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A New Wave of Industrial Policy in Asia-Pacific:

Could Resurgence lead to Structural Transformation?

Prepared by Paula Arias, Vanya Georgieva, Rahul Giri, Maria Gonzalez-Miranda, Ashique Habib, Anne-Charlotte Paret, Tatjana Schulze, Arthur Xie, Weining Xin, Yichen Xu, Dilan Yang

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ABSTRACT: This paper provides a first comprehensive assessment of industrial policy (IP) across Asia-Pacific and its potential to enable structural transformation. Building an IP database for 2009–2024, paired with a rich dataset, the paper documents a large wave of IP interventions. Subsidies dominate, followed by import-limiting measures. Novel applications of machine-learning and clustering approaches to assess IP targeting suggest that, ex-ante, about three-quarters of IP could align with structural transformation strategies, including relatively safe (“safe-bets”) and risky (“moonshots”) strategies promoting technological upgrading and diversification, and strategies to alleviate market-frictions and distortions in key sectoral nodes. IP’s ex-post linkages to trade, competitiveness, and domestic firms’ indicators are small and short-lived; sustained gains that could lead into structural transformation appear only sporadically. Our findings underscore the need for a more parsimonious and carefully-designed IP—anchored to targeting clear market-failure rationales and complemented by ambitious structural reforms—potentially enhancing effectiveness and lowering net costs.

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WORKING PAPERS

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Glossary

AE .... Advanced Economies

A-P .... Asia-Pacific Region

BACI .... Base pour l'Analyse du Commerce International

EM .... Emerging Markets

GTA .... Global Trade Alert

ICIO .... OECD Inter-Country Input–Output Database

IP .... Industrial Policies

LPDiD .... Difference in Difference Local Projection Model

ML .... Machine Learning

NACE .... Nomenclature of Economic Activities

NIPO .... New Industrial Policy Observatory

OECD .... Organization for Economic Co-operation and Development

ORBIS .... Comprehensive global database by Bureau van Dijk (now part of Moody's)

PCI .... Haussman-Hidalgo Product Complexity Index

RCA .... Revealed Comparative Advantage

RoW .... Rest of the World

TFPR .... Total Factor Productivity – Revenue

Executive Summary

Industrial policy (IP) across Asia Pacific has expanded markedly over the past 15 years. This mirrors a global resurgence in IP driven by many factors, including geoeconomic fragmentation, demographic pressures, climate transition, national security goals, technological change, and shifting global value chains. This paper provides the first comprehensive, data driven assessment of the IP wave in the region for 2009—its scale, underlying strategic intent, and measurable economic impacts. It draws from a newly constructed database of IP interventions over 2009–2024, combined with rich product characteristics, trade, production network, and firm level data.

IP in Asia Pacific mostly industrial and manufacturing sectors; subsidies dominate interventions followed by import limiting measures. Explicit efforts to promote exports are less apparent, in line with global trends. Economies in the region tend to use multiple instruments simultaneously on the same products, doing so more frequently than the rest of the world. These overlaps may reflect more intricate design strategies, though they could also reflect conflicting objectives and add to opacity.

The use of IP is consistent with the broad goal of promoting structural transformation:

- ***Machine-learning tools suggest that indicators linked to structural transformation objectives tend to drive IP targeting***. Amongst the set of indicators considered, a product's closeness to an economy's export basket is the most important predictor for IP interventions in the region. This is followed by the level of a specific sector's input/output centrality in the domestic production network, and its degree of "upstreamness" (or implicit value added). The relationship between the indicators and the likelihood of IP is non-linear.

- ***A clustering analysis suggests about three-quarters of IP deployed in the region could align with strategies to promote structural transformation***. These include:

    - ***The targeting of Safe-Bets***: a cluster of IP targets more sophisticated and often strategic products which are close to the economy's current capabilities. Such interventions would be consistent with efforts to technologically upgrade and diversify, by taking lower-risk "bets" where public support builds on existing strengths.

    - ***Targeting Moonshots***: a cluster of IP targets sophisticated and often strategic products which are far from the economy's existing comparative advantages. These could align with high-risk, high-reward attempts to leapfrog into new technologies and/or product domains.

    - ***Targeting sectors with Market-Failures / Network-Frictions***: a cluster of IP targets sectors that are central nodes in domestic production networks or that exhibit signs of frictions or market distortions (such as high markups). These could align with the notion of addressing bottlenecks, improving connectivity, and generating broader positive spillovers and cascading effects.

IP does not appear to be systematically associated with ex-post gains, with evidence suggesting only limited and short-lived effects on trade indicators and competitiveness linked to IP deployment. In other words, even if a large share of IP interventions appeared to be aligned ex-ante with structural transformation strategies, the empirical evidence indicates that IP in Asia-Pacific is rarely associated with systematic or durable economic gains ex-post.

- ***The most used IP tools in the region are not associated with systemic effects***. Domestic subsidies appear to be linked to temporary export boosts in the region, especially in EMs, but effects generally dissipate after three years. Export incentives are linked to increased exports in both Asia-Pacific and the RoW, but only temporarily. Domestic subsidies are associated with a reduction in imports (i.e., they appear to achieve short-run import substitution) for some Asia-Pacific economies, even as they are documented to raise imports elsewhere. Import-restrictions (e.g., quotas, bans) are not linked to meaningful import reductions, showing very short-lived import substitution effects, if any.[2] Importantly, analysis also shows that higher levels of government effectiveness might be associated to stronger IP's capacity to boost exports, especially for tools such as domestic subsidies.

- ***IP seems associated with temporary competitiveness boosts in already-competitive products, yet appears generally ineffective otherwise***. With competitiveness measured via revealed comparative advantage (RCA), both subsidies and export incentives are only linked to improvements in RCA for products in which the economy was already competitive. These gains, however, are not durable and do not extend to non-competitive products—i.e., the very products where structural transformation would require the greatest lift.

An in-depth analysis of the potential effects of IP on firm-level data also suggests mixed evidence. Large structural transformation shifts through major sectors (i.e., agriculture, industry and services) may take decades to coalesce, and hence may not be easily observable in the 15-year window covered by the data. Recognizing this limitation, the firm level analysis based on ORBIS data (for a smaller sample of economies in the region satisfying minimal data availability) seek out signs of IP possibly being linked to shifting productivity and/or production inputs (labor and capital) in targeted sectors/products.

- ***The firm-level data starkly suggests that IP interventions are systematically associated with lower-productivity industries in most Asia-Pacific economies.*** Furthermore, following an IP intervention, median firm productivity tends to decline rather than improve. Decomposing changes in aggregate productivity shows no consistent evidence of technological upgrading among targeted firms; improvements, when observed, are often driven more by reallocation dynamics or by changes among non-targeted firms.

- ***No IP tool shows a systematic durable impact signaling potential structural transformation at firm level.*** Across the region, domestic subsidies generate gains—albeit temporary—in capital and labor in AEs, but show no impact in EM firms. Import-restricting measures are associated to reductions in TFP in EMs, with lasting negative/adverse effects. Export incentives tend to reduce productivity in targeted firms. There is, however, one nuanced positive result: IP targeted at relatively higher-complexity products entailing possible "*safe-bets*" and *"moonshots*" is linked to a clear increase in *capital* investment in targeted sectors. Even so, within our estimation horizon, this does not translate into measurable productivity and/or employment gains.

In sum, the greater use of IP in Asia-Pacific appears unlikely to be delivering on beneficial structural transformation; whether it delivers on other national objectives is beyond the scope of this paper. While most IP interventions appear aligned with strategies searching for structural transformation, measurable ex-post associations to deployed IP are often weak, temporary, or even negative, especially in EMs. At the same time, as argued in many other studies, IP could entail important fiscal costs, generate misallocation, and lead to unintended adverse consequences. This highlights the need for much more parsimonious, better-designed IP, grounded in clearly identified market failures and supported by robust cost-benefit analysis. Importantly, some results indicating more durable positive effects in advanced economies hint at the potential benefits of relatively strong institutional frameworks and carefully designed policy architectures. This is consistent with other findings in the literature, suggesting that complementary and ambitious horizontal structural reforms may not only deliver broad, durable productivity gains on their own, but also enhance the effectiveness of any well-targeted IP (Baquie and others, 2025).

[2] In general, the paper documents several differences in effects in Asia-Pacific and ROW which may point to region-specific design features, a hypothesis that could be explored in future work.

I. Introduction

Over the last decade, Industrial Policy (IP) has increasingly been used in Asia-Pacific (A-P). At first glance, the rising number of IP interventions in the region appears to go hand-in-hand with a well-documented worldwide surge (Juhász and Lane, 2023, Evenett and others, 2023 and 2025, IMF 2024b, Baquie and others, 2025), driven, at least in part, by a host of globally shared challenges. Geoeconomic fragmentation has brought about rising uncertainties— along with shifts in trade, investment and financial integration patterns. At the same time, longer-term structural changes from demographic pressures, climate change and the energy transition, jointly with the drive for more national security, rapidly evolving automation and digitalization technologies, pose opportunities but also significant risks—prompting action by policymakers.

This paper investigates whether the IP wave in Asia-Pacific has been aimed at driving structural transformation that can support growth and development, and assesses the extent to which it has succeeded in doing so. Relying on a newly built dataset of IP interventions covering 2009-2024, extracted from policy announcements recorded in the Global Trade Alert (GTA) database, this paper is, to our knowledge, the first attempt to provide a comprehensive and systematic assessment of the recent IP surge with a broad Asia-Pacific coverage—documenting its features, and exploring its potential strategies and effects. It first presents the evolution of IP since 2009, its composition and characteristics along various dimensions. It then deploys novel approaches to investigate the relationship to strategies which may promote structural transformation. First, it identifies the importance of related indicators for predicting IP targeting via machine learning models; second, a clustering analysis allows to go beyond stated IP objectives to recover potential strategy types embedded in the pattern of interventions. Finally, the paper evaluates the ex-post associations of IP with external and domestic dimensions, to gauge whether IP could facilitate structural transformation.

Beyond the explicit focus on Asia-Pacific, this paper contributes to the existing IP literature in several ways, bringing new insights. We adopt the IMF definition according to which IP corresponds to *targeted government interventions aimed at supporting specific domestic firms, industries, or narrowly defined economic activities to achieve certain national (economic or non- economic) objectives* (see reference paper on how to address IP in IMF Surveillance work, IMF, 2024a). While this definition of IP is well accepted, it is also quite broad; so, its operationalization requires judgement. Various recent and very important studies precede our work and have developed IP databases extracted from the GTA via text-mining techniques; these are generally based on various filters to further narrow the type of measures that may qualify as IP (i.e., Juhász and Lane, 2023; and the New Industrial Policy Observatory, NIPO, by Evenett and others, 2023 and 2025). As discussed in section III on data, while we follow the lead by these previous studies, we operationalize our definition with fewer ex-ante filters. This provides us not only with a complementary database with broader regional coverage, but also with a broader inclusion of vertical policies meeting our definition of IP, which may have structural transformation implications.

Our analysis confirms the large scale of IP implemented in Asia-Pacific and identifies important patterns. The use of IP has been on the rise in the region since 2009—the start of our sample period. Emerging market economies (EMs) have continued to expand IP use over the past decade and have been joined by a marked increase of IP in advanced economies (AEs). In both Asia-Pacific and the globe, IP interventions are mostly dominated by subsidies, followed by import-limiting measures. Asia-Pacific stands out for applying a layering approach—that is, imposing multiple types of IP tools on the same products or sectors more often than the rest of the world (RoW).

This paper also develops a new approach to help understand the underlying intent of IP in the region—and whether it is linked to structural transformation objectives. The resurgence of IP at a global level suggests a broadening of underlying motives—likely interrelated to the complex and likely interrelated structural challenges facing the global economy: the need to response to geo-economic fragmentation and national security pressures, demographic pressures, and evolving climate and technological trends. Efforts to better understand the motivations of the new surge of IP worldwide were first tackled through the innovative New Industrial Policy Observatory (NIPO) database (Evenett and others, 2023 and 2025), which provides with an insightful text-based extraction of motivations on IP interventions based on explicit statements by policymakers recorded in the GTA including on national security, geopolitical concerns, supply resilience outside agriculture/food, strategic sector development, and climate change response.[3] The NIPO provides a key lens about the growing importance of all of these motives in newly deployed IP—including in Asia-Pacific, while unveiling that a non-trivial share (around 1/3) of IP interventions lack an explicitly stated motivation; moreover, analytical work based on the NIPO database also documents the presence of retaliatory dynamics around IP. Overall, the information provided by the NIPO suggests that objectives tend to be high level, can be opaque, not always be explicitly (or fully) stated, and overlap (i.e., a single IP intervention may have more than one objective). Importantly, IP may have structural transformation implications across explicitly identified goals (such as those in NIPO); at the same time, achieving the policymakers' goals (even those that are non-economic in nature) may necessitate actual economic structural transformation to be achieved. Hence, our analysis presents a complementary lens to that provided by existing literature, as it assesses the actual ex-ante alignment of deployed IP interventions with strategies for promoting structural transformation, regardless of whether this was the motive explicitly stated by the policymaker. We do this by looking at the relationship between IP interventions with many relevant indicators that can help disentangle the actual implicit strategy of the deployed policy based on its targeting.

Evidence suggests that an important share of IP targeting in the region aligns with ex-ante strategies for promoting structural transformation. First, looking at predictors of IP related to such strategies, we find the closer a product is to an economy's own export basket, the higher the likelihood of that product being targeted by IP. That said, nonlinearities are also uncovered: for example, some products that are distant from an economy's export basket, are more likely to be targeted by IP as the distance grows; this suggests that other important factors may be considered when deciding whether and where IP is deployed—following a range of factors and strategic considerations. Second, we rely on a clustering methodology to investigate whether IP can be sorted into alignment with various possible strategies to achieve structural transformation. The results unveil the presence of four broad clusters; of these, three clusters—accounting for about three quarters of observations in the exercise—align with potential structural transformation strategies. These strategies range from enhancing technology upgrading through leapfrogging (i.e., targeting *moonshots*); gradually fostering products/sectors of relatively higher complexity, yet sufficiently close to the economy's existing export basket to provide a low-risk approach (i.e., targeting *safe-bets*); or developing specific sectors with increased connectivity in the production network to generate positive economic spillovers and/or sectors where available metrics indicate the possible presence of market imperfections (i.e., targeting products and sectors facing *market failures and frictions*, and/or *sectors of high interconnectedness*).

While this ex-ante assessment of IP deployed in Asia-Pacific over the last 15 years suggests potential for structural transformation, a second important question is whether this effort has had any actual systematic impact. To this end, the paper seeks to identify indication of systematic and durable effects following IP deployment in the region. This exercise faces several important challenges. Some are linked to the insufficient granularity in macro-level data that may be paired with the product- and tool-specific IP database developed for this analysis. Another important caveat is that significant shifts in an economy's structure (for example, the reallocation of resources from agriculture to industry, and later to services) may take decades to coalesce. Therefore, the relatively short data span in the available IP database used in this paper (nearing 15 years), only allows for a modest approach to answering this question. The analysis proceeds along two complementary

[3] The NIPO groupings have been polished through various stages of research and improvements of the database. The H-NIPO database (developed in Evenett and others 2025) groups interventions around four broadly identified explicit motives: (i) national security and/or geopolitical concerns; (ii) resilience/security of supply chains (non-food), (iii) domestic competitiveness in strategic sectors, and (iv) climate change mitigation and other environmental objectives. More recently, the latest NIPO 2.0 Methodological Note (https://globaltradealert.org/reports/new-industrial-policy-observatory-nipo), published in the GTA database, further polishes the motives into: (i) National security, (ii) Resilience/security of supply (non-food), (iii) Strategic competitiveness, (iv) Geopolitical concern, (v) Climate change mitigation, and (vi) Digital transformation (in progress).

dimensions to evaluate whether IP interventions are associated with broad-based, systematic and durable effects pointing to structural transformation. First, it focuses on external outcomes, relying on trade-based data: it examines whether IP measures in Asia-Pacific are associated with (statistically) significant and durable changes in trade flows and/or revealed comparative advantage (RCA) at the product level (following Baquie and others, 2025, Huang and others, 2025, and IMF 2025). Second, the paper gauges the domestic effects of IP based on firm-level data from the ORBIS database (with a set up building from that in Baquie and others, 2025, and Machado Parente and others, 2025). This is based on the premise that, to generate structural transformation, IP interventions should foster shifts in productivity and/or factors of production (labor and capital) into targeted products/sectors. In other words, it is expected that effective and well-focused IP should trigger a domestic reallocation of resources observable at more granular level within the industrial sector.

The paper gauges empirical findings against a few broad considerations of what might constitute success. First, to find robust signals of potentially durable economic shifts that may be linked to IP, outcomes should significantly improve for targeted products or firms compared to *untargeted* counterparts. Second, to trigger transformation, improvement must be durable. Providing targeted support to an industry may raise its output; yet, for that increase to qualify as a success at promoting structural transformation, the near-term improvement should unlock a persistent improvement— indicating, for instance, that firms in the industry have caught up with new technologies, and/or that some hurdle or market failure has been overcome. The study of both parts are assessed through a difference-in-difference local projection model (LPDiD), which allows to identify control groups and study differential outcomes in the near- to medium-term. Third, the channel and magnitude of impact may vary by economic characteristics, which are explored through various broad data cuts.

Results provide mixed evidence of the effectiveness of IP in Asia-Pacific, with mostly transitory effects on trade and competitiveness stemming from some IP tools. In particular, domestic subsidies and export incentives deployed in the region are associated with higher exports, but the effect is only temporary. In contrast, domestic subsidies and import-limiting measures are not associated with any significant import substitution effect in Asia-Pacific.[4] These results also reflect the large degree of heterogeneity across economies, with a few cases (mainly the AEs in Asia-Pacific, for some tools) yielding more lasting effects. Specifically, the short-term boost observed in exports is mainly led by East Asian AEs; domestic subsidies on imports are also associated with effective (yet temporary) import-substitution in the region's AEs. Analysis also shows that higher levels of government effectiveness might be associated with stronger IP's capacity to boost exports, especially for tools such as domestic subsidies. This result is consistent with that reported in Baquie and others (2025), suggesting that stronger institutional frameworks appear to be associated with higher IP effectiveness. On competitiveness, domestic subsidies and export incentives are followed by higher competitiveness only when products are already competitive, and the lift in competitiveness is often temporary, consistent with results in the literature for a broader global sample.[5] Importantly, our results confirm those by Baquie and others (2025), suggesting that economies with stronger institutional settings (and government effectiveness) tend to observe a more pronounced impact on trade indicators in targeted products/sectors following IP deployment, suggesting an important role for structural reform not only in potentially obviating the need for IP, but also in possibly improving its potential performance.

There is also no systematic increase in firm productivity, employment, or capital accumulation in response to IP in targeted sectors/products, with only a handful of cases showing durable effects that may contribute to structural transformation. Domestic subsidies and import measures are associated with some boost to (revenue-based) TFP over the medium term, but these are largely insignificant. Export incentives are followed by lower TFP, with the effect transitorily significant. In the case of employment, domestic subsidies have a negative and significant effect, while the effects of the other two IP tools is not significant. Finally, there is no

[4] This contrasts with results in Rotunno and Ruta (2024), which suggest an inability to trigger import substitution based on domestic subsidies or import-limiting measures for the broader global sample.

[5] Baquie and others (2025) and Huang and others (2025) similarly find that the positive effects of IPs on products' competitiveness are mainly driven by those that are initially competitive, and domestic subsidies are associated with a temporary improvement in trade competitiveness in the short term.

significant effect across policy levers on capital, except for a negative effect on domestic subsidies observed in the medium term.[6] While all pointing to mixed results and a nuanced relationship between IP and firm performance, these results are somewhat different from the existing literature likely due to sample differences—including IP and economy coverage.[7] The mixed results reported in this paper mask substantial heterogeneity across economies and strategies: the East Asian Miracle economies seem to be able to gather growth in some of the targeted products/sectors.[8] There is also some indication that IP strategies targeting more complex and trade-oriented products (e.g., those targeting products/sectors resembling "*moonshots*" or "*safe-bets*"), may be more effective, durably raising production inputs (particularly capital), although they appear ineffective at boosting productivity. More broadly, there is suggestive evidence that IP may, in fact, target firms in less productive industries, and that IP does not lift such lower productivity in targeted industries vis-à-vis non-targeted ones.

