCA + 10^{-3}$ for domestic subsidies (Panel (a)) and export incentives (Panel (b)). Dashed lines are 90% confidence intervals. Standard errors are clustered at the country-product level.

F.4 Alternative RCA Measure Adjusted for Imports

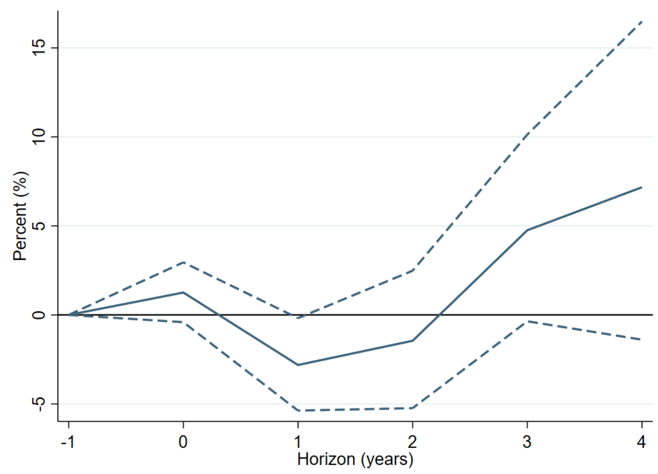


Figure B.23: RCA Adjusted for Imports, All Products

Sources: GTA (2022), Juhász et al. (2023), and author's calculations.

Notes: RCA measure is adjusted for imports, such that $\ln(RCA^{exports}+10^{-3})-ln(RCA^{imports}+10^{-3})$. Solid line is the estimated percent change in $\frac{RCA^{exports}+10^{-3}}{RCA^{imports}+10^{-3}}$. Dashed lines are 90% confidence intervals. Standard errors are clustered at the country-product level.

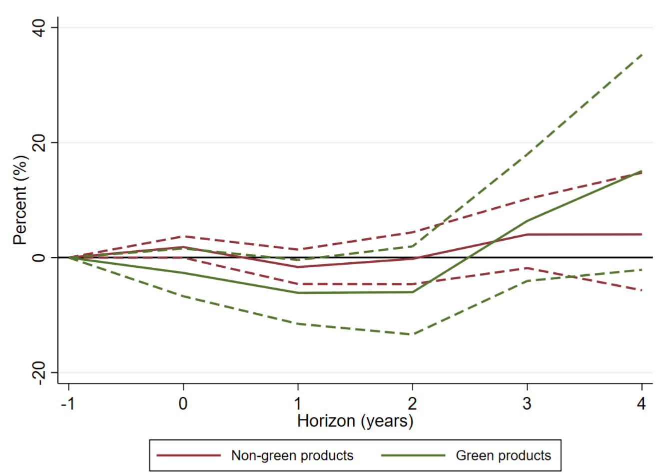
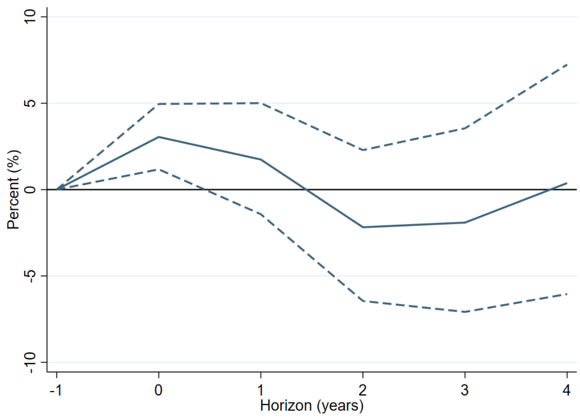


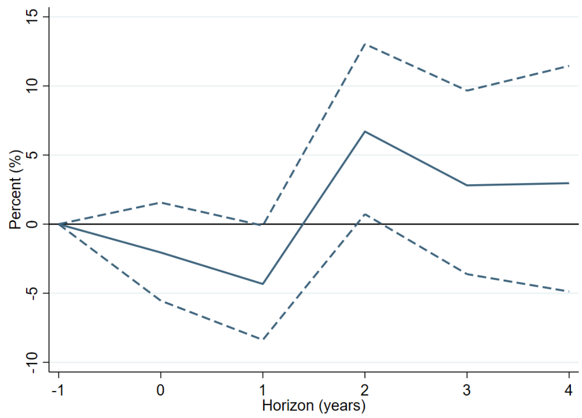
Figure B.24: RCA Adjusted for Imports, Green vs. Non-Green Products

Sources: GTA (2022), Juhász et al. (2023), and author's calculations.

