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Industrial Policy Since the Great Financial Crisis

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ABSTRACT This paper extends the New Industrial Policy Observatory (NIPO) dataset from 2009 to 2023 by employing large language model techniques to identify policy motivations. We document widespread industrial policy adoption across advanced and emerging market economies since the Great Financial Crisis, which was implemented primarily through subsidies and trade restrictions. We identify a structural break around 2020, characterized by accelerated policy activity and the emergence of "new industrial policies" motivated by supply chain resilience, national security, and geopolitical concerns, in addition to policies focused on competitiveness and climate objectives, which were already prevalent in previous years. Policies have targeted dual-use and various advanced technology sectors, as well as their upstream inputs, such as critical raw materials and minerals. We find that geopolitical risk and tit-for-tat retaliation have played a greater role in driving industrial policy after 2020, and that this support extends beyond existing sectors of comparative advantage.

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Introduction

Recognizing that private sector initiative alone will not attain societal goals, many governments have increasingly turned to industrial policies, defined here as selective government interventions targeting specific firms, sectors, or geographic regions. This is not the industrial policy of yesteryear, however, as the set of motives for such selective intervention has widened. Moreover, contemporary industrial policy tends not to involve the direct state ownership and control of commercial activities witnessed in the decades after 1945. Along with the considerable sums of public money now being allocated to industrial policy, a matter of potential concern on public finance grounds, there is a need to better understand what steps governments are taking, which economic activity is being favored, whether these interventions are effective, and why.

Unlike monetary and fiscal policy, no agency has been assigned the task of collecting information on industrial policy interventions worldwide. Moreover, there is no alignment on what policy interventions in practice constitute industrial policy. The intertemporal dimension of relevant policy choice is underdeveloped as well—something this research seeks to remedy. In short, current policymaking has moved ahead of the underlying evidential base concerning industrial policy dynamics and their consequences. In these circumstances, the risk of policy mistakes being made is high. Furthermore, in an interconnected world trading system with limited agreement on what constitutes appropriate industrial policy choices, the risk of escalating trade disputes triggered by industrial policy measures is ever present.

In this paper, we introduce a new dataset which is a historical extension of the New Industrial Policy Observatory (NIPO) to the period following the Great Financial Crisis (GFC), which is when monitoring of trade distorting policy intervention by the Global Trade Alert (GTA) began. The NIPO is a monitoring exercise launched as a collaboration between IMF staff and the GTA, and originally covered industrial policy developments from January 2023 onwards (Evenett et al., 2024). The NIPO's definition of industrial policy is sourced from the IMF policy paper *Industrial Policy Coverage in IMF Surveillance—Broad Considerations* (IMF, 2024), that is, any targeted government intervention aimed at developing or supporting specific domestic firms, industries, or economic activities to achieve national economic or noneconomic (e.g., national security, public health, or environmental) objectives.[1] The acronym's reference to "new industrial policy" aims to encompass measures with an emerging and expanding set of objectives, as described in detail below, in addition to more traditional objectives, such as promoting sectoral "competitiveness".

The Historical NIPO (H-NIPO) is constructed by selecting policies recorded by the GTA which meet the above IMF definition of industrial policy, based on two criteria. First, including those measures which have at least one of four potential industrial policy motives, obtained by using NIPO data on motives for the year 2023 as a learning sample and employing a large language model (LLM) to identify motives of GTA policies between 2009-2022 (years for which data is available). Second, including measures targeting certain strategic sectors consistent with modern industrial policy objectives (e.g., advanced technology, low-carbon technology, dual-use products, semiconductors, etc.) based on pre-defined product lists also used in the NIPO. The new dataset is therefore the set of measures which meet either one or both inclusion criteria and covers 2009-2023, including data from the learning sample.

[1] The views expressed in this paper are those of the IMF staff and do not necessarily represent the views of the IMF's Executive Board.

Based on these selection criteria, the H-NIPO encompasses 34,248 distinct policy interventions worldwide and the date at which they were announced, implemented, and possibly withdrawn, between the years 2009-2023. Out of these interventions, 85 percent are trade distortive, meaning they shift conditions of competition in favor of local firms, whereas the remaining 15 percent are liberalizing on a non-discriminatory basis. Around 52 percent of measures are by Advanced Economies (AEs) and the other 48 percent by Emerging Market and Developing Economies (EMDEs). The three most active players, China, the European Union, and the United States, together account for around 53 percent of interventions.