Overall, results are consistent with the view that IP should be parsimoniously deployed and accompanied by sound and ambitious structural reforms that improve institutional frameworks. The lack of evidence of significant and systematic signs of structural transformation linked to IP may be important for policymakers to consider when calculating the cost-benefit analysis of IP, even as they perceive gains along other dimensions. A rapid and wide expansion may be particularly at risk of substantial IP design weaknesses, with resulting low (or no) gross gains and potentially high economic costs, including large fiscal costs and unintended consequences including cross-sector and cross-border spillovers. Sound IP should target well-identified market failures, be time-bound and cost-effective, and anchored by strong governance to reduce rent-seeking and resource misallocation (Cherif and others, 2022, IMF 2024a). Keeping horizontal structural reforms in sight is also critical, as they typically bring broader benefits than IP. Moreover, given that structural reforms may help strengthen IP performance (as shown by Baquie and others, 2025), there is a strong case for pursuing an ambitious structural reform agenda that may complement—if not replace—IP to support effective structural transformation.

Several important caveats apply to the analysis in this paper which warrant cautious interpretation of the results for guiding policy action. First, this paper only seeks to identify some of the potential gross benefits of IP deployment for structural transformation, and at the same time abstracts from economic costs. This implies that even positive results must be interpreted cautiously for guiding policy action. In terms of benefits, IP may be delivering on other objectives of policymakers which are beyond the scope of this paper. On costs, recent literature suggests that actual economic costs of IP implementation may be important (Garcia-Macia and Sollaci, 2025), and that carefully considering tradeoffs—including via a comprehensive cost-benefit analysis—is required before and during IP deployment to avoid net burdens. Moreover, targeting other than well-identified market failures can bring about important distortions and broader risks of resource misallocation (IMF 2024b, IMF 2025). Second, the relatively short sample period—covering less than one and a half decades—limits our ability to draw *definitive* conclusions on whether IP leads to structural transformation, which could take several decades to fully materialize. Therefore, the analysis focuses on whether there could be signs for potential structural transformation following IP deployment. The short time dimension, together with relatively small economy coverage compared to a global sample, also results in relatively wide confidence bands, warranting caution in the interpretation of some of the statistically insignificant results. Third, while the empirical analysis seeks to mitigate endogeneity concerns, the complex nature of IP targeting—as found in the analysis—implies that endogeneity cannot be fully addressed. The results on trade, competitiveness, and firm performance should therefore not be interpreted as establishing causal relationships—as also noted in similar studies leveraging similar methods as those used in this paper,

[6] Baquie and others (2025) and Machado Parente and others (2025) found that subsidies discriminating against foreign interests (as those used in this exercise) are linked to short term improvements in productivity and payroll, which fade or turn negative in the medium term. Export incentives are linked to short term declines in firm performance followed by medium term gains.

[7] In particular, Baquie and others (2025), Huang and others (2025), Machado Parente and others (2025) and IMF (2025) relied on the Juhász and Lane IP Database which, while also extracted from the GTA, differs from that in this paper as well as from the NIPO database in coverage by economic jurisdiction, IP measures, and time horizon.

[8] As the scope of this paper is to examine regional and cross-border patterns, we do not undertake deep dives into specific economies. The documented heterogeneities across economies underline the importance of a deeper investigation into individual economy's experiences, supported by more detailed information on IP design and data on targets than available in our datasets.

including Baquie and others (2025), Machado Parente and others (2025), Huang and others (2025), and IMF (2025).

The rest of this paper is organized as follows. Section II provides a brief literature review, clarifying on this paper contributions, section III provides background on the data and methodology; section IV discusses initial stylized facts on IP in Asia-Pacific; section V discusses the implicit ex-ante IP strategies identified in the region; section VI discusses the assessed impact of IP on trade and competitiveness, section VII gauges the effects on firm-level productivity and production factors, and section VIII concludes.

II. A Brief Literature Review and Contributions

Against the backdrop of resurgence of IP, the literature has also been revitalized. Recent data-driven work documents this resurgence and its changing composition across instruments and objectives (Juhász and Lane, 2023; Evenett and others, 2023, 2025; IMF, 2024b; Baquie and others, 2025). In parallel, a large body of earlier literature—spanning classic debates on import substitution and export promotion (Krueger, 1985), lessons from East Asia (Stiglitz, 1996), historical perspectives (Chang, 2002), and modern frameworks on structural transformation and comparative advantage (Hausmann and Klinger, 2006; Hidalgo and others, 2007; Hausmann, Hwang, and Rodrik, 2007; Lin, 2012)—highlights both the promise and the pitfalls of targeted interventions, including risks of misallocation and capture (Baquie and others, 2025; Garcia-Macia, Kothari, and Tao, 2025).

This paper contributes to the literature in three ways.

- ***First, it further advances measurement and scope.*** Although the definition of IP is well-accepted, it is also quite broad, making it difficult to operationalize. Unlike other work relying on GTA text-mining techniques (i.e., Juhász and Lane, 2023; and the New Industrial Policy Observatory, NIPO, by Evenett and others, 2023 and 2025), the mining technique to form the database in this paper relies on a broader definition of IP that does not filter based on stated objectives or motives, and does not seek to extract interventions targeting only pre-selected strategic sectors ascribed to IP. Instead, all vertical policies that affect a specific sector (or product) are counted as IP. The resulting broader set of IP measures in the dataset provides a wider regional coverage that can be more fully studied in the context of the machine learning and clustering exercises (below).

- ***Second, the paper offers novel approaches to infer the implicit strategies underlying IP***. It builds from machine-learning methods to identify non-linear correlates of IP targeting, as well as a k-mean clustering exercise that maps observed interventions into strategy groupings that speak directly to the structural-transformation literature—seeking to identify strategies targeting “*safe bets*” near existing capabilities (Hausmann and Klinger, 2006; Hidalgo and others, 2007), more ambitious “*moonshots*” consistent with mission-oriented perspectives (Mazzucato, 2015, 2018), as well as interventions shaped by production-network considerations (Liu, 2019; Georgieva, 2025a) and market failures (Stiglitz (1994, 2000, 2012). These analyses offer a new lens into the implicit “IP strategies” deployed in the region.

- ***Third*, *the paper provides a systematic evaluation of the effects of IP in the region***. It examines the effects of IP along both external and domestic dimensions, with a focus on the dynamic effects and heterogeneity across income groups and initial conditions. This allows examining whether IP is associated with durable improvements or whether effects—when present—are largely short-lived. The mixed results reinforce a central message in the recent policy and academic debate: the effects of IP on economic outcomes are uneven and significantly heterogenous depending on economy/sector/product characteristics and the type of tools (Cherif and Hasanov, 2019; Cherif and others, 2022; Reed, 2024; Srinivasan, 2024; IMF, 2025; Baquie and others, 2025; Huang and others, 2025; Machado-Parente and others, 2025; Yang and Chattha, 2026).

III. Data and Methodology

The IP Dataset

The IP database used in this paper is built by extracting IP interventions from raw data on policy announcements published by the Global Trade Alert (GTA).[9] The latter compiles policy announcements,[10] providing structured information such as implementing jurisdiction, announcement date, type of intervention, and affected product or sector. It tracks over 60 types of government interventions, many of which have been associated with IP over time (Evenett and others, 2024 and 2025).

This paper adopts a broad definition of IP used for IMF surveillance work. IP is defined as *targeted government interventions aimed at supporting specific domestic firms, industries, or narrowly defined economic activities to achieve certain national (economic or non- economic) objectives (IMF 2024a*). We operationalize this as all vertical policies that target at least one product or sector. While the definition of IP is well accepted, it is also quite broad; so, its operationalization requires judgement. As in this paper, various recent studies also utilize IP databases extracted from the GTA via text-mining techniques (i.e., Juhász and Lane, 2023; and the New Industrial Policy Observatory, NIPO, by Evenett and others, 2023 and 2025). While similar, the approach followed in this paper uses *fewer* ex-ante filters to identify IP: in particular, it does not apply filters based on stated objectives or explicit motives, nor does it extract interventions targeting only a range of pre-selected strategic sectors ascribed as IP. Instead, closer to our definition, all vertical policies directed at specific sectors (or products) are considered IP.[11] In a context where identifying IP clearly and comprehensively remains an ongoing effort for the literature, we see our broader operationalization of IP's definition as complementary to the valuable insights in the above-mentioned databases and suitable to the objectives of this paper. It yields a dataset that provides greater coverage in Asia-Pacific. In addition, by not screening on explicit motives, we attempt to capture vertical sector/firm/industry-specific policies in the region which may necessitate structural transformation to achieve its (stated or implicit) motive, regardless of whether this is of a political or economic nature. We also consider interventions in sectors excluded from other databases (e.g., NIPO) such as agriculture, which continues to be targeted for sectoral diversification and upgrading in emerging markets and developing economies (or as part of a natural security/defense effort) in the region and globally. We note that alongside the benefits of a looser operational definition, we also run the risk of higher potential false positives. We use our broader dataset to investigate the presence of potential *implicit* IP strategies to promote structural transformation.

Based on GTA information, and similar to the reference papers in the field (Evenett and others, 2023 and 2025, Juhász and others, 2025), the data differentiates between IP interventions that are discriminatory against foreign commercial interests (protective policies) and those considered liberalizing, on a non-discriminatory basis. Work in this paper focuses on the former (since occurrences of the latter are marginal), using a similar approach to that in Evenett and others, 2023 and 2025, Ruta and others, 2024, Baquie and others, 2025, among other studies. Both national and supranational policies are considered, also in line with most references papers. The panel dataset is created based on the policy inception (not announcement) and removal dates of each IP intervention, to assess whether an intervention is in place in any given year. This allows to exclude the policies that were announced but ended up not being implemented. Table 1 below summarizes the assumptions supporting our analysis, and compares them with those made in key databases.

[9] GTA is an initiative launched at University of St. Gallen, housed at the St. Gallen Endowment for Prosperity through Trade.

[10] There is some scope for measurement error in comparisons across economies, arising from potential differences in reporting principles and implementation practices across economies. For example, it includes subnational policies in at least some cases, including provincial and local measures, but coverage may not be uniformly exhaustive across all jurisdictions.

[11] This economic definition of IP, based on identifying preferential policy support for some sectors or firms, may differ from legal interpretations (e.g., based on WTO frameworks).

The database in this paper shares important similarities with other databases, particularly with NIPO. Like the database developed by Juhász, Lane and others (2025) (the "Juhász/Lane" database), and the New Industrial Policy Observatory (the "NIPO" database), our IP database provides a count of the IP measures categorized by economy/jurisdiction, sector, and economic tool (Technical Annex I). It covers a total of 196 jurisdictions, including 31 from Asia-Pacific, 330 sectors, 66 individual policy tools grouped in a total of 29 broad categories based on the GTA handbook MAST classification, including both tariffs and non-tariff measures, as well as subsidies. It spans from 2009 to 2024.[12] This allows for a relatively long-term view, with observations defined by the implementing economy, intervention ID and targeted product, at the HS6-digit level; a policy may target multiple sectors/products.[13]

Table 1. Comparison with IP Datasets in the Literature

Dimension	**Juhász and others (2025)** **Measuring Industrial Policy: A Text Based Approach**	**Evenett and others (2025)** **Industrial Policy Since the GFC (H-NIPO)**	**This paper**
Definition (Conceptual)	IP defined as "intentional government action aimed at altering the composition of a domestic economy to achieve a public goal".	IP defined as "targeted government intervention supporting specific firms, sectors or activities to achieve economic or non-economic objectives." Aligned with IMF surveillance definition.	IP defined as "targeted government intervention supporting specific firms, sectors or activities to achieve economic or non-economic objectives." Aligned with IMF surveillance definition.
Definition (Operative)	Identification based on stated or implicit intent in policy text.	Identification based on motive and product/sector characteristic filters. Motive filter: Classify as IP if motive—identified using Large Language Models (LLM) for 2009-2022 and human labels for 2023—meets one or more of the pre-identified motives: (i) national security/geopolitical concerns, (ii) supply-chain resilience (non-food), (iii) strategic competitiveness, or (iv) climate mitigation. For interventions not satisfying motive filter, also include if product or sector is deemed strategic (one or more of low-carbon technology, dual-use products, advance technology products, critical minerals, medical products, chemicals, critical raw-materials, industrial raw materials, IT/digital services.	Broad sector targeting definition; vertical policies targeting at least one sector or product. No ex-ante motive and/or strategic sector filters.
Type of GTA intervention included	Both restrictive and liberalizing interventions included. Policies may also discriminate against foreign commercial interests. IP classification	Both discriminatory and liberalizing measures included, but analytical focus is primarily on	Both discriminatory and liberalizing measures included, but analytical focus is primarily on

[12] Treatment of special cases in observations (e.g., the allocation of joint policy interventions attributable at economy groups, or of products/sectors in the GTA database available only at a level other than HS6) follow that used to develop the NIPO database.

[13] The GTA is a multilingual project, using an international network of policy experts and aims for comprehensive and comparable international coverage, which helps make the exercise comparable across jurisdictions. This said, there is some risk of possible information loss for non-English speaking jurisdictions.

Dimension	Juhász and others (2025) Measuring Industrial Policy: A Text Based Approach	Evenett and others (2025) Industrial Policy Since the GFC (H-NIPO)	This paper
	determined on policy intent, regardless of policy direction.	trade-distortive (discriminatory) measures.	trade-distortive (discriminatory) measures.
Policy implementation level and jurisdiction coverage	National-level policies only (explicitly excludes subnational); supranational policies excluded. Implicitly global coverage, with 188 jurisdictions included	National, subnational and supranational policies included. (EU-level measures counted once; member-state measures separately). 75 jurisdictions accounting for ~94 percent of global GDP tracked; others excluded.	National and supra-national policies only. Subnational policies are excluded. [14] Supra-national policies are recorded separately for each economy applying the intervention at a product/sector level (e.g., an EU-level policy that results in 5 member economies each targeting a product is recorded as 5 observations, similar to H-NIPO). Implicit global coverage, with 196 (including 31 A-P jurisdictions included.
Policies included	Policies must meet IP inclusion criteria (intent). Firm-level policies included but excluded in robustness check.	Policies must meet IP inclusion criteria (motive and/or strategic sector). Firm-level policies included.	Policies targeting sectors/products (HS6). Firm-level policies excluded.
Start date considered	Announcement date. Implementation not required for classification.	Announcement, implementation and removal dates recorded. Inclusion based on announced or implemented measures.	Implementation date (policy inception). Policies considered active between implementation and removal dates.
Product/Sector level	HS 6-digit codes when available.	HS 6-digit and CPC sector codes at the 3-digit level where available.	Follows Evenett et al. (2025)
Sector/product coverage	No sector/product exclusions ex-ante. Included HS6 products if linked to observed policies.	Predefined HS6 coverage for strategic sectors (advanced tech, climate tech, dual-use, critical minerals, etc.), plus additional HS6 codes where policies meet motive criteria.	As in Juhász et al. (2025) coverage is based on observed policies.

The count measures have well-known caveats, which call for caution on use and interpretation. A key challenge is that they do not incorporate any information on the scope or intensity of each measure; the use of “count” data—which does not inform on the actual intensity of the measures—may generate some bias. In the regression analysis in the following sections, we rely on dummies indicating whether there is at least one intervention targeting the sector or product as opposed to the total count of such interventions, as the count may present a false sense of size or significance. This does not fully resolve the issue, as the approach may still assign

[14] Given that the inclusion of subnational policies in the GTA may be uneven given varying practices across jurisdictions, authors have opted not to include this set of measures in the database. This approach entails tradeoffs—while there are gains from deriving a more comparable set of measures across jurisdictions, there is also a risk that some important information may be omitted—especially given reports that, at least in some Asia-Pacific economies, local authorities serve as the primary agents for implementing IP. A more in-depth study of these cases seems warranted, but this is outside the scope of this paper.

equal weight to interventions of very different scales, which could bias the estimated economic effects of IP.[15] The costs of interventions may also vary substantially with their scope and intensity. The results should therefore be interpreted with caution: they speak to the potential economic effects associated with the presence of IPs, but not to their cost-effectiveness or overall cost-benefit profile.

Complementary Data

Several other databases are paired with IP data to complement the analysis (see Technical Annex II). These include the OECD's Inter-Country Input-Output tables, the product-level Product Complexity Index (Hausmann-Hidalgo, 1995-2021), the granular BACI[16] database for the Analysis of International Trade (1995-2022); and several other databases on sector/product attributes (e.g., sector level markups, degree of upstreamness in the value chain, and the degree of centrality in the production network). To assess the effects of IP on trade and the revealed comparative advantage (RCA), the IP database is merged with the BACI trade data at the product level. To assess the effects of IP on domestic firm-level variables, we merge the IP database with the Bureau van Dijk's ORBIS data at the industry-level; ORBIS provides harmonized firm-level financial statements, firm characteristics and industry identifiers—including the Nomenclature of Economic Activities, (NACE) codes—across millions of firms globally, enabling consistent comparisons across economies. It includes balance sheet and income-statement indicators (sales, employment, fixed assets), permitting the calculation of detailed firm-level metrics, including the estimation of firm-level total factor productivity. Product HS codes at the 6-digit level are mapped to granular 4-digit (NACE) industry codes via concordance tables. The resulting mapping allows to distinguish firm-level outcomes to IP—calculated using ORBIS—not within a 4-digit NACE industry but across industries.

IV. The Landscape of IP in Asia-Pacific

A first in-depth look at the IP data delivers several stylized facts (Figure 1a-b).[17]

- ***First, there is a recent IP surge in Asia-Pacific—alongside a broader global surge—adding to a long-standing focus of IP in the region.*** EMs have been deploying IP at least since 2009, and have accelerated implementation in recent years. In contrast, AEs have only recently amplified IP implementation, particularly since the pandemic. This recent surge in Asia-Pacific occurred alongside a broader global surge driven by both AEs and EMs.

- ***Second, IP has largely targeted industrial products in both Asia-Pacific and the RoW.*** Targeting is heavily focused on industry—with a somewhat higher intensity in the region than elsewhere; the industrial/manufacturing sectors account for around 80 percent of the IP interventions in Asia-Pacific; the share of interventions has been stable over time.

- ***Third, domestic subsidies dominate in the region as the most frequently used tool type.*** Consistent with other studies, the widespread use of domestic subsidies stands out in the IP sample in both Asia-Pacific and the RoW; this is followed by a reliance on import-limiting measures. In the RoW, the use of domestic subsidies

[15] For example, some of the effects captured in the analysis might be biased by the fact that economies whose IP interventions may be relatively larger in size might showcase stronger effect of IP on outcome variables. This is a caveat applicable to all studies on IP using count measures, and arising from the lack of information on IP intensity.

[16] "*Base pour l'Analyse du Commerce International*" (BACI) that translates into "Database for the Analysis of International Trade".

[17] Given the size of China and India, which could potentially dominate and affect the overall regional aggregates and results, the paper presents selected stylized facts and analysis separating these two economies from the rest of the region, where relevant, as a robustness check

intensified in 2020—likely speaking to COVID-era policies, and the nature of major initiatives such as the Inflation Reduction Act (IRA) in the United States. In Asia-Pacific, the use of subsidies has been longstanding since at least 2009; implementation accelerated in 2021 and stabilized thereafter. For the region (excluding China), the use of import-limiting measures was more prevalent before 2020; afterwards, the use of domestic subsidies has become more widespread, becoming the most important single tool, while import-limiting measures remain the second-most common used tool.