Notes: RCA measure is adjusted for imports, such that $\ln(RCA^{exports}+10^{-3})-ln(RCA^{imports}+10^{-3})$. Solid line is the estimated percent change in $\frac{RCA^{exports}+10^{-3}}{RCA^{imports}+10^{-3}}$. Dashed lines are 90% confidence intervals. Red lines correspond to non-green products and green lines correspond to green products. Standard errors are clustered at the country-product level. The list of green products is described in Section 2.1.4.



(a) Domestic Subsidies



(b) Export Incentives

Figure B.25: RCA Adjusted for Imports, by Policy Instrument

Sources: GTA (2022), Juhász et al. (2023), and author's calculations.

Notes: RCA measure is adjusted for imports, such that $\ln(RCA^{exports} + 10^{-3}) - ln(RCA^{imports} + 10^{-3})$. Solid line is the estimated percent change in $\frac{RCA^{exports}+10^{-3}}{RCA^{imports}+10^{-3}}$ for domestic subsidies (Panel (a)) and export incentives (Panel (b)). Dashed lines are 90% confidence intervals. Standard errors are clustered at the country-product level.

F.5 Using $\ln(RCA+1)$ as Dependent Variable

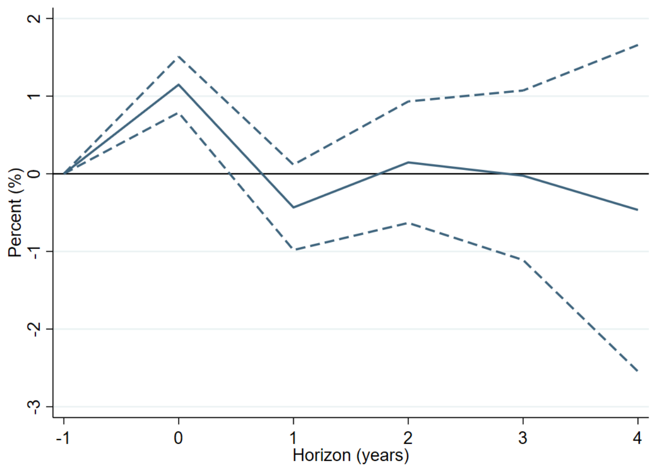


Figure B.26: Effect of IP on $\ln(RCA+1)$, All Products

Sources: GTA (2022), Juhász et al. (2023), and author's calculations.

Notes: Solid line is the estimated percent change in $RCA+1$. Dashed lines are 90% confidence intervals. Standard errors are clustered at the country-product level.

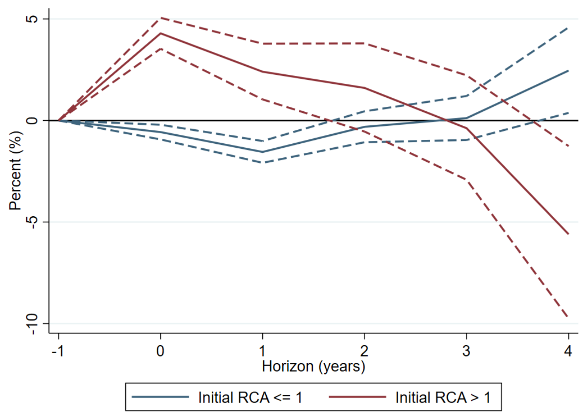


Figure B.27: Effect of IP on $\ln(RCA+1)$, by Initial RCA

Sources: GTA (2022), Juhász et al. (2023), and author's calculations.

Notes: Solid line is the estimated percent change in RCA+1. Dashed lines are 90% confidence intervals. Red lines correspond to products with $RCA_{c,p,t-1} > 1$ (initially competitive) and blue lines correspond to products with $RCA_{c,p,t-1} \leq 1$ (initially uncompetitive). Standard errors are clustered at the country-product level.