The extended dataset reveals new stylized facts about the post-GFC industrial policy landscape. First, 2020 marks a structural shift with enhanced resort to selective policy intervention. While no doubt triggered in part by the COVID-19 pandemic, the trend extends beyond that global health emergency—the number of new interventions did not diminish as countries started exiting the pandemic. Second, during and after the onset of the GFC the most frequently cited industrial policy motives were competitiveness and climate. Meanwhile, since 2020 new-style industrial policies motivations such as supply chain resilience, national security, and geopolitical concerns have come to the fore. Third, the share of countries implementing trade distorting policies, in particular subsidies, has risen markedly since the GFC. Finally, similar to the NIPO, we find that subsidies were consistently the main instrument for pursuing industrial policies in both AEs and EMDEs over the 2009-2023 period, with trade measures more commonly deployed by EMDEs.[2] AEs and EMDEs have also converged in their use of instruments between 2009-2023, as the share of subsidies decreased from 84 to 75 percent in AEs and rose from 56 to 71 percent in EMDEs, while the share of trade measures increased from 3 to 8 percent in AEs but decreased from 27 to 18 percent in EMDEs.

While improving the competitiveness of selected sectors has long been a staple of industrial policy interventions, the large share of green industrial policies is a more recent phenomenon, consistent with the fact that responses to the 2007-2008 GFC included large green stimulus programs in major economies (Agrawala et al., 2020; IEA, 2020) and similar programs were implemented also in the wake of the COVID-19 pandemic (Meckling, 2025; Rosenbloom and Markard, 2020; Steffen et al., 2020). For example, the 2008 European Recovery Plan included spending directed at improving energy efficiency, investment in clean technology, and spending on green energy such as gas, wind, and carbon capture (European Commission, 2008), and the 2020 European Green Deal and Next Generation EU recovery package emphasized grants and loans to offset the COVID-19 shock while promoting the green and digital transitions (European Commission, 2020). The American Recovery and Reinvestment Act of 2009 included substantial support for clean energy sectors, estimated at around 17% of all direct spending (Popp et al., 2020). This included renewable energy and improving energy efficiency, as well as clean transportation. More recently, the Inflation Reduction Act of 2022 included tax credits for renewable energy, energy efficiency, and electric vehicles. China also implemented significant green stimulus in the wake of COVID-19, with a focus on high-speed rail, electricity networks and water management (Gosens and Jotzo, 2020).

The rise of policies motivated by supply chain resilience, national security, and geopolitical concerns in the post-2020 period can be attributed to a confluence of factors. Widespread, albeit temporary, shortages of essential goods during the COVID-19 pandemic contributed to concerns over supply chain resilience and moves to onshore production. Another major event is the Russian invasion of Ukraine in 2022, which has triggered the reassessment of trade and investment linkages with renewed focus on geopolitical risks, and

[2] Our underlying source, the Global Trade Alert database, does not include regulatory standards, so we can take no position on the potential importance of these policies in this assessment of the evolving global industrial policy landscape.

steps to safeguard the functioning of global value chains in the face of shocks (Hoekman, Mavroidis, and Nelson, 2023).

Turning to our empirical analysis, we study changes in governments' use of industrial policy measures over time and uncover notable shifts in certain determinants around 2020. Firstly, exposure to imports of a given product from geopolitically distant trading partners turns from being negatively correlated to positively correlated with industrial policies targeting that product. This is consistent with calls for derisking having gained traction around that time. Similarly, industrial support by other countries for a given product turns from a negative to a positive driver of policy intervention, consistent with renewed tit-for-tat dynamics. On the other hand, correlation with comparative advantage switches from positive to negative, implying a shift in focus to new and less established sectors. Finally, correlation with the stock of existing industrial policies targeting a given product changes from negative to positive, consistent with the overall acceleration in interventions seen in the data and implying a growing concentration of support for certain favored sectors.

We next unpack these econometric findings by national per capita income levels and by the motives associated with the measures. We find that the post-2020 shift towards the increased use of industrial policies targeting products with higher geopolitical exposure is driven by changes in EMDEs. We further find that the trend for increased concentration of industrial policy measures in sectors with a higher stock of existing support is driven by AEs. Finally, we find that measures motivated by national security and supply chain resilience have a prominent role in accounting for many of the observed shifts in behavior, including those of derisking geopolitical exposure, renewed tit-for-tat dynamics, and increased acceleration and concentration of support.