- ***Fourth, Asia-Pacific economies tend to layer IP interventions more than the RoW***. The distribution of active tool types applied over products in Asia-Pacific vis-à-vis the RoW shows that economies in the region take a more layered approach, with a higher share of products having multiple tool types applied simultaneously. This tendency has increased over time, with now about 40 percent of products having three or more types of tools implemented at the same time in Asia-Pacific economies. Such layering may, perhaps, reflect an intricate design strategy—yet it could also yield opacity and reduce effectiveness to the extent that multiple tools may work at cross-purposes.

- ***Fifth, while the toolkit is dominated by subsidies, remaining tools seem increasingly inward-looking (import-substituting)***.

  - **Two trade-weighted indices are constructed at the economy level to gauge the direction of trade orientation in the tools**. These interpret subsidies as neutral. The first index scores whether economy interventions tend to have an import-substituting lean, while the second index scores whether there is an export-promoting lean.[18] The intention is to speak to the two high-level strategies the literature has identified: import-substituting IP (such as in Latin American in the 1970s) and export-oriented IP (as in 20th century's Asian Miracles). Maintaining separate indices helps provide granularity to the assessment, recognizing that both strategies may coexist in a single economy at a certain point in time, and be applied simultaneously across different products/sectors, including along the value chain. Results suggest that, in 2022, Asia-Pacific economies had an import-reducing lean, akin to that in the RoW; the import-reducing score has increased in both economy groupings since then. Regarding the export-promoting stance, based on 2022 data, Asia-Pacific has a neutral export-promoting score, while the RoW has a negative one; the scores have declined over time, suggesting that toolkits are becoming increasingly inward-looking globally.[19]

  - **Subsidy orientation is harder to determine.** Subsidy-type measures may plausibly pursue export promotion, import substitution, or both objectives simultaneously. Across most economy groups in the sample— including Asia-Pacific AEs, EMs excluding China, and the RoW— domestic subsidies are predominantly applied to import-competing products and goods without revealed comparative advantage (RCA).

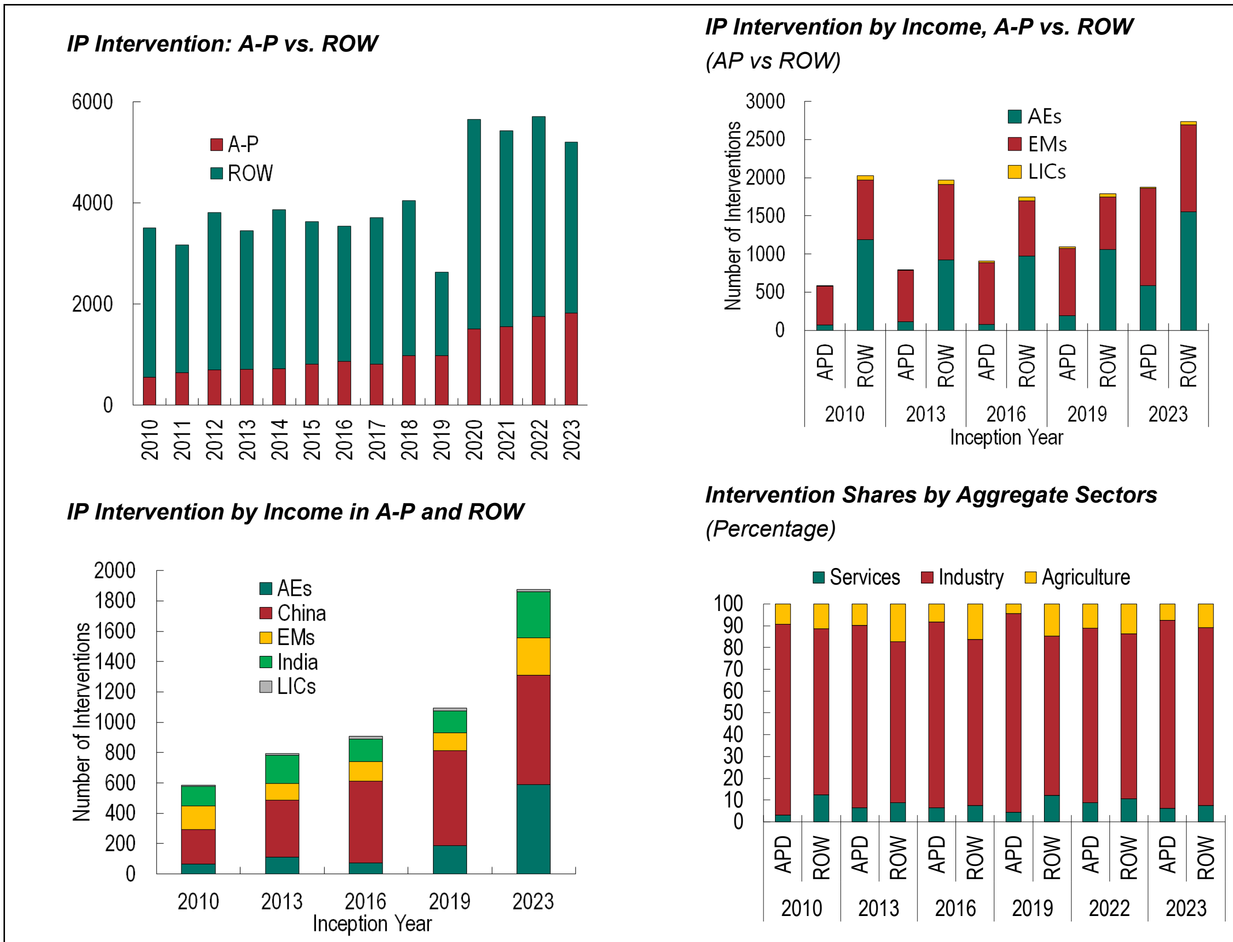
The prevalence of trade-related measures, including those that are import-limiting may be related to a range of issues. One possibility is that they are appealing given their relative simplicity and low explicit fiscal cost: providing subsidies has clear and direct budgetary spending implications, while some trade-related tools may be

[18] For exports, positive index scores are intended to signal export promoting orientation; for imports, positive index scores indicate import reducing orientation. In constructing the export-promoting index, each instrument is coded as promoting (+1), neutral (0), or reducing (-1). For the import-substituting index, instruments are coded as reducing (+1), neutral (0), or promoting (-1). See Annex Table A.2 for the instrument coding. At the economy-year-product level, the overall lean for each index is the sum of the scores across all the active interventions on that product, in the economy, and in the given year. Subsidies explicitly dedicated to foster exports (i.e., export incentives) are coded as export promoting, and as neutral for imports. Economy-level scores are obtained by averaging product level scores, weighted by the relevant trade share; the region-level score is derived through GDP-weighted averaging of economy-level scores.

[19] The indices are based on the IP stock, i.e., the characteristics of the instruments that are active in a given year. This includes policies implemented in the previous years which have not been removed. The fact that import-limiting measures being most/second-most common type of new intervention being implemented each year in the region provides a heavy import-reducing bias for the stock.

perceived as easier to deploy from a fiscal perspective (indeed, some may even be seen as revenue-raising). Some trade measures may also be perceived by policymakers as cheap to administer; this may be more attractive to countries with relatively lower capacities in the wider regional sample.[20] [21] The use of import-limiting measures may also be explained by security and resilience considerations; in some cases, it may be linked to strategies (including with developmental goals) to build complex domestic value chains; these deserve further study that goes beyond the scope of this paper. [22]

Figure 1a. Asia-Pacific IP Landscape



Sources: Global Trade Alert (GTA); BACI; IMF staff calculations

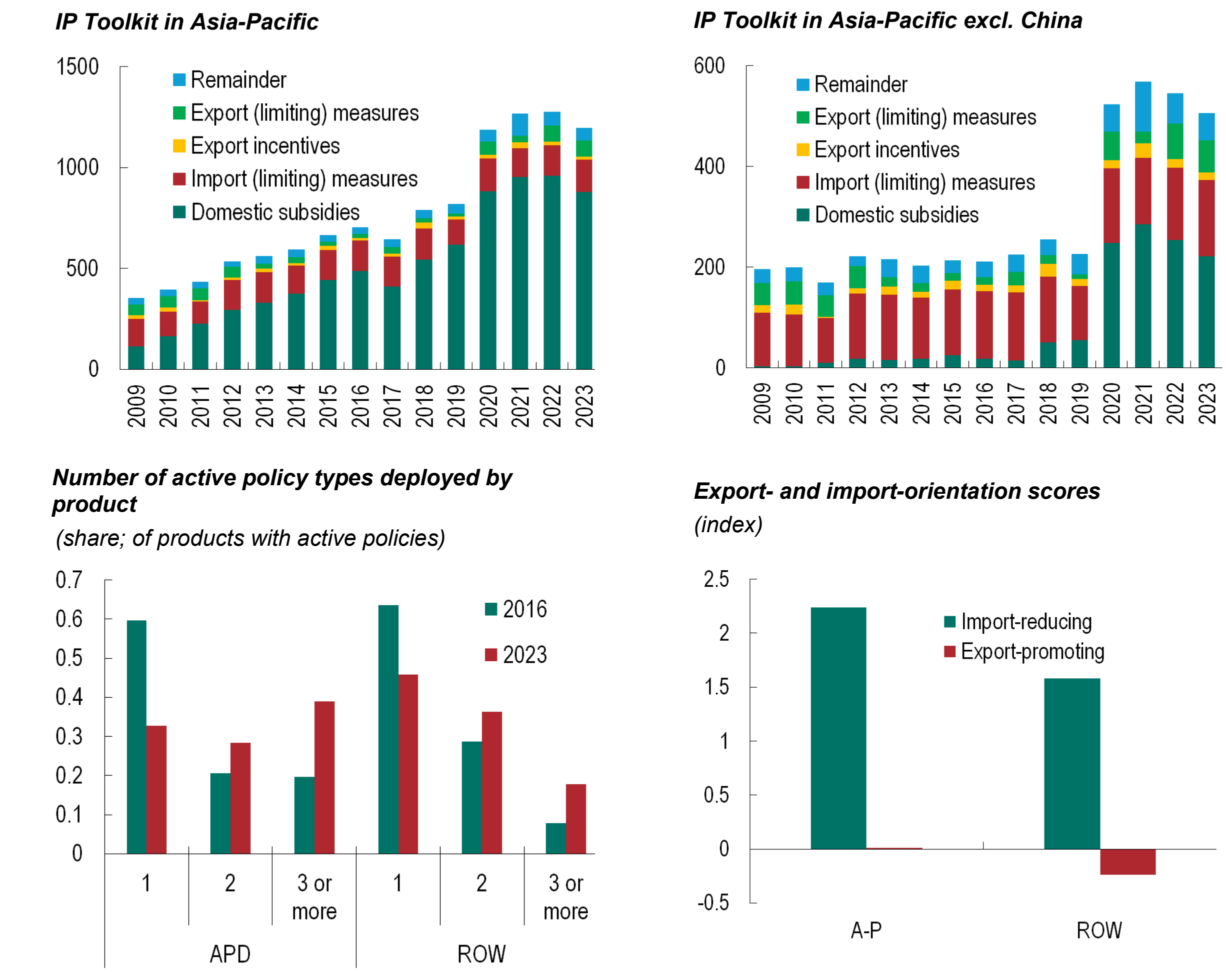
Note: IP interventions reflect the number of sectoral/vertical policies implemented as per their inception date. Does not include subnational level jurisdictions.

[20] For example, a sophisticated subsidy strategy for export promotion requires much more design and careful targeting. Even broader, cross-cutting subsidies may be harder to administer and execute in practice.

[21] Importantly, trade tools may not be the sufficiently precise to target market failures, and a number of them can also entail significant administrative burdens (e.g., a tariff may be simpler to impose than a quota; local content requirements or domestic sale obligations would be increasingly complex). See also Fernandes and Reed (2026) for a discussion on the use of IP tools and how these may depend on the capacity of policymakers.

[22] One well-known example is the Indonesian Downstreaming Strategy, which includes export and import limiting measures to foster the development of domestic value chains around the country's rich set of commodities, including to serve external markets. More recently, import- and export limiting measures have also been deployed to achieve security and resilience objectives—in particular, around food and energy security.

Figure 1b. Asia-Pacific IP Landscape



Sources: Global Trade Alert (GTA); BACI; IMF staff calculations

Note: IP interventions reflect the number of sectoral/vertical policies implemented as per their inception date. Does not include subnational level jurisdictions.

V. IP Determinants and Implicit IP Strategies

An Initial Look at IP Determinants

An initial examination of the relationship between IP in Asia-Pacific with the economic features of the targeted products/sectors unveils several regularities (Figure 2).

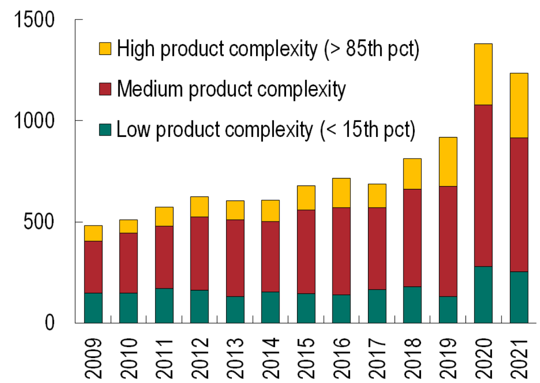
- ***First, Asia-Pacific targets mostly medium-complexity products***. IP is compared against Hausmann's product-level complexity indicator—a proxy for product sophistication based on the knowledge intensity and productive capabilities required to make a product. In principle, successfully targeting higher complexity products could be read as seeking to promote technological upgrading and development. Asia-Pacific economies tend to target more medium-complexity products, while the targeting of high-complexity products has risen over time.

- ***Second, most IP interventions by Asia-Pacific economies target products for which they have no revealed comparative advantage (no RCA).*** The second most targeted group is formed by products with longstanding comparative advantage ("Legacy RCA"). There is little targeting of products which have either recently gained or lost RCA. These results suggest that, while IP may have been used to sustain export competitiveness, its motivations are likely to extend beyond export competitiveness in the global market. In particular, the IP rationale may extend well beyond the export promotion trend prevalent in the region decades ago, against a past backdrop of increasing globalization and trade openness. Given the complexity of ongoing global challenges, resilience and security considerations clearly play a role—and other factors, including developments in the domestic social front may also weigh into the IP targeting decisions as well as on the tool choice.

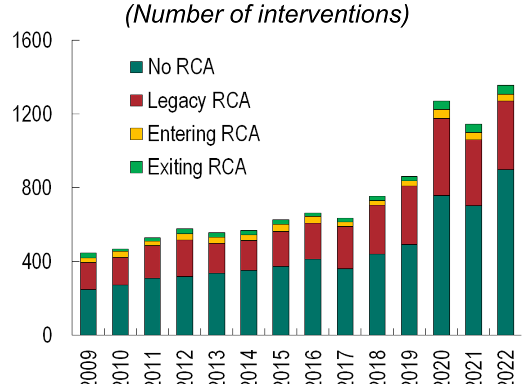
- ***Third, Asia-Pacific stands out for targeting sectors that are more "central" in the domestic production network***—i.e., those with high scores for demand and supply linkages with other sectors (Georgieva, 2025a). This may signal efforts to tackle market failures and frictions, and/or to generate positive inter-sectoral spillovers, for instance, by unlocking bottlenecks in the domestic production system.

Figure 2. A First Look at IP Targeting

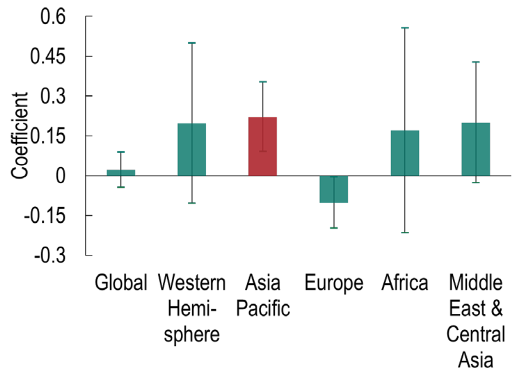
A. Interventions Targeting at Different Product Complexities - Asia-Pacific



B. Interventions Targeting at Different RCA Categories, Asia-Pacific 1/
(Number of interventions)



C. IP Targeting Sector Centrality, Globally and By Region 2/



Source: Global Trade Alert (GTA), The Growth Lab at Harvard, BACI database, Georgieva (2025a) and IMF staff calculations.

1/: Products with legacy RCA are those that were competitive (RCA>= 1) in the most recent ten years (t-10 to t-1); products with enteringRCA are those that were competitive in the most recent five years (t-5 tot-1) but not in the five-year period prior to the most recent five years (t-10 to t-6). Products with exiting RCA are those that were competitive inthe five-year period prior to the most recent five years (t-10 to t-6) butnot in the most recent five years (t-5 to t-1). Products with no RCA are those that were not competitive in both periods.

2/ From Georgieva (2025a) Estimated coefficients from panel logistic regressions of IP deployment by product against network centrality. Vertical lines show confidence intervals at 95 percent confidence.

A Multi-Dimensional Approach

While insights based on single indicators are useful, identifying the intent to promote structural transformation through IP deployed in Asia-Pacific can be challenging. The recent resurgence of IP both in the region and globally is accompanied by a broadening of underlying motives. Understanding the ultimate rationales for these interventions is therefore important for assessing their potential impacts and for evaluating whether they are poised to achieve their goals. Other existing databases have applied careful text-mining filters to the GTA to identify interventions that align with certain definitions of IP, and to extract the motivations behind IP used globally.[23] Our approach here is complementary: as already discussed, we apply a broader definition when selecting which interventions in the GTA could count as IP. Second, within that group of interventions, we apply a set of techniques (discussed below) to assess whether the ex-ante targeting of IP may be searching for structural transformation. Third, given our focus on identifying structural transformation strategies, we analyze at the product-level, which permits gathering granular information on the structural features of heterogenous products being targeted by IP.

Specifically, this paper takes a new approach to gauge the relation between the IP being put in place and a wealth of sector-specific economic indicators relevant for assessing the potential for structural transformation.

- ***First, a machine-learning (ML) tree-based model is set out to answer the following questions***: ***What product/sector characteristics related to structural transformation contributed the most to the likelihood of being targeted by IP in the region? And how have these contributions evolved over time?*** This is done in a predictive framework, where product characteristics (or predictors) at t-1 are used to forecast whether a product at time t is targeted by any IP intervention, mimicking real-world decision-making. The tree-

[23] There is significant heterogeneity in the amount of information contained in the raw GTA policy announcements; as a result, a relatively large share of intervention announcements does not include a clear view on the intended motive behind the policy—let alone the broader strategy behind it (Evenett and others, 2023 and 2025); moreover, even when the high-level objectives are stated explicitly, they might omit relevant information (e.g., additional considerations leading to IP deployment).

based model considers a broad range of indicators that proxy those most likely to unveil plausible IP strategies derived from the literature (Table 2). In particular, the ML model can process many simultaneous relationships while allowing for non-linearities and decomposing contributions to the likelihood of being targeted between various predictors. As such, it helps identify the key considerations that shape policymakers' decisions on whether and where to deploy IP interventions (Technical Annex III). We note that this is a prediction exercise, which means the results should not be interpreted as implying causal relationships.

- ***Second, a clustering exercise helps unveil the extent to which IP in the Asia-Pacific resembles structural change strategies identified by the literature.*** The clustering is based on a range of indicators capturing the visible targeting features specific to three key IP strategies in Table 2. It recognizes the multi-dimensional nature of IP drivers by relying on an a-theoretical algorithm to identify clusters (via k-means clustering) of IP interventions at the product level in a certain year, based on characteristics in the previous year—information available when choosing to target that product (Technical Annex IV). To help capture how IP could promote technological upgrading and diversification, the exercise includes indicators such as Hausmann's product complexity index, as well as a measure of product relatedness, which reflects the degree to which two products tend to be exported together globally, revealing similarities in the capabilities they require. To capture relationship with the economy's existing specialization, a measure of the distance of a product from an economy's current export basket and RCA are also included. Other indicators speak to the IP rationale of offsetting market failures and frictions, particularly in central and/or highly distorted sectors, including the degree of network centrality, and the presence of distortions in central sectors. Metrics by other complementary IP databases—particularly NIPO—are also included to provide additional insights on strategic products (e.g., reflecting resilience, security, or climate mitigation motives).