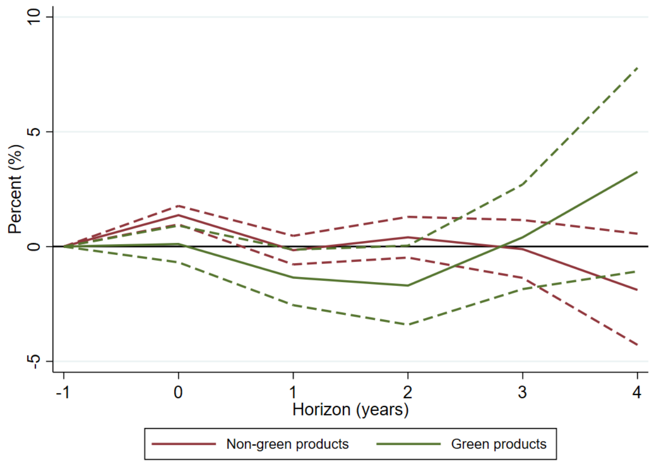
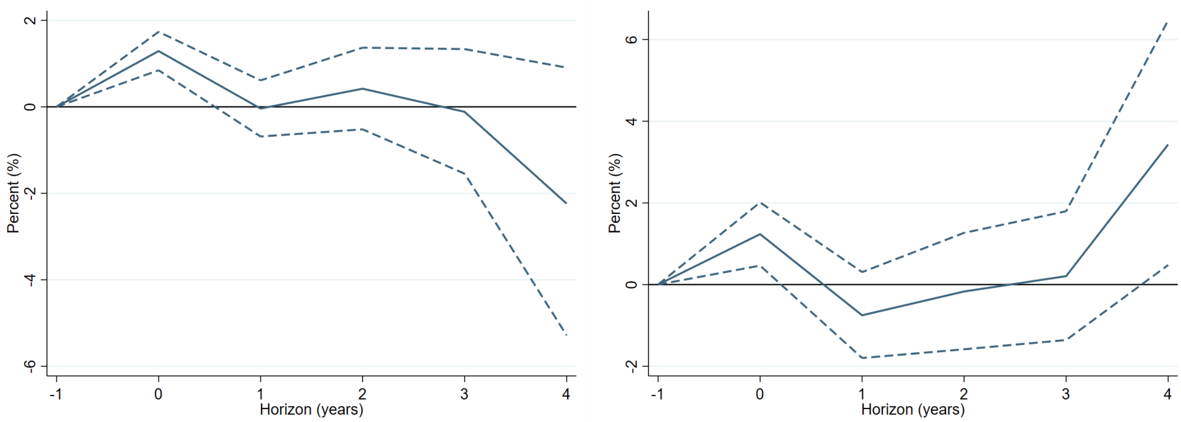


Figure B.28: Effect of IP on $\ln(RCA + 1)$, Green vs. Non-Green Products

Sources: GTA (2022), Juhász et al. (2023), and author's calculations.

Notes: Solid line is the estimated percent change in $RCA + 1$. Dashed lines are 90% confidence intervals. Red lines correspond to non-green products and green lines correspond to green products. Standard errors are clustered at the country-product level. The list of green products is described in Section 2.1.4.



(a) Domestic Subsidies

(b) Export Incentives

Figure B.29: Effect of IP on $\ln(RCA + 1)$, by Policy Instrument

Sources: GTA (2022), Juhász et al. (2023), and author's calculations.

Notes: Solid line is the estimated percent change in $RCA+1$ for domestic subsidies (Panel (a)) and export incentives (Panel (b)). Dashed lines are 90% confidence intervals. Standard errors are clustered at the country-product level.