Related Literature. In recent years several distinct approaches to documenting industrial policy interventions have been developed. The principal differentiator is the underlying source of information on policy intervention. One approach—ours and Juhász et al. (2023) —is based on inventories of policy interventions documented consistently over time deploying the same methodology. The principal inventory in this respect is that assembled by the Global Trade Alert (GTA) team. As of this writing, the GTA database includes records of over 77,700 policy interventions taken since 1 November 2008, the month G20 leaders made public commitments as to the nature of their GFC responses. These interventions include those taken at the subnational (e.g., state or provincial governments), central government, and supranational (e.g., the EU or other blocs such as GCC and Mercosur) levels. Annex I describes in detail the GTA data collection methodology.

The second source is declarations by industrial groups of subsidies received or inferences made from financial statements about below-market rate lending from state bodies, which form the basis of the OECD Manufacturing groups and industrial corporation (MAGIC) database. Version 2.0 of that database contains information on subsidy receipt by 482 industrial groups in 14 high-profile industrial sectors from 2005 to 2022 (OECD, 2025). Although, in principle over 50 economies are covered by the MAGIC database, together China, the EU-27, and the United States account for 61% of the firms in the MAGIC database. Since this database tracks firms and not states, it is possible that a multinational company in the MAGIC database is headquartered in a given country and receives state aid from another country. Incentives for foreign greenfield investments are a case in point.

The third source involves innovative applications of LLMs to published state documents at many levels of government. Fang, Li and Lu (2025) study the industrial policies of China covering 2000-2022 by reviewing some 3 million government documents at the central, provincial, and municipal level. They show that the number of new industrial policies in China rose over time until 2017-2018 where, if anything, a plateau has been followed by a slight decline. Well before 2010 there were declining shares of industrial policy intervention in favor of the agricultural and manufacturing sector, while support for services grew. They also find far fewer industrial policy announcements in the hinterland of China. Ju, Li, and Wei (2025) use LLM tools to assess US industrial policies covering 1973-2022 based on more than 18,000 congressional acts and presidential orders. They find that national security and competitiveness goals are the most prominent, with over 60% of measures being time-bound. They also find a significant impact on firms' stock prices and therefore suggestive evidence of meaningful resource allocation.

There also exist databases focused on specific countries or regions or specific types of policies. For example, the EC State Aid Scoreboard (2000-2022), EC Transparency Database (since 2016) and EC State Aid Case Database (since 2000) record spending by EU member states on state aid and provide information on individual policies. Slattery (2025) records US state-level data on expenditures on new and expanding businesses, such as grants, job training, loans, and tax incentives, such as investment tax credits, as well as firm-level discretionary subsidies, covering 2002-2017.

In addition to differences in underlying information sources, the policies classified as industrial policy vary. Our approach (as described below) includes a specific list of in-scope policy interventions that favor particular firms, sectors, or technologies. The OECD MAGIC database focuses on a particular subset of state aid. Juhász et al. (2023), to the best of our knowledge, classify a policy intervention in the GTA database as industrial policy if the GTA description of that policy reveals central government action intended to alter the composition of national economic activity by making use of selective policy intervention. Subnational government interventions are excluded, as are corporate declarations of subsidy receipt (a clear point of distinction with the MAGIC database). For their part, Fang, Li and Lu (2025) include regulatory measures affecting product markets such as health and technical standards, which are excluded from the GTA. These different approaches complement each other and jointly allow for a better understanding of industrial policy use.

The pervasive use of industrial policy of course predates our period of analysis, particularly in some large EMDEs with well-recognized data limitations on subsidies and other state interventions. In these cases, indirect methods can be useful to study the resulting distortions (Hsieh and Klenow, 2009; Rotunno, Ruta and Verma, 2025).