The IP strategies considered in the clustering exercise speak to the structural transformation objective, which guides the choice of variables included in the exercise. Two of them are related to fostering advancements in the product space—either by moving gradually from current strengths (i.e., by targeting "*safe-bet*" products), or by taking a high-risk attempt to leapfrog beyond the limits of current capabilities (i.e., by targeting "*moonshots*"). A third type (or group) of strategies advocates for explicitly addressing market failures/frictions that reduce efficiency (identified by the presence of high markups), or by enhancing sectors that are key in a value chain or a domestic production network, therefore facilitating growth and development more generally through positive spillovers and cascading effects. Importantly, the literature does not provide a blanket justification for these strategies—in line with the higher-level recommendations in economic theory, all IP, including in the case of the first two strategies (*safe-bets* and *moonshots*), is envisaged only to address a well-identified market imperfection or externality. For example, the presence of underexploited economies of scale may justify a push to expand production of *safe-bets*; developing completely new technologies (*moonshots*) might be needed to deliver public goods (e.g., vaccines, green technology).

An important caveat is that, as the clustering exercise identifies IP strategies by their most distinctive and visible features only, it cannot determine whether all identified IP meets the standard of addressing well-identified market failures. That is, in the clustering exercise, *safe-bets* and the *moonshots* are detected through indicators including the product's distance to the economy's own export basket, and RCA, among others, but there is no sufficient information on observable variables to determine whether the IP targeting the product is also aimed at addressing market failures, and whether the actual intervention could be justified on such grounds. This said, a specific group of indicators to help identify *certain* types of market frictions is included in the analysis—these are related to notion of alleviating frictions in production chains/networks, and so IP interventions clustering around such indicators would, in principle, be targeting this specific market failure.

Table 2. Measuring Key Implicit IP Strategies

Strategy	Rationale	Visible Targeting Features	Selected References
Targeting **"*Safe-Bets*"** **("Incremental Innovation")**	Supporting proven technologies or sectors with established markets to enhance productivity. The speed at which economies can transform their productive structure and upgrade their exports depends on having a path to nearby goods that are increasingly of higher value. ➢ Focus on improving existing industries with high potential as a stable way to promote growth. ➢ Justified if focused on addressing externalities (e.g., underexploited economies of scale, knowledge spillovers) not adequately absorbed by private sector and holding back economic cluster development	• Products could support technological upgrading (e.g., complex) and/or export diversification (e.g., related to other products) • Products are already in the economy's production and/or export baskets. • Products in which the economy is already competitive and/or has comparative advantage.	Aghion and Howitt (1998). Lin (2012) Hausmann and others (2006, 2007) Hidalgo and others (2007) Juhász, Lane, Rodrik (2023) Reed (2025) Rodrik (2004)
Targeting ***"Moonshots"*** **("Radical Innovation", Leapfrogging)**	Supporting breakthroughs or radical innovations, high-risk, high-reward investments in emerging sectors (e.g., AI, biotech, or advanced manufacturing). ➢ Governments lead or catalyze high-impact innovation initiatives in new areas. ➢ Justified when targeting market failures (e.g., coordination frictions, high financing costs) holding back private sector, which may not absorb potential public good aspect.	• Sophisticated products that are not in the production and/or export baskets • Products in which the economy is not yet competitive and/or has comparative advantage • Products considered strategic	Dosi, and others (2021) Hausmann and others (2006, 2007) Hidalgo and others (2007) Mazzucato (2013, 2018). Juhasz, Lane, Rodrik (2023) Reed (2025) Rodrik (2004)
Targeting **Market Imperfections** **and/or** **Alleviating Frictions in Key Points of Production Chains or Networks**	Focusing on targeting visible market failures, in particular, alleviating distortions in strategic nodes within global or domestic production networks; supporting anchor firms, connectivity along value chains. ➢ Target specific sectors and segments within value chains to improve efficiency and productivity and/or move up the value ladder.	• Products/sector that may create cascading effects by reducing distortions, because they are upstream in the value chain and/or central in the domestic production network • Distortions due to market failures (e.g., reflected in high markups and/or financing constraints).	Georgieva (2005a) Liu (2019). Juhász, Lane, Rodrik (2023) Rodrik (2004) Stiglitz (1994, 2000, 2012)

Sources: IMF staff compilations.

Results: Machine Learning

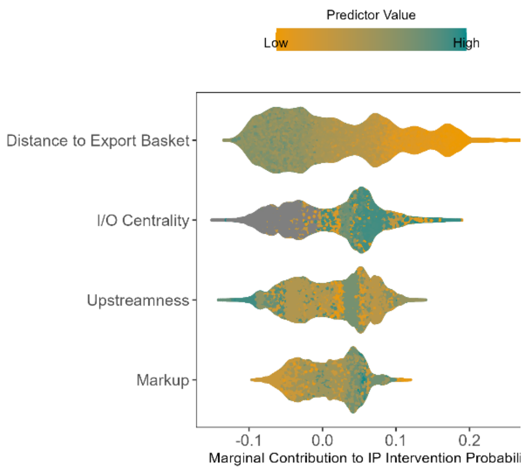
The distance to an economy's own export basket is the most important predictor for IP intervention amongst the variables considered, as revealed by the tree-based ML model estimation. Figure 3-A ranks the predictors of IP intervention in Asia-Pacific, based on their marginal contributions to the predictive power. The analysis in the figure answers two related questions, relative to the sample average: (i) *how important is each* *indicator at predicting IP?* and (ii) *how is the actual value of an indicator linked with the probability of IP targeting?* The most important factor appears to be the distance of a potentially targeted product to an economy's own export basket, with lower distances associated with a greater probability of being targeted. This is followed by Input/Output (I/O) centrality (reflecting a sector's importance as sources of supply and demand in the domestic production network as measured from input-output tables), the degree of "upstreamness" (or implicit value added) of the product, and the presence of markups (signaling potential market failures/rigidities to be addressed).

The relationship between the likelihood of deploying IP on a product and its main drivers is often non-linear. Figure 3-B plots the marginal contribution to the likelihood of IP intervention against the predictor value on the x-axis. A greater distance to current export basket is negatively correlated with the likelihood of IP intervention but only up to a point, after which, the likelihood of IP intervention increases with the distance. In other words, IP tends to target products that are closer to an economy's own export basket but for certain products which are very distant from an economy's own export basket, they are more likely to be targeted if they are further away. This suggests that IP could have been deployed to support structural transformation both in a less risky way—by targeting those close to an economy's existing exports—but, in some other instances, to pursue more ambitious leaps into new products that are farther away from the economy's expertise. Similarly, high price markups in the targeted sectors show an overall upward slope, suggesting IP tends to target products with higher markups (i.e., a proxy for the presence of market failures, consistent with results in Baquie and others, 2025), but the relationship reverses at one point, suggesting other factors being considered. IP tends to target products that are more central in the production network, but only up to a point; similarly, IP overall tends to target downstream products but the likelihood of being targeted by IP increases when it comes to very upstream products, such as metals or fuel.

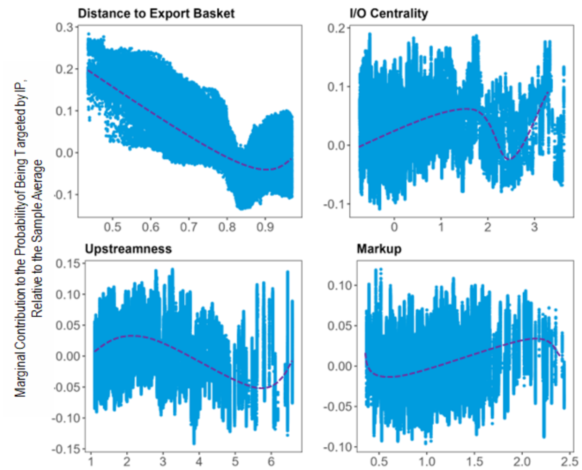
Overall, there is no single dominant predictor for IP interventions: the contributions differ across income levels and change over time, revealing that the reasons for IP are complex, multi-faceted and time-evolving. Examination of the average contribution of the predictors (relative to sample average) in three periods for AEs and EMs (Figure 3-C and 3-D) shows these changing patterns. In AEs, RCA has long been an important targeting feature; in contrast, the contribution from network production centrality has risen over time; this suggests that IP in AEs has moved increasingly towards more highly connected (though not necessarily tradable) sectors that may deliver positive spillovers. For EMs, IP initially targeted products closer to their export basket; however, production centrality, market distortions, and upstreamness have gained importance since 2020. The nonlinear relationships show that IP interventions are not dominated by a single characteristic, leading to the clustering exercise in the next section.

Figure 3. Tree-based Investigation of IP Determinants

A. Ranking of IP Predictor Values



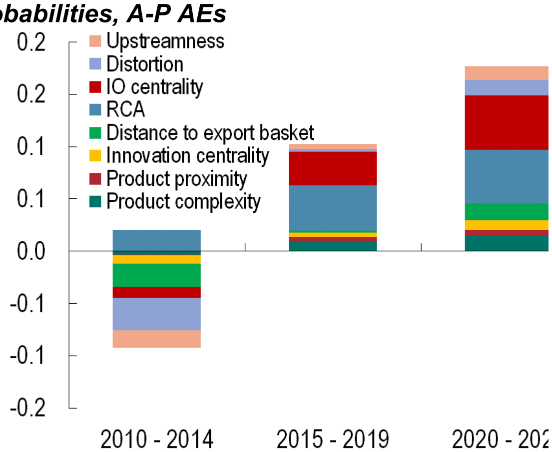
B. Probability of IP intervention vs. Predictor Value



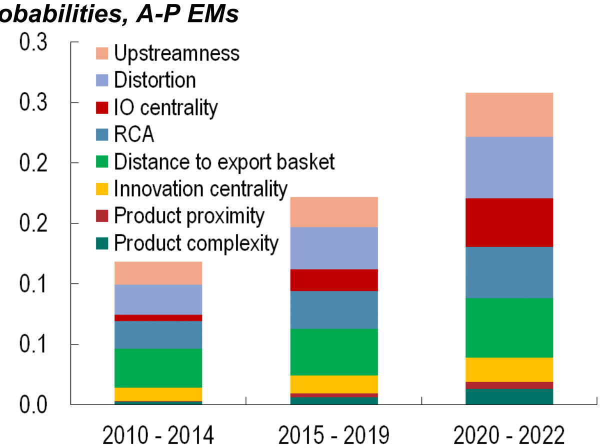
Source: IMF staff estimates.

Notes: Each dot represents one observation (one economy-product-year), and its color indicates the predictor value, with orange being low and green high. Therefore, the value of the contribution (and its negative or positive sign) and color together illustrate how the predictor value affects the probability of being targeted by IP. For example, for the distance to export basket, the top predictor in the sample, most green dots (observations further away from an economy's export basket) are to the left (i.e., reduce the probability, relative to the sample average) and orange dots (observations closer to an economy's export basket) to the right (i.e., increase the probability, relative to the sample average). The left chart plots the top predictors which account for the first 60 percent of the total contributions to the IP intervention probability.

C. Evolution of Contribution to IP Targeting Probabilities, A-P AEs



D. Evolution of Contribution to IP Targeting Probabilities, A-P EMs



Sources: IMF staff estimates.

Notes: Y-axis shows the marginal contribution of different variables to the probability of a product being targeted by IP in the following year, relative to the sample average. For each year, the average across all products is shown.

Results: Clustering Exercise

The clustering exercise seeks to assess the extent to which IP might align with structural transformation strategies. As noted earlier, it is based on an a-theoretical algorithm, which allows all IP interventions—both for Asia-Pacific and the RoW—to cluster flexibly around groups of indicators characterizing the products and sectors targeted by the interventions.[24] The identified clusters are then assessed to determine the extent to which they can be clearly linked to the IP strategies in Table 2 above. Before turning to the results, the following points of emphasis and caveats may help clarify the objectives of the exercise and the results' interpretation:

- ***First, we do not presuppose that the generated clusters need to align with an IP strategy***. Once clusters are generated, we assess whether they are meaningfully distinguishable from each other, and among those which are, we apply judgement based on each cluster's distinctive characteristics to identify aligned strategies if possible. [25] Exactly how we do so cluster-by-cluster is elaborated on below.

- ***Second, the exercise does not seek to identify which observations qualify as IP***. All the observations considered, regardless whether we can align them with one or more strategies, meet this paper's operationalized definition of IP. Those "un-clustered" observations may be linked to other strategies or motivations, for which it was difficult to find identifying available indicators for the whole sample at a sufficiently granular level (for example, IP strategies focused on preserving/creating employment). Alternatively, some of the un-clustered observations may represent measures deployed without a holistic strategy in mind and/or reflect possible inclusion errors in the sample, as discussed earlier.

We find that the algorithm-generated clusters can be mapped to three identifiable types of IP strategies, which together cover about three-quarters of the total Asia-Pacific IP interventions in the dataset.

- ***First, a cluster aligns with the "Safe Bets" IP strategy***. A first cluster, accounting for over a quarter of IP interventions in Asia-Pacific, appears consistent with promoting products/sectors that are "*safe bets*". We come to this interpretation based on considering the distribution of characteristics of the observations assigned to this cluster, as illustrated by the plots of the medians and interquartile ranges for the considered characteristics in Figure 4-A. First, products in this cluster tend to be *attractive*: they are relatively higher in complexity and closely related to other products already in the economy's expertise, hence supporting export diversification. About half of them are products regarded as "strategic". Second, most observations in this cluster tend to be *safe targets*, in the sense that the targeting economy already exhibits revealed comparative advantage in that product, and/or the product is close to the economies' existing specialization measured by a low distance to the export basket. These two distinctive features—product attractiveness and closeness to the economies' current specialization, leads us to label the product-level interventions in this cluster as consistent with a "safe bets" IP strategy. At the same time, the distribution of indicators of sectoral distortions or centrality do not seem particularly distinctive from the overall sample, suggesting relatively weak alignment with a strategy of correcting distortions in key sectoral nodes.[26] IP in this cluster can be understood as supporting proven technologies or sectors with established markets, in line with arguments that economies can transform their productive structure and upgrade their exports by exploiting paths to nearby goods that are increasingly

[24] Of the about 3.5 million product-level discriminatory and vertical policies, we are able to get data on all the variables (and therefore cluster) about 86 percent. All ratios reported on the fraction of observations in various clusters are relative to the about 3 million assigned observations.

[25] As an example, we allowed for but did not find clusters distinguished by strategies focused on targeting sunset or infant industries (or more precisely in our exercise, products), at least in the way proxied these strategies in our exercise. We included both current RCA and 5-year lagged RCA, as the joint values of these can proxy for a defensive strategy to support a sunset industry (lagged RCA>1, current RCA<1) or to accelerate the growth of an infant one (lagged RCA<1, current RCA>1). These combinations do not appear as distinguishing features for our clusters.

[26] Though we note that somewhat higher upstreamness above the sample average for most interventions in this cluster.

of higher value, as discussed by Hausmann and others (2006, 2007) and Hidalgo and others (2007).[27] In other words, these products are within reach in the domestic production matrix—and hence, directing public support via IP toward their expansion appears to be a relatively low-risk endeavor, including from a technological standpoint.

- ***Second, a cluster aligns with the "Moonshots" IP Strategy***. A second significant cluster in Asia-Pacific is consistent with an IP strategy aiming for "*moonshots*", based on an assessment of the distribution of characteristics as shown in Figure 4-B. Like the safe bets cluster, the targeted products in this cluster tends to be *attractive*, with relatively high complexity and interrelatedness. However, unlike the safe-bets cluster, the targeted products are *not within the economy's current specialization*, as indicated by the absence of revealed comparative advantage and high distance from the current export basket. These two distinctive features of the distribution of characteristics of this cluster—*attractive* products which are *far from current specialization*—leads us to interpret these as consistent with *moonshot* strategies. At the same time, the distribution of characteristics associated with sectoral centrality and distortions does not appear to be particularly distinctive in this cluster. Therefore, the product-level interventions in this cluster may speak to efforts to radically expand an economy's production frontier, in line with arguments advocating supporting breakthroughs or radical innovations through high-risk, high-reward investments in emerging sectors (e.g., AI, biotech, or advanced manufacturing).[28] In Asia-Pacific, interventions in this cluster account for about 30 percent of total IP interventions.

- ***Third, another cluster aligns with an IP strategy of targeting "Market Imperfections and Alleviating Frictions in Key Points of Production Chains or Networks"***. A third cluster (Figure 4-C) has the distinguishing features of being linked to sectors that have high "centrality" in the domestic production input-output network and/or potential market distortions that need addressing (proxied by the presence of markups). This hints at a strategy geared towards offsetting frictions and market failures and lifting bottlenecks.[29] The products in this cluster do not stand out for their attractiveness, which suggest *safe bet* and *moonshot* strategies may not be particularly relevant here. These account for slightly less than 20 percent of interventions in Asia-Pacific.

- ***Finally, it is difficult to map a strategy for the remaining group of interventions***. This cluster (Figure 4-D) comprises seemingly unattractive low-complexity products, unrelated to the economy's specialization (i.e., low RCA), and in sectors that are neither particularly central to the production network nor distorted. It is difficult to assign to any specific structural transformation ambition based on available data and the conceptual framework depicted in Table 2. Of course, policymakers may have other rationales to foster these sectors and products not captured in the analysis that may explain their targeting (e.g., employment protection).

Clustering results show that Asia-Pacific stands out relative to the RoW in targeting *Key Nodes to Alleviate Market Failures and Frictions*; the region's AEs are highly focused on *moonshots,* while EMs are highly balanced across IP strategies. Asia-Pacific has a much higher incidence of IP in the *key nodes* cluster compared to the RoW (Figure 4-E). AEs in Asia-Pacific also stand out for targeting *moonshots* more intensely than AEs elsewhere. Interestingly, the targeting of EMs in the region is broadly balanced across the three strategies, while EMs in the RoW appear much more intensely focused on *moonshot*-type bets. This pattern is partly influenced by the relatively larger propensity of China to focus on "*safe bets*"; excluding this economy, the region's EM's focus on *moonshots* rises to levels similar to those observed in EMs in the RoW. Importantly, products that are "safe-bets" are economy-specific in this analysis, depending on how close a product is to each economy's

[27] See Aghion and Howitt (1998), Rodrik (2004), Hausmann and others (2006 and 2007), Hidalgo and others (2007), Lin (2012), Juhász, Lane, and Rodrik (2023), and Reed (2025).

[28] See Rodrik (2004), Hausmann and others (2006, 2007), Hidalgo and others (2007), Mazzucato (2013, 2018), Dosi, and others (2021), Juhasz, Lane, and Rodrik (2023), and Reed (2025).

[29] See Stiglitz (1994, 2000, 2012), Rodrik (2004), Georgieva (2025a), Liu (2019), Juhász, Lane, and Rodrik (2023).