F.6 Excluding Covid-19 Period

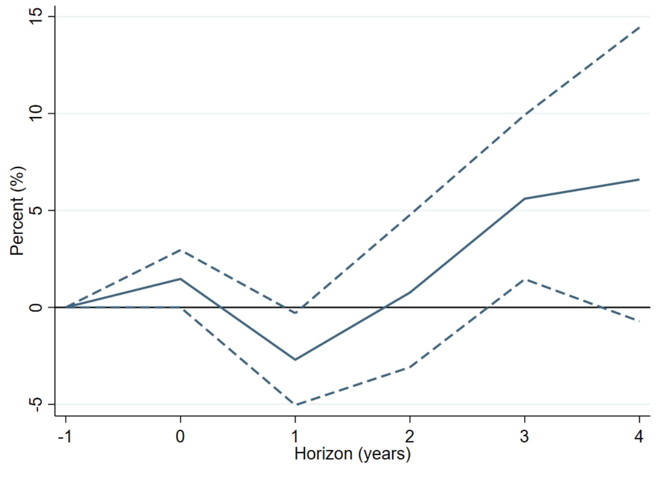


Figure B.30: Effect of IP on $\ln(RCA + 10^{-3})$, All Products, Excluding Covid-19 Period

Sources: GTA (2022), Juhász et al. (2023), and author's calculations.

Notes: The clean sample excludes units treated in 2020. Solid line is the estimated percent change in $RCA + 10^{-3}$. Dashed lines are 90% confidence intervals. Standard errors are clustered at the country-product level.

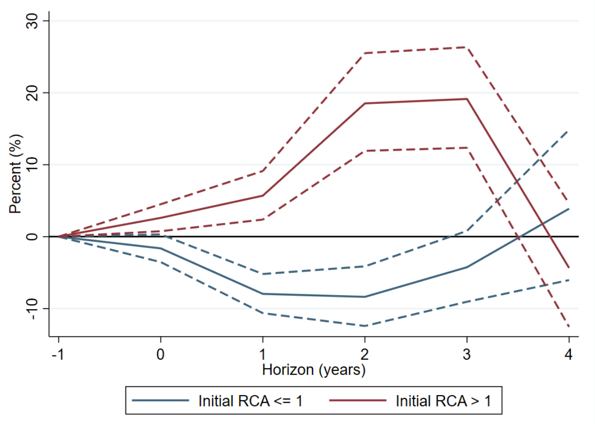


Figure B.31: Effect of IP on $\ln(RCA + 10^{-3})$, by Initial RCA, Excluding Covid-19 Period

Sources: GTA (2022), Juhász et al. (2023), and author's calculations.

Notes: The clean sample excludes units treated in 2020. Solid line is the estimated percent change in $RCA + 10^{-3}$. Dashed lines are 90% confidence intervals. Red lines correspond to products with $RCA_{c,p,t-1} > 1$ (initially competitive) and blue lines correspond to products with $RCA_{c,p,t-1} \leq 1$ (initially uncompetitive). Standard errors are clustered at the country-product level.

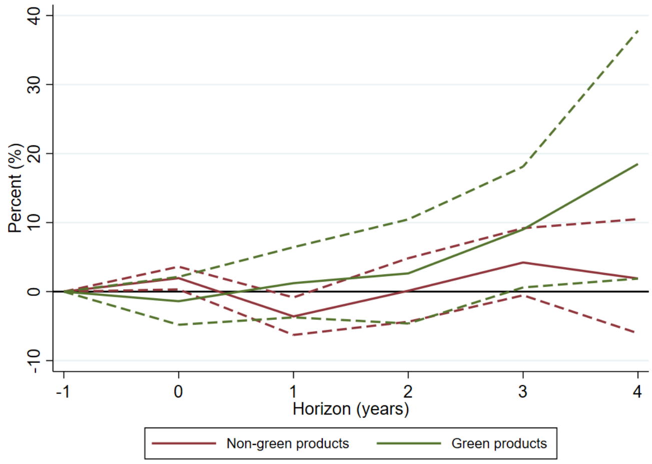
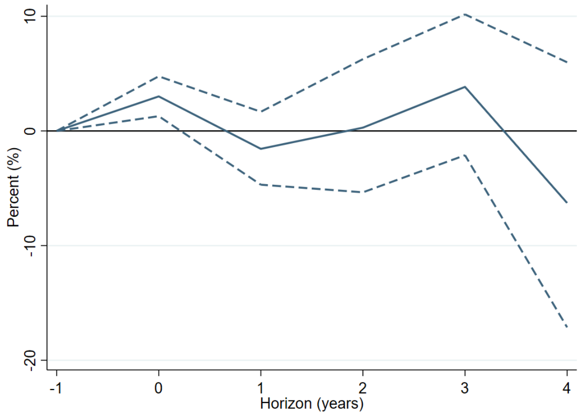