This paper is closely related to Juhász et al. (2023) who create a language-based classification system for industrial policies which they apply to some 47,000 entries in the GTA database covering 2009-2020. They find industrial policy use has expanded since 2010, with subsidies and export promotion measures being the typical instruments. They also find industrial policy use to be correlated with revealed comparative advantage. In contrast to their methodology which relies on the analysis of the description of GTA measures to match their definition of industrial policy, our classification system relies on including measures which have an LLM-identified industrial policy motive (including new industrial policy motives related to non-economic objectives) as well as measures which target certain strategic sectors. This methodology is better able to capture policies in EMDEs given their more frequent use of export and import barriers, policies for which the GTA descriptions are often short and factual, and do not elaborate on motives behind such measures. In contrast, AEs employ more subsidy programs for which GTA descriptions tend to be more elaborate. Furthermore, Juhasz et al. (2023) exclude firm-level disclosures of subsidies, which make up the bulk of China's subsidy measures in the GTA. Indeed, the top five users of industrial policies in their dataset are all AEs (Germany, Japan, Brazil, USA, Canada), with China not included in the top ten.Recent years have also seen a large number of research papers seeking to estimate the effects of industrial policy intervention. Some estimate the impact of selective policy intervention at the sectoral level (Barwick, Kalouptsidi and Zahur, 2023; Goldberg et al. 2024; Barwick et al. 2025), while others focus on the impact on trade flows and competitiveness (see, for example, Rotunno and Ruta, 2024 and Huang et al., 2025), and on firm-performance (Machado Parente et al. 2025). Baquie et al. (2025) study empirically the relationship between industrial policies and sectoral performance for a broad set of countries and highlight the role played by structural factors in amplifying the impact of industrial policies. Place-based policy intervention has been studied as well. For example, Criscuolo et al. (2019) studied how changes in rules for area-specific subsidies affected the economic performance of targeted areas. Focusing on European countries, Brandao-Marques and Toprak (2024) track the performance of listed non-financial firms who received state-aid between 2016 and 2023. Focusing on China, Aghion et al. (2015) find that industrial policies allocated to competitive sectors or those that foster competition in a sector increase productivity growth. There is also a strand of the literature focusing on the long-term impacts of industrial policies, focusing mostly on the policies pursued by the Republic of Korea in the 1960s and 1970s (see Choi and Levchenko, 2025; Lane, forthcoming; Choi et al., 2024). In addition, several papers have relied on theoretical models to quantify the welfare implications of industrial policies (Hodge et al. 2024; Lashkaripour and Lugovskyy, 2023; Bartelme et al., 2025).

The rest of the paper is organized as follows: Section 2 describes the methodology used in creating our dataset, Section 3 takes a first look at the data and presents some stylized facts, while Section 4 analyzes determinants of these trends. Section 5 concludes.

Methodology of the Historical NIPO database

The H-NIPO dataset contains state measures that have been implemented or announced between January 1, 2009 and December 31, 2023. This is meant to complement the original NIPO monitoring exercise which began on January 1, 2023 and is being updated monthly.[3] These datasets are compatible and can be combined (accounting for the overlapping years), although the NIPO contains additional information on trade coverage and subsidy values as well as more disaggregated motives.[4] Each entry in the database refers to a distinct state intervention, and sometimes multiple interventions are attributable to a single state act or law. Below, we describe the criteria for inclusion in the extended NIPO and provide additional information on the type of policies covered.

The monitoring covers a sample of 75 jurisdictions which make up 94 percent of global GDP (see Annex II) and were selected because they have been consistently tracked through the longstanding GTA commercial policy monitoring initiative, which has at its core the G-20 economies.[5] Out of these, 53.6 percent are Advanced Economies (AEs) and 46.4 percent are Emerging and Developing Economies (EMDEs).[6] Each region is represented: 13 jurisdictions are in the Asia Pacific (28.5%), 31 in Europe and Central Asia (28.6%), 9 in Latin

[3] The NIPO is a live database that is updated monthly, including with respect to historical measures. Importantly, recording lags may exist as information becomes available at different speeds across various jurisdictions.

[4] In the NIPO the motives of national security and geopolitical concerns are two distinct motives, and digital transformation has been recently included as a new motive.

[5] EU-wide measures are recorded only once, but measures by individual EU member states are counted separately. The same logic applies to other supranational jurisdictions.

[6] The AEs are: Australia, Canada, Hong Kong SAR, Iceland, Israel, Japan, New Zealand, Norway, Singapore, Korea, Switzerland, Taiwan Province of China, United States of America, United Kingdom, and the European Union and 19 EU individual members (Austria, Belgium, Croatia, Czechia, Denmark, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Netherlands, Poland, Portugal, Slovakia, Slovenia, Spain and Sweden); The rest are classified as EMDEs (Annex II).