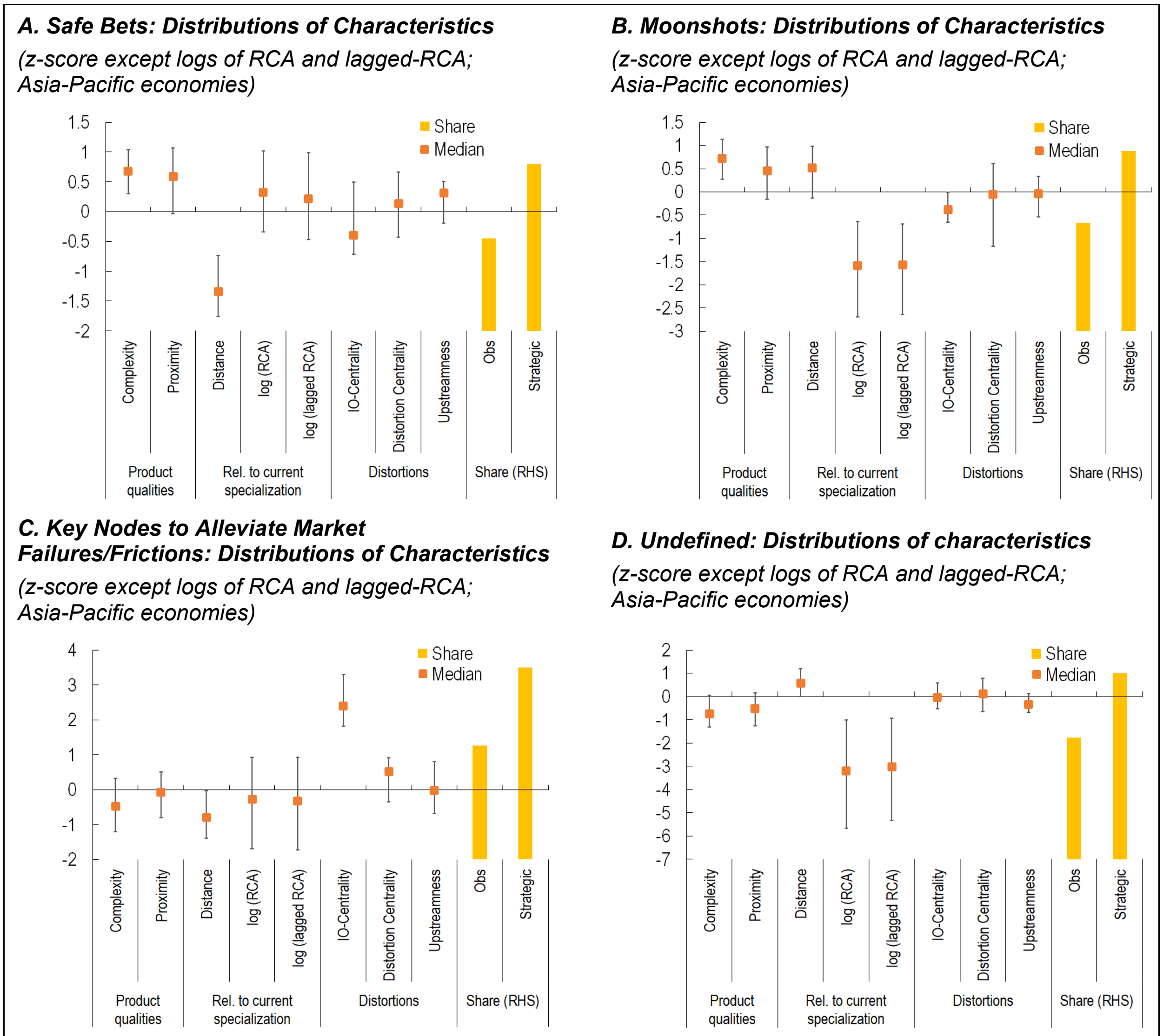
current specialization level; whenever an economy has developed a relatively broad export basket and diversified production structure, more products are close to its existing areas of specialization and therefore deemed "safe" from its perspective.

An inspection of the IP tools used for the different strategies confirms the reliance on trade-related measures, second to subsidies. As it is well documented in recent literature, the use of domestic subsidies dominates across regions and income groups—this tool is also the most used across the estimated clusters. That said, import-limiting measures remain the second most used tool: while the shares in Asia-Pacific are smaller than in RoW, these interventions tend to be persistent and remain in effect over a large set of products. There are some other distinctive features, which we note. A deeper investigation of these patterns and their drivers we leave for future work.

- ***For AEs in the region, the use of subsidies predominate through IP strategies (Figure 4-F)***. They represent a key share of the interventions through the strategies (at 45-60 percent). The second most used tools are export-limiting measures, including to support *safe-bets* and *moonshots*. One possible explanation is that this may be signaling an increasingly complex targeting design and specific objectives. For example, some of the export-limiting measures may be linked to the desire of re-directing the use of these products towards domestic sectors (including as inputs for other targeted products); while difficult to show with the data, national security considerations might also be at play. Interestingly, AEs in the RoW seem to deploy a much lower share of subsidies (except for sectors with market failures/network frictions), and lean heavily on import-limiting measures—in a more traditionally protective pattern.

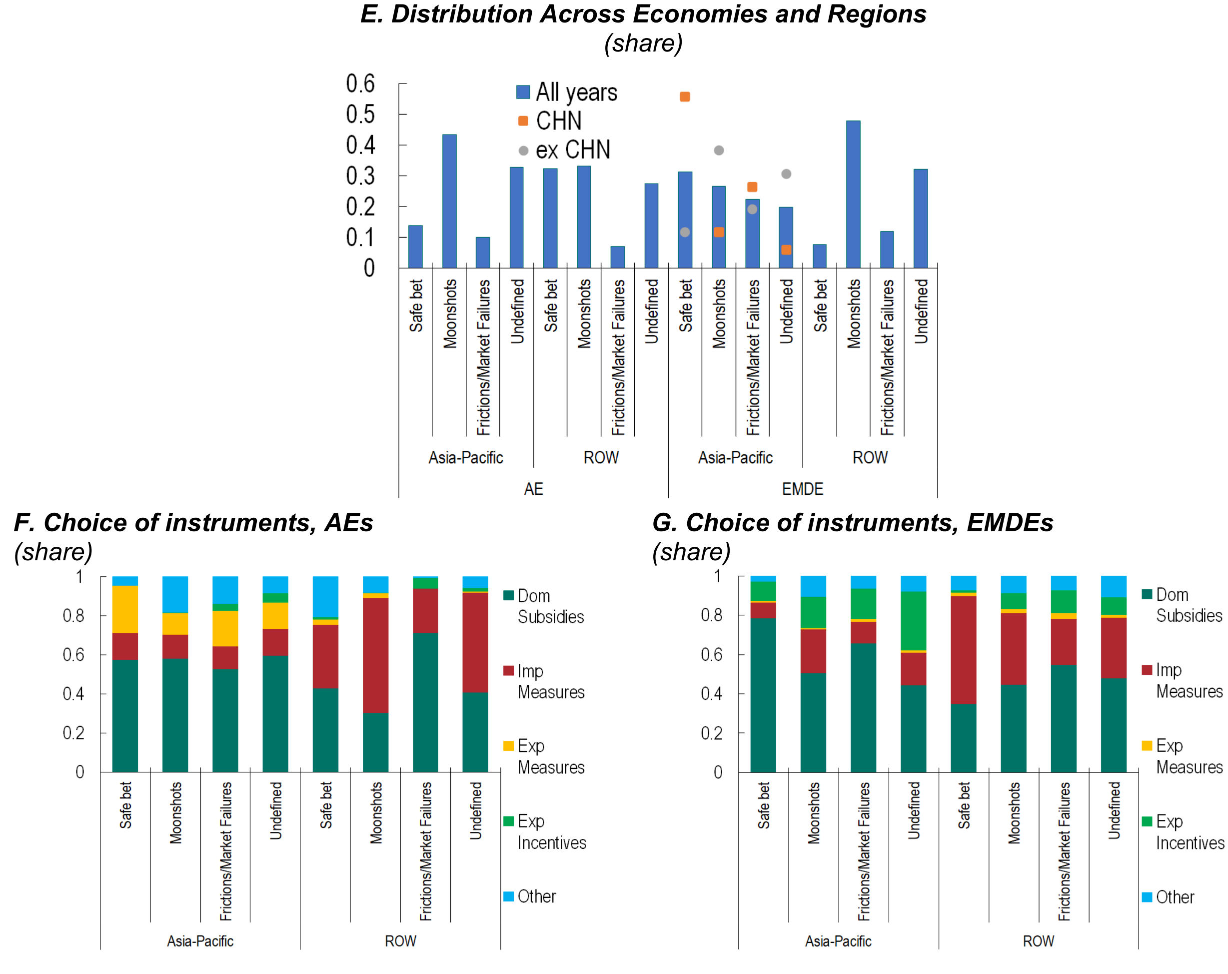
- ***Asia-Pacific EMs stand out vis-à-vis the RoW for the heavy use of subsidies and of export incentives (Figure 4-G)***. This hints at an attempt to leverage external markets in boosting the *safe bets* and *moonshots.* The RoW generally uses fewer subsidies and imposes a higher share of import-related measures, particularly to develop *safe-bet* products and sectors.

Figure 4. Clustering and Implicit IP Strategies



Sources: IMF staff calculations

Figure 4. Clustering and Implicit IP Strategies (Concluded)



Sources: IMF staff calculations

VI. IP: Trade and Competitiveness

This section examines how various IP tools affect a range of external outcomes in targeted products—including exports, imports, and revealed comparative advantage (RCA). There are at least three important reasons for looking into these variables when assessing IP performance. First, while the paper previously documents signs of an inward-looking, import-substituting lean in the overall IP toolkit, the large share of (neutral-leaning) subsidies in the overall toolkit calls for an assessment on the impact not only of imports, but of other external sector variables. A second reason is that even import-substitution strategies are not mutually exclusive with improved exports: assume, for instance, that an economy successfully targets a *moonshot* product via import-restrictions: this may transition from being net importer to becoming a net exporter, gaining space in global markets. A third reason is that examining the sustainability of dynamics in RCA informs us not only about trade patterns, but also whether the underlying IP targeting is successfully embedding structural (technological/cost) improvements in the selected products.

This empirical strategy allows for the comparison of IP-treated versus untreated products. The estimation approach uses the local projection difference-in-difference methodology (LPDiD), following recent literature, including Ruta and Rotunno (2024), Baquie et al. (2025) and IMF (2025). The LPDiD setting allows comparing effects for IP-treated products (targeted by a specific IP intervention), to outcomes for untargeted products. As underlined by Baquie and others (2025), the LPDiD approach addresses biases derived from estimating heterogeneous treatment effects for observations treated at different points in time.[30,31] It uses product data (at the HS6-digit level) over the period 2009-2022. The estimated model is the same as the one used in Baquie and others (2025),[32] with the exception of the dependent variable, as we also assess the possible effects of IP on trade variables, namely product level exports and imports (while they focus only on RCA). The dependent variable is the log difference in the value of exports from, imports by, or RCA in economy i in HS 6-digit product k over the horizon considered, and the independent variable is a dummy taking the value of one if the treated economy introduces at least one IP in year t and zero otherwise. Controls include a dummy that is equal to one if the product is treated by at least one other IP intervention concurrently, and well as lags of the treatment and non-IP shock. Product-year, economy-year and product-year fixed effects are added as well. The economy-year fixed effects should help to control for macroeconomic policies that may be implemented in the economy concurrently. We focus on the discriminatory IP interventions, with data from our IP database, merged with product level trade data from the BACI database (Technical Annex II).[33]

IP and Trade Metrics

Overall, the link between IP tools and either trade flows or competitiveness is not durable*.* The assessment covers the most used IP instruments: domestic subsidies, export incentives, and import-limiting measures, and gauges their effects on export and import values (Table 3).

- **There is some evidence of successful export promotion through IP interventions, but the link between IP and increased exports does not persist.**
  - ***Domestic subsidies are linked to an increase in exports in Asia-Pacific; however, durability differs by income group***. In general, the link is of a similar order of magnitude in Asia-Pacific and the Rest of the World (RoW) and the link tends to dissipate after around three years. A more granular view by income level suggests that the short-term boost observed for the full regional sample is largely driven by a temporary increase in exports in the region's EMs, excluding the largest economies in the region.[34] In contrast, the link between IP and stronger exports in AEs is mixed: there are some sporadically significant positive coefficients after three and five years for the East Asia AEs, while the remaining AEs do not showcase significantly higher exports of products targeted by IP, relative to non-targeted ones.
  - ***Export incentives are associated with stronger exports of targeted products both in Asia-Pacific and the RoW, yet the improvement in exports is only temporary****.* The ex-post association between IP and exports is stronger for Asia-Pacific, although it tends to fade a little bit faster than in the RoW. The

[30] In practice, this method cleans the sample, which means that the clean treatment group is restricted to first time IP treatments up to L preceding periods (i.e. the control group excludes products treated between t-L and t-1 and between t and t+h, where l and h are chosen to be 2)

[31] Following Baquie and others (2025), Ruta and Rotunno (2024) and IMF (2025a), we differentiate between IP interventions that are discriminatory against foreign commercial interests and those considered liberalizing, on a non-discriminatory basis, focusing on the former (since occurrences of the latter are marginal). This classification is provided directly by the Global Trade Alert (GTA).

[32] See their online annex for specifics on the estimated model.

[33] One caveat that seems important noting is that the effect of IP interventions might reflect economy specific macroeconomic policies implemented in the economy concurrently. This would be the case to the extent their effect is not entirely controlled for through the economy-year fixed effects of the regressions.

[34] Large EMs refer to China and India.

assessment by income group reveals that this pattern is led by the region's AEs, and more specifically East Asia AEs.

- ***Government effectiveness appears to be a key determinant enhancing IP impact, both in Asia and the RoW.*** We also examine export dynamics in targeted products (relative to untargeted ones) splitting the sample based on the degree of government effectiveness indicators (Annex V). Results suggest that the improvement in exports following IP based on domestic subsidies is much stronger for economies with higher government effectiveness; this effect is visible both in Asia-Pacific and economies in the RoW. Similarly, the deployment of export incentives appears to have a stronger and durable association with an increase in targeted exports (relative to untargeted products) for Asia-Pacific economies with higher government effectiveness.[35] These results are in line with those by Baquie and others (2025), which also suggest that improved institutional frameworks may be linked with higher IP effectiveness.

- ***In line with the revealed import-substituting lean, Asia-Pacific economies are slightly more successful than the RoW in curbing product level imports when they implement IP, although success remains sporadic:***

  - ***Domestic subsidies in Asia-Pacific AEs are associated with effective yet temporary import-substitution.*** Consistent with what is well documented by recent literature for the global IP sample (Ruta and Rotunno, 2024), results indicate that subsidies applied to imported products in the RoW are associated with an *increase* (rather than reduction) in imports. In contrast, economies in Asia-Pacific overall do not show any systematic increase in imports of the targeted products, relative to non-targeted ones. Importantly, Asia-Pacific AEs see a *decline* in imports of subsidized products two to three years after subsidies are put in place, compared to non-targeted products.

  - ***Import limiting measures (such as import quotas or bans) are not linked to a reduction in imports of targeted products in Asia-Pacific as a whole, yet masking economy specific effects.*** Asia-Pacific EMs see a significant, yet short-lived reduction in imports one year after implementation, while East Asia AEs see a reduction from implementation to the second year post-implementation. This comes in contrast to the RoW, where there is a limited, but significant *increase* in imports when import-limiting measures are implemented consistent with other findings in the literature (see Ruta and Rotunno, 2024), followed by a small reduction three to four years afterwards. Interestingly, zooming in on RoW economies whose government effectiveness is strong (above median) leads to imports being significantly lower for products targeted by import limiting measures relative to untargeted ones. This effect is not seen for Asia-Pacific economies with strong government effectiveness (see Appendix V).

[35] Please note regressions run on economies for which government effectiveness is lower (i.e. below group median) appears less reliable due to the smaller number of observations available in this group.

Table 3. Heatmap: IP Effects on Exports and Imports

	Year after intervention	0	1	2	3	4	5
Effect on exports	**Export incentives**						
	Rest of the World	6.5	8.0	12.4	7.4	7.9	7.9
	Asia-Pacific	18.9	22.0	14.2	10.0	20.8	59.9
	Asia-Pacific AEs	26.0	36.0	21.6	-19.2	-25.2	40.2
	East Asian AEs	16.1	28.9	30.6	5.3	25.8	35.0
	Other AEs	16.8	11.4	-8.3			
	Asia-Pacific EMs	4.1	-7.2	-0.7	10.4	29.8	56.8
	Large EMs	8.4	8.6	14.0	22.7	26.1	103.2
	Other EMs	10.5	-6.1	-22.1	-228.1		
Effect on exports	**Domestic subsidies**						
	Rest of the World	2.0	4.7	4.3	2.2	2.7	0.9
	Asia-Pacific	5.3	5.7	3.5	7.8	4.3	4.9
	Asia-Pacific AEs	0.4	-3.4	-5.0	5.6	32.1	33.5
	East Asian AEs	6.4	0.7	0.0	9.8	79.6	101.5
	Other AEs	-8.3	-17.7	-29.2	-37.6	33.5	10.5
	Asia-Pacific EMs	5.1	7.0	6.5	12.1	5.1	5.2
	Large EMs	0.6	1.5	-15.3	-24.5	-18.5	25.1
	Other EMs	13.1	14.0	11.5	17.6	1.7	6.2
Effect on imports	**Import limiting measures**						
	Rest of the World	5.5	-0.8	-1.6	-3.6	-5.6	0.2
	Asia-Pacific	1.5	-1.4	1.3	20.7	30.0	22.1
	Asia-Pacific AEs	-5.0	-4.6	2.5	4.5	-21.2	-35.9
	East Asian AEs	-15.1	-18.6	-13.4	-10.1	45.0	0.0
	Other AEs	15.8	17.9	8.1	6.8	6.1	27.8
	Asia-Pacific EMs	1.7	-7.8	-11.8	6.6	-1.2	5.4
	Large EMs	-86.0	-231.4	175.9			
	Other EMs	1.1	-8.4	-15.6	4.4	-0.3	6.0
Effect on imports	**Domestic subsidies**						
	Rest of the World	3.4	6.5	9.8	6.9	8.2	10.7
	Asia-Pacific	-0.4	0.1	-0.3	1.0	-1.1	-2.0
	Asia-Pacific AEs	-1.4	-6.3	-7.3	0.8	-30.3	-4.0
	East Asian AEs	-3.7	-6.1	-4.4	-5.0	8.9	60.5
	Other AEs	6.4	-3.8	-12.3	0.9	-40.5	-44.0
	Asia-Pacific EMs	-0.6	0.3	0.2	0.7	-5.7	-6.9
	Large EMs	-0.5	5.6	1.5	-13.6	-17.7	30.7
	Other EMs	2.8	2.9	6.3	3.7	-6.5	-26.4

Source: Staff Estimates.

Note: Table shows effect of IP intervention on exports/imports (coefficient in percent) in each year after the product level IP intervention,highlighted in green and orange respectively if the coefficient is significant at the 5 percent level and positive or negative (respectively), and in gray if the coefficient is not significant, for each subgroup breakdown (by income category and further breakdown within each income category). Blank cells indicate that there were not enough observations for the estimate to be run.

In short, we find a lack of a systematic and durable link between IP and trade flows over the last fifteen years. IP tools may be correlated with trade flows in Asia-Pacific economies—either by boosting exports or triggering import substitution. However, the link is short-lived and not generalized to all Asia-Pacific economies, suggesting that mechanisms at play may not be fostering fundamental, structural changes to the productive and trade structure in the targeted sectors. For instance, exports levels may be boosted by the fiscal support received by exporters (via subsidies and/or export incentives), which may facilitate, say, a one-off, temporary expansion in exports via reduced costs and improved pricing; however, it is unclear that this gain is systematically transformed into a structural gain by exporters (e.g., by embedding more efficient cost structures). Similarly, the evidence on the temporary link between IP and imports in Asia-Pacific raises questions on whether domestic industries being propped up by IP can entrench gains over time, become competitive and replace imports in a cost-effective manner; to the extent that the cost structure is not improved, these costs will ultimately be passed to consumers (e.g., via lower quality), and/or will require protracted financial support. Exploring this further is outside the scope of this paper. The drivers of the stronger effects of the new IP observed in the region's East Asian AEs also deserve a more in-depth examination. Given the long history of these economies with IP and likely lessons learned on IP design during that process, the results may suggest that fostering such impacts on trade may be feasible under some IP designs that embed the appropriate incentives. Additional analysis (shown in Annex V) dividing economies according to their level of government effectiveness also reveals that some tools (domestic subsidies in particular) might support IP's capacity to boost exports more in economies whose government effectiveness is stronger. Finally, the result contrasts with the broadly shared conclusion according to which (primarily export promoting) IP by East Asian economies in the 1960's to 1990's have been successful (the Asian Miracle, see Stiglitz, 1996). Unfortunately, the timespan of the available data does not allow us to compare the difference in the link between IP and economic outcomes during that period to the results presented above (focusing on data over 2009-2022).