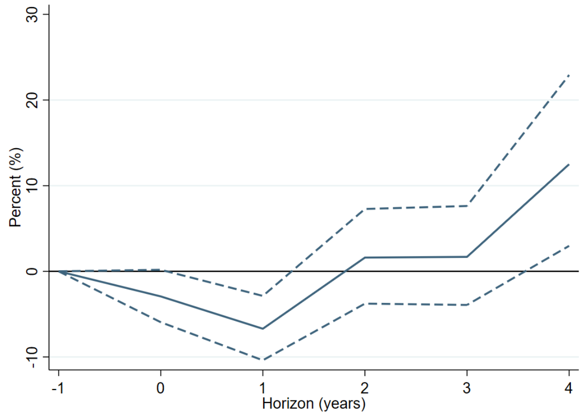
Figure B.32: Effect of IP on $\ln(RCA + 10^{-3})$, Green vs. Non-Green Products, Excluding Covid-19 Period

Sources: GTA (2022), Juhász et al. (2023), and author's calculations.

Notes: The clean sample excludes units treated in 2020. Solid line is the estimated percent change in $RCA + 10^{-3}$. Dashed lines are 90% confidence intervals. Red lines correspond to non-green products and green lines correspond to green products. Standard errors are clustered at the country-product level. The list of green products is described in Section 2.1.4.



(a) Domestic Subsidies



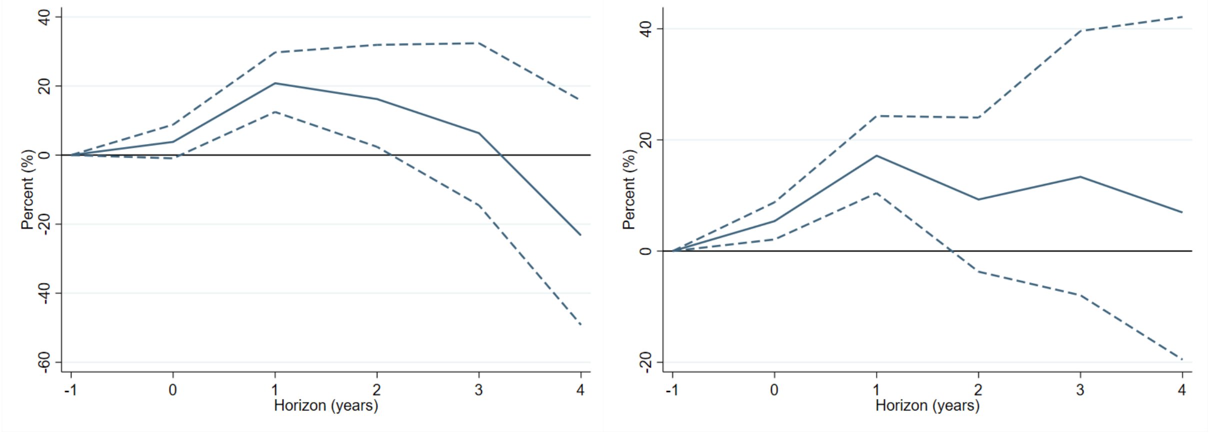
(b) Export Incentives

Figure B.33: Effect of IP on $\ln(RCA + 10^{-3})$, by Policy Instrument, Excluding Covid-19 Period

Sources: GTA (2022), Juhász et al. (2023), and author's calculations.

Notes: The clean sample excludes units treated in 2020. Solid line is the estimated percent change in $RCA + 10^{-3}$ for domestic subsidies (Panel (a)) and export incentives (Panel (b)). Dashed lines are 90% confidence intervals. Standard errors are clustered at the country-product level.

F.7 All Subsidies in GTA



(a) RCA

(b) RCA adjusting for Imports

Figure B.34: Effect of All GTA Subsidies on RCA

Sources: GTA (2022) and author's calculations.

Notes: The clean sample excludes units treated in 2020. Solid line is the estimated percent change in $RCA + 10^{-3}$ for *all* domestic subsidies (Panel (a)) and a similar analysis but adjusting RCA for imports (Panel (b)). Dashed lines are 90% confidence intervals. Standard errors are clustered at the country-product level.