American and the Caribbean (11.5%), 9 in the Middle East and North Africa (1.7%), 2 in North America (21.3%), 4 in South Asia (6.8%), and 7 in Sub-Saharan Africa (1.6%).

An important element in our classification of industrial policies is the policy motive. The GTA data manually records whether measures announced or implemented starting in 2023 are associated with any of a predefined set of stated industrial policy motives (see below).[7] A key contribution of this paper is to extend this dimension of the data by assigning, via LLMs, inferred policy motives to GTA policies also in prior years based on the textual description of the policy intervention in the GTA database. For this, we use the RoBERTa LLM following the methodology developed by Huang et al. (2025). In brief, we use the existing NIPO dataset for 2023 as the learning sample and fine-tune the model for each motive by providing the policy description as input and indicating whether it belongs to that particular motive as the output. The model is then run separately for each motive on all GTA measure descriptions in the 2009-2022 period and assigns it the inferred motive if its likelihood exceeds a certain threshold.

Inclusion in the H-NIPO database

The H-NIPO dataset relies on information collected by the GTA team and aims to identify new industrial policy measures implemented by governments around the world.[8] To be part of the H-NIPO database, the GTA measures need to be either (1) associated with a predefined set of industrial policy motives or (2) cover at least one of a predefined set of products or service categories.[9,10] These inclusion criteria are explained in detail below.

Motives

The first inclusion criterion we consider is the motive for policy intervention as identified by the LLM model. The H-NIPO database includes GTA measures with one of the following four identified motives: national security or geopolitical concerns, security of supply chains (for non-food products), strategic competitiveness, or climate change mitigation concerns.[11] An entry in the H-NIPO database can be associated with more than one motive. The motives are defined as follows:

- **National security and/or geopolitical concerns:** The identified motive of the action refers explicitly to the current or future military security of the implementing country or specifically quotes “national security” or refers to countering the risk from a country or a class of countries (e.g. autocracies), even in the absence

[7] However, the decision to include a measure in the GTA database is in no way dependent on the stated or perceived motive of a policy intervention. A policy intervention is included in the GTA databased based on seven objectively verifiable factors, as laid out in the GTA methodological handbook. The information in the GTA database on the stated motive of a policy was collected in addition to that necessary to determine inclusion in the GTA database.

[8] Information on the GTA data collection process can be found in Annex I.

[9] A small set of GTA measures are classified as an industrial strategy or plan but only starting from 2023, and are therefore not a relevant inclusion criteria for the historical extension of the NIPO.

[10] By construction, the H-NIPO database is a subset of the GTA database of policy interventions.

[11] The H-NIPO treats national security and/or geopolitical concerns as one motive given their relatively small number to facilitate identification by the LLM, while these are treated as two separate motives in the NIPO. Moreover, the H-NIPO does not include digital transformation as a motive, although this was included in the NIPO following its launch, again due to the small number of such measures.

of a specific reference to national security.[12] Sanctions against Russia related to the war in Ukraine are considered based on a geopolitical concern.

- **Resilience/security of supply chains (non-food):** The identified motive of the action refers to improving the stability or security of local supplies of non-food products now or in the future.
- **Domestic competitiveness in strategic sectors:** The identified motive of the action refers to the promotion of domestic competitiveness or innovation in a strategic product or sector.
- **Climate change mitigation and other environmental objectives:** The identified motive of the action refers to climate change mitigation or the transition to a low-carbon economy.

Assigning Motives using Large Language Model[13]

The motives associated with a given policy intervention are inferred using the RoBERTa Large Language Model with a sequence classification layer on top. With the pretrained model, we performed the following procedures:

First, we fine-tuned the model using the NIPO dataset. For each stated motive, we provided the policy description as input and a binary true/false value as the output, indicating whether the policy belongs to the stated motive. In this step, we split the NIPO dataset into two groups, one for training, and another for testing. Using the training datasets, we trained the model for 10 epochs.

Second, we used the fine-turned model to determine the motive for intervention policies not covered by NIPO. We input the policy description into the model to predict the likelihood of it being associated with the given motive.

Third, since the model's results can vary depending on various factors even with a consistent set of inputs, we repeat the procedures ten times to improve the accuracy of the model's predictions. This yields ten sets of probabilities for each intervention policy corresponding to each motive. We then calculate the weight of each set using the F1 score derived from the testing dataset in the first step.