Impact on Revealed Comparative Advantage (RCA)

The paper now turns to the impact of IP on RCA, which measures an economy's relative efficiency and specialization. A higher RCA for a product means an economy can produce it more competitively, as indicated by relative specialization in the product in export markets. Using the same LPDiD approach as above, we focus on the two IP tools most relevant for export competitiveness, namely, domestic subsidies and export incentives. Results also suggest mixed patterns across tools, products and economy groupings (Figure 5).

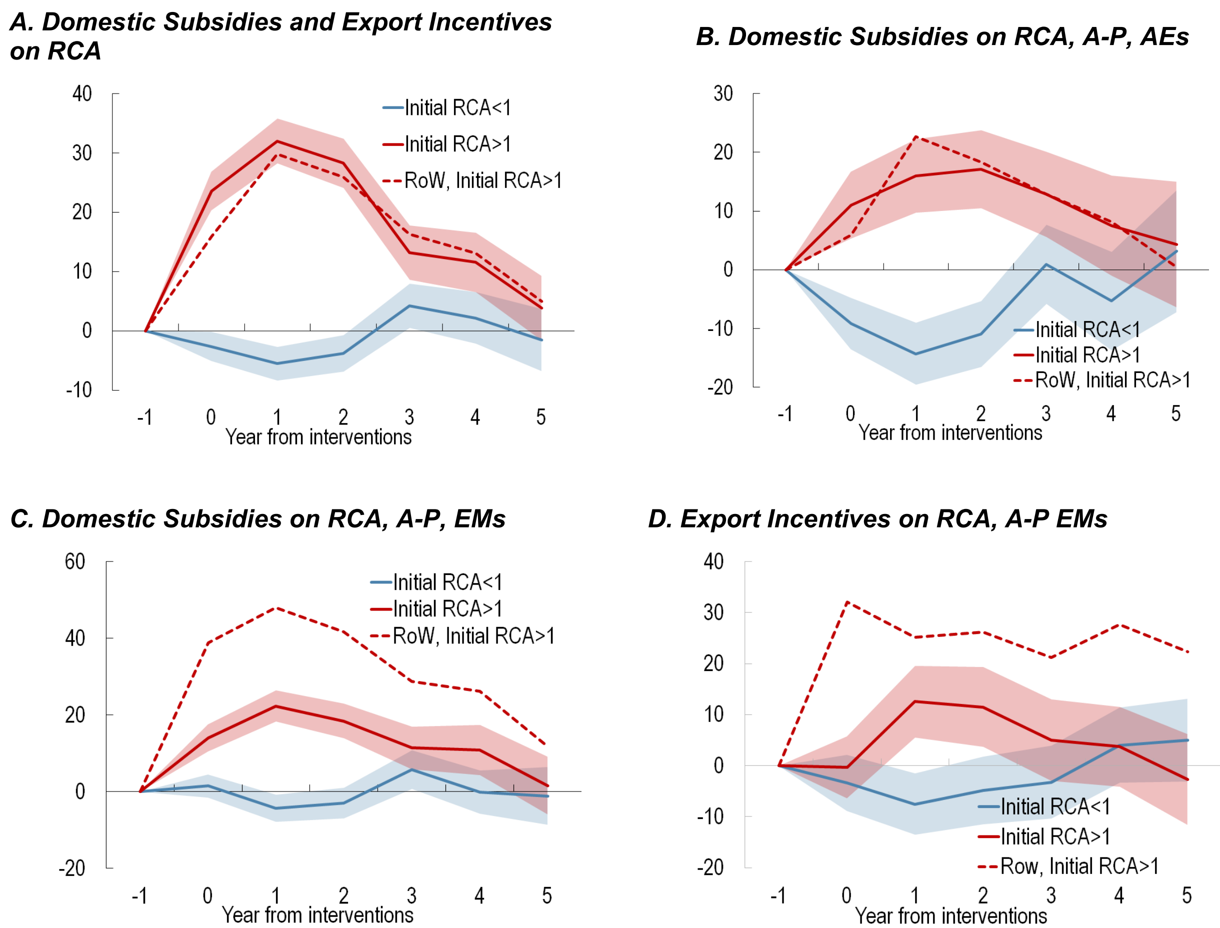
- ***IP interventions (both domestic subsidies and export incentives) are associated with a rise in RCA in Asia-Pacific, but only for products that are already competitive**.* There is no substantial difference in the effects observed in Asia-Pacific as a whole and the RoW.

- ***The association of domestic subsidies with RCA is short-lived**.* For AEs in the region, there is a temporary lift that dies off over time, suggesting that the increase in competitiveness could be derived from the immediate cost support provided by the IP measures, rather than durable (and slowly built) enhancements of structural productivity. The region's EMs show similar dynamics, with an immediate—but decaying—lift to RCA for already competitive products.

- ***Export incentives by EMs in Asia-Pacific have a delayed associated increase on RCA, yet this is more durable than that in the RoW**.* The relationship in the region is very short-lived and only observed in products that are already competitive (i.e., trading significantly in the international markets). The association for export incentives deployed by EMs in the RoW is more long-lasting products' competitiveness, compared to that observed in Asia-Pacific EMs. For AEs, export incentives deployed in the region have some temporary positive association on RCA, especially for products that are not yet competitive, but these dissipate over the medium term.

Overall, the results indicate that IP has only a limited, non-systemic relationship with competitiveness in Asia-Pacific over the last fifteen years. As discussed earlier, Asia-Pacific mostly targets non-competitive products: this implies that the possibly "effective" IP interventions identified in this section—which are linked to products that are already competitive—are the exception rather than the rule, and definitely not broad-based. In other words, only a small fraction of IP interventions may temporarily boost the presence of a few of the region's (already competitive) exports in global markets.

Figure 5. Impact on Competitiveness



Sources: BACI database, GTA database, and IMF staff calculations.

Notes: Each chart shows the estimations from a difference-in-difference local projection model regressing Exports/Imports/RCA (in log term) on the presence of each type of IP tool at the economy-product level, with controls including the presence of other IP tools, lagged Exports/Imports/RCA (in log term), economy-product fixed effect, economy-year fixed effect, and product-year fixed effect and the effect assuming to stabilize in two years. Shaded areas show the 90 percent confidence intervals.

VII. IP and Firm-Level Domestic Outcomes

In this section, we move on to an assessment at the firm level, to evaluate whether IP leads to domestic production shifts that may signal possible structural transformation. As documented earlier, the orientation of IP in Asia-Pacific (as well as the RoW) appears inward-looking, with about two-thirds of the IP being applied to products with no comparative advantage.[36] It is, then, possible that the actual effect of IP in the region may be most clearly reflected on domestic variables, specially within the industry/manufacturing sector, in which most of the IP interventions are implemented. Along these lines, the paper now turns to examine whether IP interventions are associated with any significant and long-lasting changes at the firm-level in targeted sectors, based on ORBIS firm-level data. This data is mapped to IP interventions via industries at the 4-digit level for a subset of economies in Asia-Pacific for which sufficient data is available. These include Australia, China, India, Japan, Korea, Malaysia, New Zealand, Thailand, and Vietnam. As in the literature, we use ORBIS because it provides the best data available for analysis across economies. However, we note that the sample may be subject to representativeness bias, owing both to limited economy coverage and the potential overrepresentation of firms in the formal sector. At the same time, resulting biases may be limited to the extent the selection is not be based on IP targeting—i.e., the dimension of comparison we are interested in. Broadly, we seek to derive insights that may reflect regional patterns to the extent possible; the individual results should be read with the above caveats in mind. Furthermore, we acknowledge that these findings are not necessarily generalizable to all economies in the Asia-Pacific region and must be interpreted with caution.

A first—and striking—empirical regularity is that, in Asia-Pacific, IP is systematically associated with *lower* productivity industries (Figure 6). This is clear from plotting the distribution of firms' Total Factor Productivity (TFP, measured by the Revenue-Based TFP, and obtained from Diez and others, 2021, who apply the estimation procedure by Ackerberg, Caves & Frazer, 2015, to ORBIS data). The distinct TFP levels—distinguishing targeted from untargeted firms[37]—is clear across the sample for all economies in the region, except Japan. This pattern is robust to excluding agriculture from the sample, and remains broadly similar when excluding both agriculture and services, although the distributions change somewhat and overlap between targeted and non-targeted distributions for some economies (e.g., Australia and New Zealand). It must be noted, however, that this is a mere (even if strong) association. In particular, the pattern does not indicate whether: (i) IP systematically targets *ex-ante* less productive firms/sectors (e.g. to correct a market failure); (ii) IP is, in fact, *ex-ante* mis-targeted, or if (iii) firms become *less* productive after an IP intervention (e.g. due to capital, credit misallocation or other distortions).

Most economies in the sample appear to experience a *decline* in the median productivity of the firms in the targeted sector following an IP intervention. Looking at the pattern on the distribution of firms two years *preceding* the first IP intervention, and *after* the intervention, suggests a generalized shift of the mass of firms toward the left, implying a loss in average productivity. Moreover, the median firm TFP of IP-targeted firms before, during, and after the IP intervention sees a decline in median productivity including until three years after the

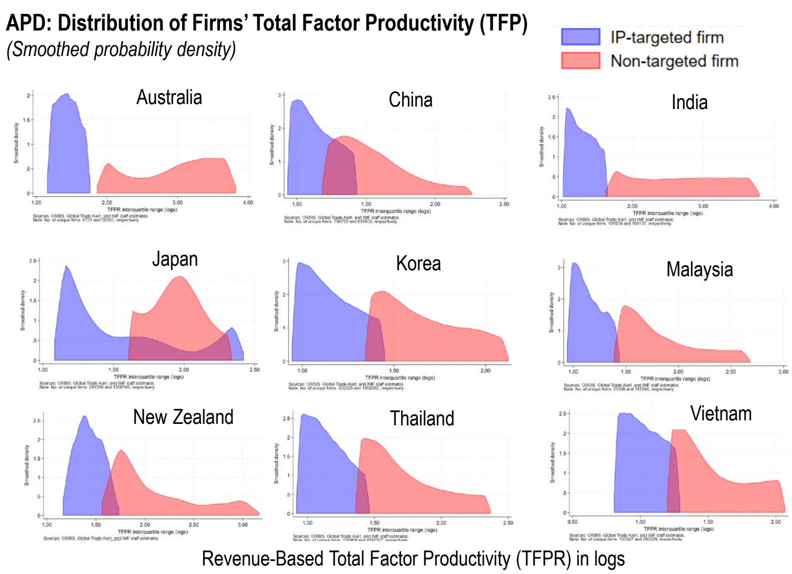
[36] This would also be consistent with a large share of IP strategies focused on low-RCA products, as identified in [IP Paper 1]. About a 30 percent of IP interventions in the region is consistent with a strategy targeting *moonshots* (strategic and relatively sophisticated products, often tradeable, but for which the economy has low RCA). Some 25 percent of the IP interventions in the region are associated to safe bets (products with high RCA, often strategic, but closer to the economy's export and production basket). In addition, about twenty percent of IP measures are applied to products/sectors with low RCA and that are likely facing market failures/frictions and/or have high connectivity in the domestic production network (but may not be tradable, e.g., transport services). Finally, about 25 percent of IP measures have low RCA, and do not have a clear rationale based on the metrics used to identify implicit IP strategies but might be pursuing diverse unidentified objectives that are not directly related with structurally transforming the economy (e.g., sustaining employment in the industrial sector).

[37] Targeted firms are those facing at least one IP intervention in their 4-digit industry in their lifetime over the sample horizon, while untargeted firms are those that never experience an IP intervention over the sample horizon.

intervention. While this pattern does not demonstrate causality, from this vantage point, there is no evidence of a systematic productivity catch-up across economies, at the aggregate level, linked to IP.

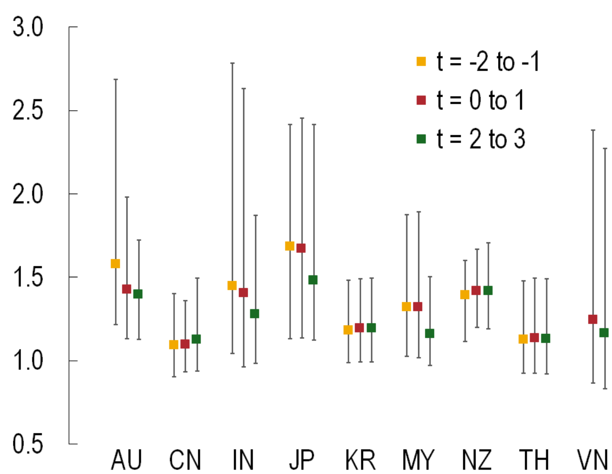
Figure 6. Distribution of Firms' Total Factor Productivity: Targeted vs Untargeted Firms

A. Asia-Pacific: Distribution of Firms' Total Factor Productivity-Revenue (TFP)
(Smoothed probability density)



Sources: Global Trade Alert, ORBIS, and IMF staff estimates.
Notes: Industrial Policy (IP) interventions mapped at the NACE 4-digit level to ORBIS for the period 2009-2022. TFPR estimation follows Ackerberg, Caves & Frazer (2015) and Diez et al. (2021). Chart x-axis shows interquartile range of log(TFPR) for each group of firms in a given country.

B. Distribution of Firms' Total Factor Productivity: Before and After First IP Intervention (t=0)
(In log(TFPR), median (dot) with whiskers (25th and 75th percentiles))



Sources: Global Trade Alert (GTA), ORBIS and IMF staff estimates.

Notes: Industrial Policy (IP) interventions mapped atr the NACE-4-digit level to ORBIS for the period 2009-2022. TFPR estimation follows Ackerberg, Caves & Frazer (2015) and Diez and others (2021). Chart y-axis shows the median, 25th and 75th percentiles of log(TFPR) computed for each intervention timing.

Evidence also suggests that when productivity changes take place in IP-targeted firms, these generally do not seem to be associated with technological improvements. The analysis relies on a dynamic Olley-Pakes decomposition of the total change in the aggregate TFP of IP targeted firms over 2015-2019—as per Melitz & Polanec (2015) and Diez, Fan, and Villegas-Sanchez (2021).[38] This allows to assess the contributions from incumbent firms improving their own technology ("*within firm component*"), incumbent firms gaining market share ("*reallocation component*"), as well as that from firms entering and/or exiting the market. The decomposition (Table 4) shows mixed results, with some large contributions from incumbent firms' improving their technology but also reverse impacts in some other economies. Importantly, TFP changes in firms that are non-targeted by IP appear to be larger. While the picture is mixed across economies in the region, the positive changes in aggregate TFP among non-IP targeted firms are large (relative to IP-targeted firms), often partly driven by improvements in firms' technology.

In sum, IP targeting does not appear to be associated with improved domestic firm outcomes in Asia-Pacific via productivity changes in a systematic or meaningful way. While not claiming causality, the findings raise the question whether IP is ex-ante in fact mistargeted, systematically reaching less productive firms, for example due to mismeasurement or misperception of the relative productivity of industries, or for motivations other than to promote structural transformation.

Table 4. Heatmap: Decomposition of Change in Aggregate Productivity 2015-19

	IP-Treated					No-IP Treatment				
Country	Incumbent technology	Incumbent gaining market share	Entrant	Exitor	Total change in TFP *(In percent)*	Incumbent technology	Incumbent gaining market share	Entrant	Exitor	Total change in TFP *(In percent)*
Australia	-0.51	3.08	-0.56	-0.44	1.57	0.93	-0.18	9.09	-0.35	9.49
China	2.08	0.67	-1.24	4.12	5.63	0.44	1.68	-1.26	11.26	12.12
India	1.85	-1.07	-0.70	0.76	0.83	1.95	0.29	0.43	-0.60	2.07
Japan	1.21	-0.23	-0.11	-0.29	0.59	1.12	0.44	0.80	-0.91	1.45
South Korea	0.32	-0.30	0.00	0.11	0.12	0.82	-1.06	0.65	0.36	0.77
Malaysia	-0.99	-1.78	-0.09	-0.14	-3.00	0.57	-1.87	0.54	-1.50	-2.25
New Zealand	-2.53	-3.22	-2.46	17.00	8.80	0.40	-0.96	1.98	1.26	2.68
Thailand	0.93	-0.26	-0.67	-0.03	-0.03	1.01	0.28	0.36	-0.97	0.68
Vietnam	1.17	-0.24	2.27	0.57	3.77	0.08	1.12	-0.33	-0.42	0.44

(green)	Contributes Positively
(orange)	Contributes Negatively

Source: ORBIS Database and IMF Staff Estimates.

The paper now explores the association of IP with both productivity and production inputs (capital and labor) in the average firms in the region—seeking to detect any durable shifts. The approach continues to rely on the LPDiD framework, which allows us to follow an average firm in a sector "treated" by IP, relative to the average firm in a "non-treated" sector that serves as a control group.[39] In terms of instruments, the analysis focuses on the three main levers used in the region: domestic subsidies, import-restricting measures and export incentives, chosen given their current or historical prevalence in our IP dataset. Potential effects are assessed across three outcome variables: TFP, and two main factors of production (employment and capital). We note that the analysis is conducted at the industry level, examining the industry-average capital, employment, and TFP. As a result, the effects could reflect a combination of within-firm effects and between-firm distributional effects. For

[38] The period is chosen due to data limitations and to abstract from the COVID shock.

[39] Specifically, the approach allows to follow a specific average firm in a 2-digit NACE sector, whose (4-digit) industry gets "treated" by IP relative to a firm in a "non-treated" industry that serves as a control group. LPDiD regressions are run with the treatment being a discriminatory IP intervention, while also controlling for liberalizing IP interventions and other fixed effects and lags.

example, a negative effect on employment and capital could reflect that IPs—for example, subsidies—increase the number of small firms rather than a reduction in employment and capital in larger firms. We also caution that, given the complex nature of IP targeting as found in the analysis above, the empirical analysis would not be able to fully address endogeneity concerns. Therefore, the results should not be interpreted as establishing causal relationships.

The analysis delivers four main findings (Figure 7):

- ***First, for the Asia-Pacific sample, the association of IP with domestic firm outcomes (productivity, capital and labor) is mixed and generally insignificant.*** Across policy tools and outcome variables, none of the results are significant nor aligned with what may be perceived as a possible IP objective, such as raising productivity, or triggering an increase in production inputs and—therefore—output. Regression results show that TFP of the average targeted firm falls when export incentives are put in place, and the effect is transitorily significant; domestic subsidies and import measures have slightly positive effects on TFP, but these are largely insignificant. In the case of employment, domestic subsidies have a particularly negative and significant effect, while the impact of the other two IP tools (i.e., export incentives and import restrictions) is not statistically significant. Finally, there is no significant effect across policy levers on capital, except for a negative effect on domestic subsidies.

    - ***AEs in the region, however, show some positive—albeit transitory—associations in response to domestic subsidies; other IP tools appear ineffective.*** Domestic subsidies are linked to a—somewhat delayed—increase in both employment and capital in targeted sectors' firms in AEs. However, this does not appear to be durable: the lift takes at least two years to appear and loses significance by the fifth year. Other IP tools (export incentives and import-limiting measures) show no significant associations with TFP or production inputs. Notably, AEs in the RoW do *not* seem to experience any significant increase in capital and/or labor after being targeted by domestic subsidies, even on a temporary basis.

- ***Second, firms in Asia-Pacific EMs tend to see significantly negative associations with IP.*** In contrast with the relationships observed in AEs from domestic subsidies—i.e., a temporary increase in capital and labor in targeted sectors—the same tool seems to trigger a reduction of employment and capital in the average targeted firm for EMs. Separately, import-restricting measures lead to a long-lasting effect lowering average TFP for EMs, suggesting that import-substitution type of policies may have more detrimental effects on productivity for EMs, without the possible offset of increasing the factors of production.

    - ***EMs in Asia-Pacific in fact tend to see more negative effects from IP than their RoW peers.*** Asia-Pacific EMs display larger and more significant negative effects in TFP, employment and labor in response to domestic subsidies and import measures than EMs in the RoW. Domestic subsidies generate a temporary, yet significant, reduction in employment and capital of targeted firms, while import-limiting measures trigger a significant and durable deterioration of TFP.

    - ***IP on relatively more complex products—particularly implemented via "safe-bets" and "moonshot" strategies—appear to be associated with an increase in capital in targeted sectors.*** The focus is on examining whether some of the IP strategies identified earlier on in this paper bear any effect on firm-level data outcomes. The analysis is based on the two dominant characteristics for *moonshots* and *safe-bets*—namely, product complexity, and RCA—into the product space. The "*moonshots*" products are identified as those with higher complexity products for which the economy does not have RCA; "*safe-bets*" are those with higher complexity products, for which the economy already has RCA; the remaining interventions are taken as a residual set (Table 5).

Results show that IP targeting moonshots and safe-bets—either via export incentives or domestic subsidies—are associated with durable effects: both seem to be followed by a long-lasting and significant expansion in capital. On the other hand, the effects of IP on employment is mixed across tools; this may be linked to an increase in capital intensiveness induced by IP. Finally, the effects on TFP are, once more, not significant—one possibility is that TFP effects to produce relatively higher complexity products takes longer to acquire and hence it is not visible in the timeframe of the exercise. Another alternative is that IP support delivers on scaling up production by raising inputs (particularly via capital increases) but does not necessarily trigger technological or productivity changes.

Table 5. Mapped IP Strategies

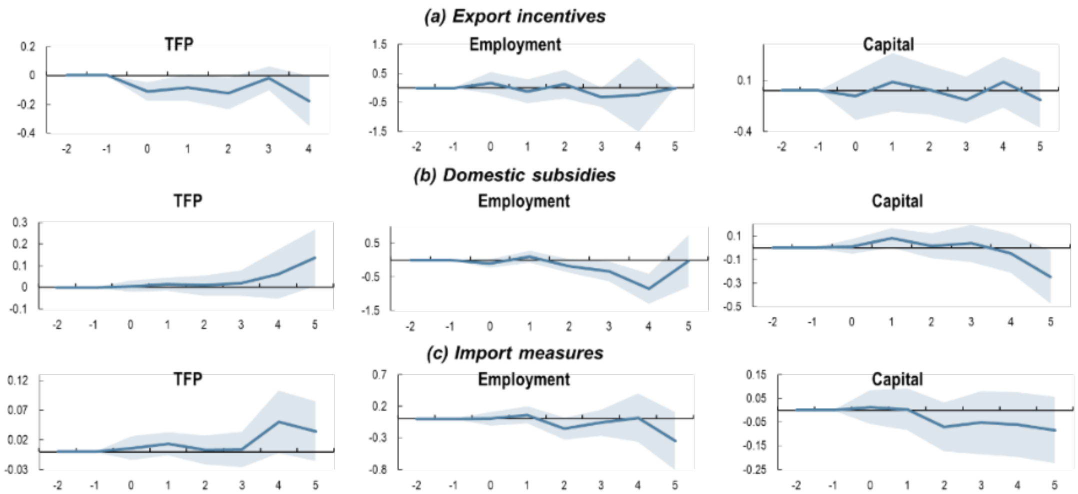
Cluster characteristics

Cluster label		Defining product/sector characteristics	
		Above-average complexity?	Revealed comparative advantage?
	Moonshots	✓	✗
	Safe bets	✓	✓

The trade/competitiveness results presented in section VI and the firm-performance dynamics just discussed are not necessarily inconsistent, and differences could be due to composition/heterogeneity effects. One may wonder how to reconcile the trade/competitiveness results with the firm-level dynamics. While a full reconciliation is difficult given the differences between datasets, a common challenge in the literature, we note channels which could reconcile the findings. For example, we find IP measures (export incentives and domestic subsidies) are followed by increased exports—though not always and not durably—but at firm level we see no improvements in employment, capital, or TFP. Similarly, domestic subsidies reduce imports, while at firm level employment and capital tend to decline and TFP improvements only materialize over the medium term in some economies. These results are not necessarily internally inconsistent, and could be due to composition/heterogeneity effects (e.g., specific products/sectors, intensive versus extensive export margins, etc.). It is important to note that the two analyses are conducted at different levels of granularity: the trade/competitiveness analysis provides product-level evidence whereas the firm-performance analysis is conducted at the industry level. In particular, export incentives and subsidies can boost exports through (i) intensive-margin expansion by existing exporters (higher utilization/working-capital relief), and/or (ii) price-competitiveness and reallocation effects (market share shifting toward more export-oriented firms), which can raise aggregate exports even if average employment, capital, and measured TFP in the median firm respond only with a lag. For domestic subsidies, the improvements in domestic outcomes are mostly statistically insignificant within the medium-term time horizon focused in the paper, potentially reflecting the large heterogeneity across industries, firm types, intervention design, and other dimensions and the fact that it takes longer to build domestic capacity, especially for products that are not produced at scale domestically. As a result, these insignificant results are not necessarily in contradiction with the decline in imports. The short-run declines—though not statistically significant—in employment and capital could reflect adjustment and restructuring, and the delayed TFP improvement is consistent with implementation/learning lags as firms retool and reorganize production.

Figure 7. Impact of IP – Firm Level Data

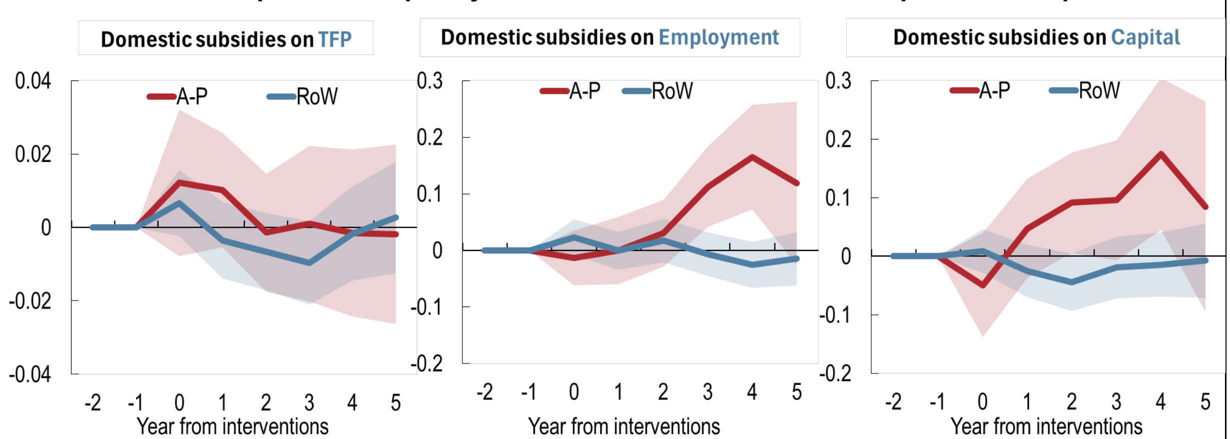
A. *A-P: Impact by Tool on Domestic Outcomes (Whole Sample): Aggregate results are mixed*



Sources: Orbis database, GTA database, and IMF staff calculations.

Notes: Each chart shows the estimations from a difference-in-difference local projection model regressing industry-average TFP, employment and capital value on the presence of corresponding discriminatory industrial policies at the country-product level, with controls including the presence of other IP tools, lagged exports (in log term), country-industry, industry-year and country-year fixed effect and the effect assuming to stabilize in two years. Shaded areas show the 95 percent confidence intervals.

B. *A-P AEs show some positive temporary effects for domestic subsidies on production inputs*

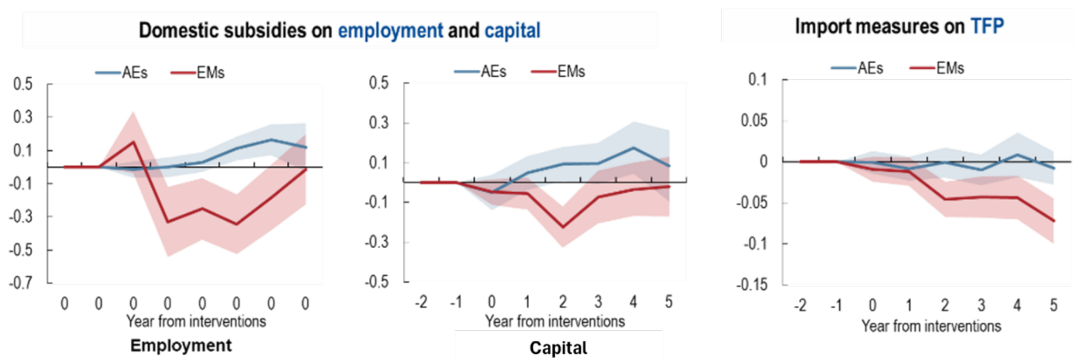


Sources: Orbis database, GTA database, and IMF staff calculations.

Notes: Each chart shows the estimations from a difference-in-difference local projection model regressing industry-average TFP, employment and capital value on the presence of discriminatory domestic subsidies at the country-product level, with controls including the presence of other IP tools, lagged exports (in log term), country, industry and year fixed effect and the effect assuming to stabilize in two years. Shaded areas show the 95 percent confidence intervals.

Figure 7. Impact of IP – Firm Level Data (Concluded)

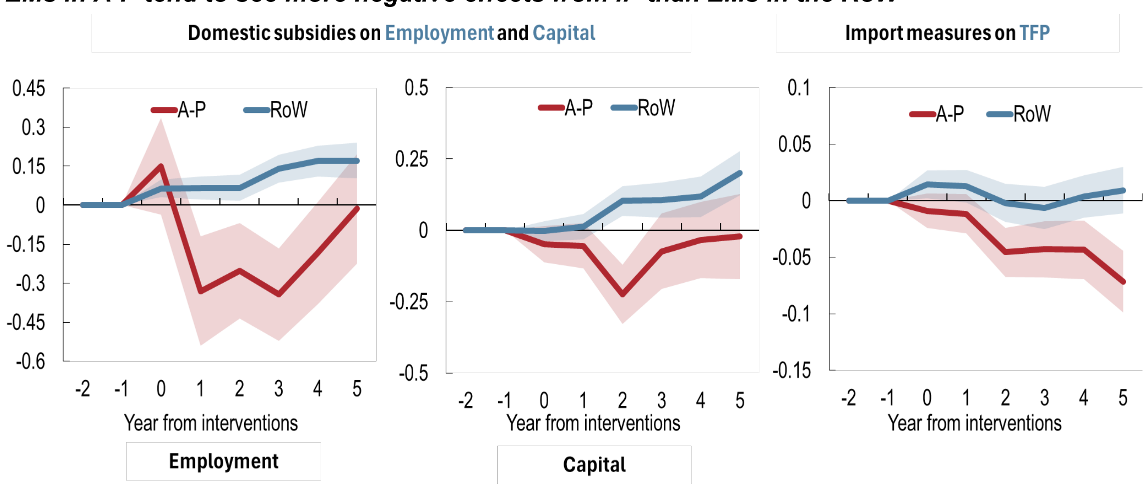
C. EMs in A-P tend to see more negative effects from IP than the region's AEs



Sources: Orbis database, GTA database, and IMF staff calculations.

Notes: Each chart shows the estimations from a difference-in-difference local projection model regressing industry-average TFP, employment and capital value on the presence of corresponding discriminatory industrial polocies at the country-product level, with controls including the presence of other IP tools, lagged exports (in log term), country, industry and year fixed effect and the effect assuming to stabilize in two years. Shaded areas show the 95 percent confidence intervals.

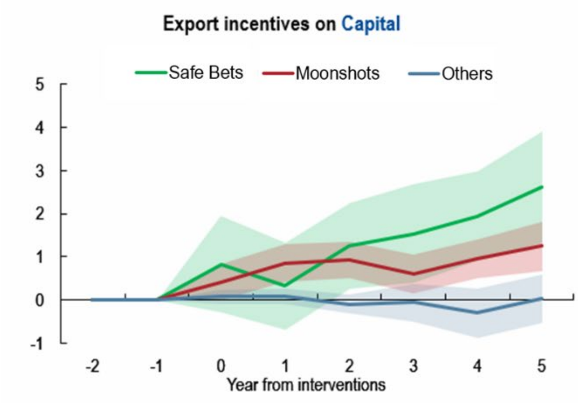
D. EMs in A-P tend to see more negative effects from IP than EMs in the RoW

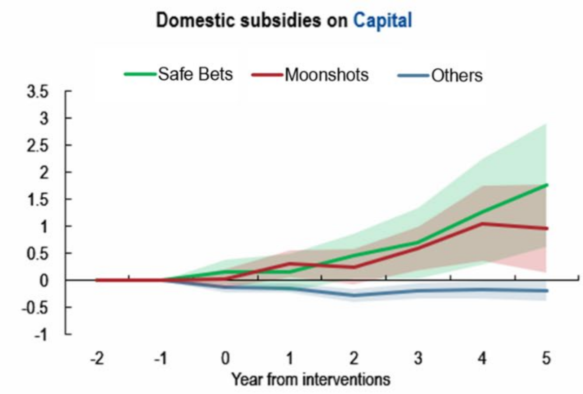


Sources: Orbis database, GTA database, and IMF staff calculations.

Notes: Each chart shows the estimations from a difference-in-difference local projection model regressing industry-average TFP, employment and capital value on the presence of corresponding discriminatory industrial policies at the country-product level, with controls including the presence of other IP tools, lagged exports (in log term), country, industry and year fixed effect and the effect assuming to stabilize in two years.. Shaded areas show the 95 percent confidence intervals.

E. IP targeting more complex products in the region appears to deliver a durable increase in capital





Sources: Orbis database, GTA database, and IMF staff calculations.

Notes: Each chart shows the estimations from a difference-in-difference local projection model regressing industry-average TFP, employment and capital value on the presence of corresponding discriminatory industrial policies at the country-product level, with controls including the presence of other IP tools, lagged exports (in log terms), country, industry and year fixed effect and the effect assuming to stabilize in two years. Shaded areas show the 95 percent confidence intervals.

VIII. Conclusion

Over the last decade, IP has increasingly been used in Asia-Pacific. A systematic and comprehensive assessment of these interventions and their potential for promoting structural transformation suggests several takeaways.

- **First, IP interventions in the region are diverse in means and target characteristics, with tool choice pointing to an inward-looking lean.** The region tends to target different types of products through a range of tools, mostly serving the industry/manufacturing sectors, especially in products with no revealed comparative advantage. Like in the RoW, many of the interventions seem inward-oriented, rather than focused on promoting exports (and trade more generally). The region also tends to layer different types of IP interventions significantly more heavily than the RoW, which risks opacity and lack of effectiveness if the various measures work at cross-purposes.

- **Second, Asia-Pacific economies' IP target choices could align with strategies that could potentially unlock structural transformation, from an ex-ante point of view**: a relatively large fraction (about three quarters) of the IP interventions in the region target *moonshots* and *safe-bet* products—all with relatively high complexity—and/or sectors that are *strong connectors in the domestic production networks, and/or appear to have market imperfections.*

Broadly, we do not find evidence that IP is systematically associated with delivering durable effects that could bring structural transformation in Asia-Pacific. Economies' IP in the region have, at times, been associated with positive effects—for instance, to trigger an increase in export values and/or competitiveness in targeted products, and/or to generate a shift in at least some inputs of production toward firms in targeted sectors. However, the effect is not systematic—and rather limited to specific cases. Moreover, it also tends to lack durability, which raises questions about the underlying mechanisms making IP appear effective. Putting methodological caveats related to causality aside, even if some tools geared at fostering exports/competitiveness appear to generate a boost, the fact that it is often only temporary suggests that it may be the result of financial assistance temporarily lowering costs (and pricing) for specific products, rather than structural changes in production or market structures that lift productivity and/or competitiveness. Notably, some of the few cases of durable effects identified in the analysis—both at macro and firm-level—point at positive results in East Asian AEs. While an in-depth case study of these economies is outside the scope of this paper, they suggest, together with our preliminary analysis differentiating weaker from stronger government effectiveness economies, that solid institutional frameworks, and past experience of generating positive results from IP (e.g., during the 20th century Miracle Economy period) could be factors making IP more "effective" (at least for some specific tools such as domestic subsidies).

Finally, the results underscore the need for proceeding cautiously with IP in the region, and to press ahead with needed horizontal structural reforms to strengthen institutional frameworks. Given the large-scale IP increasingly deployed for at least fifteen years, the lack of systematic empirical evidence on gross benefits related to structural transformation is striking. It is important to note that policymakers may have other objectives in mind which we do not assess. While estimating the cost of the implemented IP deployed so far is out of the scope of this paper, such costs will need to be balanced against the modest evidence of gains through structural transformation, alongside perceived gains in other dimensions (also not covered in this paper). This heightens the case for a careful and parsimonious deployment, based on a thoughtful design, well-justified by the need to address market failures, and backed by a solid cost-benefit analysis. Finally—and importantly—results confirm the need to complement IP with broad horizontal structural reforms and strengthening institutional frameworks and government effectiveness (in line with Baquie and others 2025, IMF 2025), as this may support IP effectiveness and even obviate the need for IP altogether.

Annex I. Technical Annex

The list of jurisdictions and breakdown of Industrial Policy tools by category, following the MAST classification from the GTA database (with few exceptions) are shown in Table A1 and A2.

Table A1. List of Jurisdictions

Asia-Pacific (31 jurisdictions)	**Rest of the World (165 jurisdictions)**		
Australia	Afghanistan	Albania*	Algeria*
Bangladesh	Angola*	Anguilla	Antigua and Barbuda*
Bhutan	Argentina*	Armenia*	**Austria**
Brunei Darussalam*	Azerbaijan*	Bahamas, The*	Bahrain*
Cambodia	Barbados*	Belarus*	**Belgium**
China*	Belize*	Benin	Bermuda
Fiji*	Bolivia*	Bosnia and Herzegovina*	Botswana*
Hong Kong SAR	Brazil*	Bulgaria*	Burkina Faso
India*	Burundi	Cabo Verde	Cameroon
Indonesia*	**Canada**	Cayman Islands	Central African Republic
Japan	Chad	Chile*	Colombia*
Korea	Comoros	Congo, Republic of	Costa Rica*
Lao P.D.R.	Croatia*	Cuba	**Cyprus**
Malaysia*	**Czech Republic**	Côte d'Ivoire	Democratic Republic of the Congo
Maldives	**Denmark**	Djibouti	Dominica
Mongolia*	Dominican Republic*	Ecuador*	Egypt*
Myanmar	El Salvador*	Equatorial Guinea*	Eritrea
Nauru*	**Estonia**	Eswatini*	Ethiopia
Nepal	Faeroe Islands	Falkland Islands	**Finland**
New Zealand	**France**	Gabon*	Gambia, The
Papua New Guinea	Georgia*	**Germany**	Ghana
Philippines*	**Greece**	Grenada	Guam
Samoa	Guatemala*	Guinea	Guinea-Bissau
Singapore	Guyana*	Haiti	Honduras
Solomon Islands	Hungary*	**Iceland**	Iran*
Sri Lanka*	Iraq*	**Ireland**	**Israel**
Taiwan Province of China	**Italy**	Jamaica*	Jordan*
Thailand*	Kazakhstan*	Kenya	Kuwait*
Tonga	Kyrgyz Republic	**Latvia**	Lebanon*
Vanuatu	Lesotho	Liberia	Libya*
Vietnam*	**Lithuania**	**Luxembourg**	Madagascar
	Malawi	Mali	**Malta**
	Mauritania	Mauritius*	Mexico*
	Moldova	Montenegro, Rep. of*	Montserrat

Asia-Pacific (31 jurisdictions)	Rest of the World (165 jurisdictions)		
	Morocco*	Mozambique	Namibia*
	Netherlands	New Caledonia	Nicaragua
	Niger	Nigeria*	North Macedonia*
	Norway	Oman*	Pakistan*
	Panama*	Paraguay*	Peru*
	Poland*	**Portugal**	Puerto Rico
	Qatar*	Romania*	Russia*
	Rwanda	Saudi Arabia*	Senegal
	Serbia*	Seychelles*	Sierra Leone
	Slovak Republic	**Slovenia**	Somalia
	South Africa*	South Sudan	**Spain**
	St. Kitts and Nevis*	St. Lucia	St. Vincent and the Grenadines
	Palestine	Sudan	Suriname*
	Sweden	**Switzerland**	Syria*
	São Tomé and Príncipe	Tajikistan	Tanzania
	Togo	Trinidad and Tobago*	Tunisia*
	Turkey*	Turkmenistan*	Turks & Caicos Islands
	US Virgin Islands	Uganda	Ukraine*
	United Arab Emirates*	**United Kingdom**	**United States of America**
	Uruguay*	Uzbekistan	Venezuela*
	Yemen	Zambia	Zimbabwe

Note: Economy groupings follow the IMF World Economic Outlook classification. Advanced economies are shown in bold and emerging market economies are marked with an asterisk.

Table A2. List of Intervention Tools

Classification in Paper (9 categories)	Share (% out of APD Total)	MAST Classification	Share (% out of APD Total)	Intervention Type	Share (% out of APD Total)	Scoring for export promoting index *(see note)*	Scoring for import reducing index *(see note)*
1. Import measures (incl. anti-dumping)	26.1	D1 Antidumping	4.1	Anti-circumvention	0.1	0	1
				Anti-dumping	4.0	0	1
		D2 Countervailing measure	0.4	Anti-subsidy	0.4	0	1
		E1 Non-automatic import-licensing procedures other than authorizations for SPS or TBT reasons	1.8	Import licensing requirement	1.8	0	1
		E2 Quotas	0.8	Import quota	0.8	0	1
		E3 Prohibitions other than for SPS and TBT reasons	1.2	Import ban	1.2	0	1
		E6 Tariff-rate quotas (TRQ)	1.0	Import tariff quota	1.0	0	1

Classification in Paper (9 categories)	Share (% out of APD Total)	MAST Classification	Share (% out of APD Total)	Intervention Type	Share (% out of APD Total)	Scoring for export promoting index *(see note)*	Scoring for import reducing index *(see note)*
		F7 Internal taxes and charges levied on imports	1.4	Internal taxation of imports	1.4	0	1
		Tariff measures	15.4	Import tariff	15.4	0	1
2. FDI and capital flow measures	4.1	Capital control measures	0.8	Control on personal transactions	0.0	0	0
				Controls on commercial transactions and investment instruments	0.6	0	0
				Controls on credit operations	0.1	0	0
				Repatriation & surrender requirements	0.0	-1	0
		FDI measures	3.1	FDI: Entry and ownership rule	2.0	-1	1
				FDI: Financial incentive	0.6	1	1
				FDI: Treatment and operations, nes	0.6	0	0
		G Finance measures	0.1	Competitive devaluation	0.0	1	1
				Trade payment measure	0.1	-1	1
		I2 Trade-balancing measures	0.0	Trade balancing measure	0.0	1	1
3. Local content measures	2.6	I1 Local content measures	2.6	Local content incentive	0.3	0	1
				Local content requirement	0.3	0	1
				Local labor incentive	0.1	0	1
				Local labor requirement	0.1	0	1
				Local operations incentive	0.0	0	1
				Local operations requirement	0.3	0	1
				Local value-added incentive	1.4	0	1
				Local value-added requirement	0.0	0	1
				Localization, nes	0.1	0	1
4. Non-tariff barriers to trade (incl. safeguards)	0.8	B Technical barriers to trade	0.0	Technical barrier to trade	0.0	0	1
		C4 Import monitoring, surveillance and automatic licensing measures	0.0	Import monitoring	0.0	0	1
		D31 General (multilateral) safeguard	0.7	Safeguard	0.7	0	1
		D32 Agricultural special safeguard	0.1	Special safeguard	0.1	0	1

Classification in Paper (9 categories)	Share (% out of APD Total)	MAST Classification	Share (% out of APD Total)	Intervention Type	Share (% out of APD Total)	Scoring for export promoting index (see note)	Scoring for import reducing index (see note)
5. Other measures	2.6	Instrument unclear	1.6	Import-related non-tariff measure, nes	1.2	0	1
				Instrument unclear	0.4	0	0
		Migration measures	1.0	Labor market access	0.9	0	0
				Post-migration treatment	0.1	0	0
		N Intellectual Property	0.0	Intellectual property protection	0.0	0	0
6. Domestic subsidies	47.9	L Subsidies (excluding export subsidies under P7)	47.9	Capital injection and equity stakes (including bailouts)	1.4	0	0
				Financial grant	34.9	0	0
				Import incentive	0.1	0	-1
				In-kind grant	0.2	0	0
				Interest payment subsidy	0.5	0	0
				Loan guarantee	0.8	0	0
				Price stabilization	0.6		
				Production subsidy	1.2	0	0
				State aid, nes	0.2	0	0
				State aid, unspecified	2.6	0	0
				State loan	2.6	0	0
				Tax or social insurance relief	2.7	0	0
7. Public procurement	1.1	M1 Government Procurement Market Access Restrictions	0.1	Public procurement access	0.1	0	1
		M2 Government Procurement Domestic Price Preference	0.1	Public procurement preference margin	0.1	0	1
		M3 Government Procurement Local Content Requirement	0.8	Public procurement localization	0.8	0	1
		M5 Government Procurement Tendering Process	0.0	Public procurement, nes	0.0	0	1
8. Export (limiting) measures	9.2	P3 Export licenses, export quotas, export prohibition and other restrictions other than sanitary and phytosanitary or technical barriers to trade measures	3.2	Export ban	1.0	-1	0
				Export licensing requirement	1.1	-1	0
				Export quota	1.0	-1	0
				Export tariff quota	0.0	-1	0
				Foreign customer limit	0.0	-1	0
		P4 Export price-control measures, including additional taxes and charges	3.0	Export tax	3.0	-1	0

Classification in Paper (9 categories)	Share (% out of APD Total)	MAST Classification	Share (% out of APD Total)	Intervention Type	Share (% out of APD Total)	Scoring for export promoting index *(see note)*	Scoring for import reducing index *(see note)*
		P9 Export measures, nes.	3.0	Export-related non-tariff measure, nes	0.4	-1	0
				Financial assistance in foreign market	2.5	1	0
				Local supply requirement for exports	0.1	-1	1
9. Export incentives	5.7	P6 Export-support measures	5.7	Export subsidy	0.2	1	0
				Other export incentive	0.6	1	0
				Tax-based export incentive	1.1	1	0
				Trade finance	3.7	1	0

II. Complementary Data and Indicators

Base pour l'Analyse du Commerce International (BACI) - CEPII. Includes sectoral export and import values for each economy, annually, at the HS6-digit level, until 2022. Because the BACI database uses the 1992 vintage classification, a v1992 to v2012 conversion table is needed to convert it into the 2012 vintage classification used in the GTA database. Because the 2012 vintage is more granular, some 1992 product codes correspond to several different 2012 codes. This creates duplicates from the vintage 1992 point of view, which are dropped for further analysis (in other words, an intervention that was affecting several products under the 2012 vintage that corresponds to only a single product under the 1992 classification is summarized in only one line in the merged database).

- The products that are in the GTA database (targeted by some IP) but not in BACI are not kept in the merged database, as these products are presumably not traded. Information on products that are in BACI (i.e. traded) in some years, but not in the GTA database (i.e., not targeted by IP) are kept, as these are part of the control (untreated) groups in the local projection regressions, and are assigned zero values for the IP part. This is kept only in the years in which we have BACI data, not assuming any trade values for the years in which information is missing, which leads to unbalanced panels for both exports and imports.

- Using BACI export values, the analysis computes Revealed Comparative Advantage (RCA), which is then used to construct measures of product relatedness and distance. Product relatedness is a product-level measure that captures the likelihood that two products are co-exported globally with RCA>1, following the product-space methodology of Hausmann and Klinger (2006), Hidalgo and others. (2007) and its implementation in Fortunato, Razo, and Vrolijk (2015). Distance is a economy–product–year measure that aggregates these product relatedness values to capture how close a product is to an economy's existing export capabilities.

Production Network Centrality – OECD ICIO. The analysis uses sector-level production-network centrality indicators calculated by Georgieva (2025a). These measures are derived from the OECD Inter-Country Input–Output (ICIO) tables, which provide harmonized economy–industry transaction matrices. Using these IO linkages, Georgieva computes eigenvector centrality, a standard network metric capturing how strongly each sector is connected to other highly connected sectors.

Product Complexity Index (PCI) – Hausmann & Hidalgo (2011). The PCI follows the methodology of the Hausmann–Hidalgo Atlas of Economic Complexity, which uses global trade patterns to infer the capability content of each product. It reflects both the diversity of economies exporting a product and the sophistication of their export baskets. The paper uses the HS-4 (HS-1992) PCI values for 1995–2021 to characterize product sophistication.

Upstreamness – Antràs and others. (2012), based on GTAP Input–Output Tables. Upstreamness is obtained from the Global Trade Analysis Project (GTAP) input–output tables and constructed following Antràs and others, (2012). This indicator measures a sector's average distance from final demand in the value chain, with higher upstreamness reflecting a greater reliance on downstream industries to reach final consumers.

Markups – Orbis (Bureau van Dijk), estimated using Ackerberg, Caves & Frazer (2015). Sector-level markups are constructed from Orbis firm-level financial data and estimated using the production-function approach of Ackerberg, Caves, and Frazer (2015). The industry-level markup measures used in the paper follow the implementation prepared in Baquie and others. (2025).

External Financial Dependence (EFD) – Orbis (Bureau van Dijk), following Rajan-Zingales (1998). EFD captures sector-level financing needs. In this paper, EFD is based on the implementation developed in Baquie and others. (2025), who construct it using Orbis firm-level data following the Rajan–Zingales approach.

Distortion Centrality – Liu (2019), using Orbis, GTAP IO Tables and Rajan-Zingales (1998). Distortion-centrality indicators combine Orbis-based markups or external financial dependence with GTAP input–output linkages, applying the production-network methodology of Liu (2019). This generates sector-level measures of how distortions in a sector propagate through the production network. The paper uses the distortion-centrality series constructed in Baquie and others. (2025).

III. Machine Learning: A Random Forests Approach

The ML exercise employs widely-used tree-based ML classifiers, given that they can capture complex, nonlinear relationships while remaining relatively transparent compared to many other models. In particular, random forests are chosen.

Random forests (Breiman, 2001) consist of many decision trees in an ensemble. A decision tree (Breiman and others., 1984) partitions the predictor space by asking a sequence of binary questions. Starting from all observations at the root, the algorithm chooses a split on one predictor that best separates the data into two binary outcome groups according to a criterion such as Gini impurity or information gain. Each split divides the data into more homogeneous nodes with respect to the outcome (for example, targeted by IP interventions vs. not targeted). This splitting process continues until some stopping rule is reached (minimum node size, maximum depth, or lack of further improvement). The terminal nodes (leaves) contain predicted outcome probabilities, and classification is done by assigning new observations to the leaf they fall into and taking the majority class in that leaf.

Within the ensemble, each tree is estimated on a bootstrap sample of the data, and at each split the algorithm considers only a random subset of the available predictors. This "double randomization" (over observations and variables) decorrelates the trees. Each tree casts a vote for an outcome, and the forest prediction is the majority vote. In expectation, averaging across many diverse trees reduces variance and improves out-of-sample accuracy, while still capturing nonlinearities and high-order interactions without explicit specification.

However, ensembles are less interpretable than a single tree. This is where Shapley values (Strumbelj and Kononenko, 2010; Lundberg and Lee, 2017) are useful. Shapley values originate from cooperative game theory. Consider a game in which several players jointly produce a payoff; the Shapley value assigns to each player their average marginal contribution to the payoff, computed over all possible orders in which players could join the coalition. Translating this to machine learning: the game is the model's prediction for a specific observation; and the players are the predictors. The payoff is typically defined as the difference between the prediction for that observation and a baseline (such as the average prediction over the sample). For a given observation, the Shapley value of a predictor measures how much that feature, on average, changes the prediction when it is added to a set of other predictors. The sum of all predictors' Shapley values equals the difference between the individual prediction and the baseline, which provides an additive decomposition of the prediction into marginal contributions of each predictor.

In the ML exercise, predictors include a product's Hausmann product complexity index, implicit product relatedness (which reflects patterns of co-exporting that signal similar capabilities), distance to an economy's export basket (which captures how a product is interrelated with an economy's own export specialization), centrality in the production or innovation network (which captures the potential spillovers to other products), upstreamness (which captures a product's position within the production process), markups (which captures the extent to which there is market failure), RCA (which captures the product's competitiveness in the global market). The hyperparameters which are tuned include the maximum depth of the trees and the subsample ratio of features to be used when constructing each tree.

IV. Clustering Exercise

The exercise is implemented in three steps: (i) we construct a high-dimensional database of indicators at the product level that reflect various theories; (ii) an a-theoretical algorithm (k-means clustering) is used to partition the IP dataset based on characteristics; and (iii) the generated clusters are assessed against theoretical IP rationales to see if there is any alignment.

The dataset. As in the rest of the analysis, the dataset is defined at the HS 6-digit level; indicators which are defined at the sector level are mapped to product codes using concordance tables (see Annex II). Several variables are winsorized (top and bottom 2.5 percent) for outliers. Most variables are standardized by computing z-scores, excepting lagged and current RCA for which the natural log is used as log(RCA) equal to zero provides the economically meaningful threshold between having (>0) and not having (<0) RCA. Of the about 3.7 million product level observations, we are able map all variables to about 3 million.

The algorithm. The k-means algorithm in Stata is used to partition the dataset into clusters. Briefly, the algorithm takes the number of clusters (k) as a user-specified input and partitions the dataset to minimize a distance measure.

Application. We consider values of k, starting from 2 and working upwards. We settle on k = 6. Note that, in general, the clusters that emerge need to align with any economic theory. As we vary k, the dataset tends to separate along key characteristics from low values of k, such as high/low product complexity versus high/low sector centrality measures. As k increases, these separations persist and separation along high and low RCA also emerges. The test of whether clusters are meaningful is within cluster coherence and clear between-cluster variation. While the algorithm by design will generate however many clusters are allowed, we find that beyond six, the economic distinctions between clusters appear marginal.

Comparison to theory. The clusters are compared against theoretical IP rationales as discussed in the main text. We do this by comparing the distribution of characteristics of the clusters as presented in Figure 4. Given we have multiple indicators that speak to the same rationales, the algorithm generates two similar clusters that align with the tackling market failures and frictions rationale. We therefore pool the observations in these clusters. Similarly, there are two similar clusters that both do not align with any specific rationale. These are then pooled into the undefined cluster, to arrive at the 4 clusters presented in Figure 4.

V. IP and Product Level Trade – Additional Results

The table below shows results of the LPDiD regression looking at the increase in exports/imports of products targeted by IP interventions (relative to untargeted ones), breaking down the sample into a group of “weak” Government Effectiveness (GE) for which this variable is below median (for AP economies, and RoW economies separately), and a group of economies for which the variable is above median. We assign all economies the average value of government effectiveness over the sample period to make sure all economies stay in the same GE group over time (which is needed to keep enough lags necessary for the LPDiD regression), and our proxy for government effectiveness is the Government Effectiveness indicator of the World Bank’s Worldwide Governance Indicators (WGI).

Table A3. Exports and Imports’ Responses to IPs, by Level of Government Effectiveness

	Year after intervention	0	1	2	3	4	5
	Export incentives						
Effect on exports	RoW - Weak GE	9.2	9.5	14.1	5.3	7.8	8.7
	RoW - Strong GE	0.6	5.6	9.3	-4.4	-9.8	-10.4
	Asia Pacific - Weak GE	6.0	16.3	-24.3			
	Asia Pacific - Strong GE	18.7	23.3	12.4	18.1	19.5	58.0
	Domestic subsidies						
Effect on exports	RoW - Weak GE	4.9	5.9	0.6	-3.4	-9.4	-35.9
	RoW - Strong GE	1.4	3.9	4.5	3.9	6.3	7.9
	Asia Pacific - Weak GE	32.8	132.7	54.7	98.0		
	Asia Pacific - Strong GE	5.0	5.2	3.8	7.2	5.7	7.7

	Year after intervention	0	1	2	3	4	5
	Import limiting measures						
Effect on imports	RoW - Weak GE	16.0	15.4	17.2	13.3	15.7	9.6
	RoW - Strong GE	-1.2	-8.6	-13.1	-14.9	-16.6	-1.9
	Asia Pacific - Weak GE	9.1	14.3	-15.0	62.9	72.7	83.7
	Asia Pacific - Strong GE	0.2	-4.0	0.2	10.7	11.0	9.0
	Domestic subsidies						
Effect on imports	RoW - Weak GE	1.0	11.8	12.5	11.3	11.9	15.7
	RoW - Strong GE	3.5	5.6	8.2	4.7	5.2	6.8
	Asia Pacific - Weak GE	5.5	-52.4	-34.2	-16.5		
	Asia Pacific - Strong GE	-0.2	1.0	0.5	0.7	-1.2	-6.0

Note: Table shows effect of IP intervention on exports/imports (coefficient in percent) in each year after the product level IP intervention, highlighted in green and red respectively if the coefficient is significant at the 5 percent level and positive or negative (respectively), and in gray if the coefficient is not significant, for each subgroup breakdown (by level of institutional quality proxied by the WGI indicator on Government Effectiveness, with "weak" and "strong" categories separated by the median by country, calculated separately for AP countries and the RoW). White cells indicate that there were not enough observations for the estimate to be run.

VI. Firm Level Analysis

The paper uses a local projection DiD (LPDiD) design on an economy-industry-year panel, which is a common practice used in the IP literature, including in Baquie, 2025. The specification regresses the long lags of outcome variable on a policy dummy indicating whether the examined industrial policy is in place for a given sector and year. The regressions control for the presence of any other policies in the contemporary period and the previous 2 years, as well as up to 2 lags of the outcome variable. The model includes industry-year, year-economy, economy-industry fixed effects for the baseline analysis for the whole Asia-Pacific. Due to sample size limitations, for all heterogeneity analyses, we include only industry, year and economy fixed effects.

- **Panel: economy-industry-year, LPDiD specification:**
- $y_{c,p,t+h} - y_{c,p,t-1} = \beta_h \, \Delta IP_{c,p,t} + \sum_{l=1}^{2} \theta_{2l} \, y_{c,p,t-l} + \theta_3 \Delta nonIP_{c,p,t} + \theta_3 \sum_{l=1}^{2} \theta_{4l} \, \Delta nonIP_{c,p,t-l} + \alpha_{c,p} + \delta_{c,t} + \rho_{p,t} + \epsilon_{c,p,t}$
  - β_h - coefficient of interest: projected effects of IP h periods after the intervention
  - Controls
  - Up to 2 lags of outcome variable y

- Dummy variable of whether there exists any policies other than the IP in question, $nonIP_{c,p,t-l}$, at present and up to 2 lags historically
- For Asia-Pacific baseline results, included industry-year, year-economy, economy-industry interaction effects
- For heterogeneity analysis within a region, we include only industry, year and economy as fixed effects due to data availability concerns

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