Finally, we compute the weighted average of the probabilities and classified the policy as having a particular inferred motive if the weighted probability exceeded 60%. Each policy can therefore be associated with between 0 and 4 motives.

Product or Service Categories

As in Evenett et al. (2024), a second inclusion criterion relates to the types of products that are targeted by policy interventions. The H-NIPO database specifically includes policy interventions from the GTA database that relate to the following salient groups of goods and services that are often critical to achieving the motives described above. This allows us to capture new industrial policy interventions that governments may not

[12] In the H-NIPO, national security and/or geopolitical concerns are treated as one motive to increase the size of the learning sample for the LLM, whereas in the original NIPO these are two distinct motives. Classes of countries can be defined by political system (e.g. autocracies), alliance (e.g. NATO, "axis of evil"), ideology (e.g. liberal) or geography.

[13] Technical details for the classification procedure can be found in Annex III.

explicitly describe as such. The groups are defined by a list of six-digit Harmonized System (HS) subheadings (for products) and CPC codes (for services) and are as follows:[14,15]

- **Low-Carbon Technology:** Low carbon technologies include technologies and machines such as wind turbines, solar panels, biomass systems, and carbon capture equipment. Low carbon technology products produce less pollution than their traditional energy counterparts and can play a role in the transition to a low carbon economy.
- **Dual-use products:** dual-use items are goods, software, and technology that can be used for both civilian and military purposes. Although this category covers HS codes of hydrogen and steel, iron and aluminum, we have created separate product categories to account for measures targeting these particular products given their prevalence in the data.
- **Critical minerals:** minerals necessary for producing a broad range of goods used in everyday life and modern technologies.[16]
- **Advanced technology products:** products relating to medical and industrial applications of advanced scientific discoveries, medical science, opto-electronics; products that are able to process increased volumes of information; electronics, robotics; materials that allow for further development and application of other advanced technologies (optical fiber cable and video discs); aerospace products; and nuclear technology.
- **Medical products:** medical consumables or non-durable products, including medicines and vaccines as defined in the GTA's Essential Goods Initiative; medical equipment.
- **Chemicals**: products from the HS chapters 28 (inorganic chemicals) and 29 (organic chemicals, except those included in the previous category of medical products related to the production of medicines), 32 (tanning or dyeing extracts), 38 (chemical products n.e.c), and individual chemicals or groups of chemicals from the Rotterdam and Stockholm Convention.
- **Critical Raw Materials Downstream Industry**: products used for the production of end products such as batteries, ICT products, or PV Cells.
- **Industrial Raw Materials**: tariff lines from the Industrial Raw Materials list by the OECD (2024).
- **IT or digital services:** technological research, digital or IT services.[17]

Broad Categories of Policy Instruments

The NIPO database includes 58 policy instruments which fall under 7 broad types of interventions (Table 1). These categories aim to capture the gamut of tools used to pursue selective policy intervention and broadly follow the relevant chapters of the International MAST classification of non-tariff measures. An important caveat

[14] The 2012 edition of the HS nomenclature is used. The sectoral scope of the NIPO database is unrestricted and can include measures covering any goods and/or services if one of the other inclusion criteria are met.

[15] There are no readily available lists for technological collaboration, technological sectors, or technological products. Based on existing initiatives and media reports, the GTA team has extended its coverage to computing-related technologies including microelectronics, quantum information systems as well as artificial intelligence. Their monitoring was also expanded to include clean energy technologies such as batteries and electric vehicles. The notion of technological goods relevant for this project may evolve in response to policy developments. The below definitions only serve to help identify innovative forms of technology-related trade or foreign investment restrictions which may have been missed by tracking the existing set of GTA policy instruments. Close monitoring of government intervention in technology sectors ensures that this project is not confined to the existing set of GTA policy instruments.

[16] A list of such minerals deemed critical was assembled by IMF staff when the originally NIPO database was assembled.

[17] These are identified by the CPC codes 623, 831, 834, 839, 841, 842, and 843 (according to the UN Central Product Classification (CPC) version 2.1).

is that the dataset does not contain information on industrial policy pursued through product market regulation and standards, other technical barriers to trade (TBTs), or sanitary and phytosanitary measures (SPS), given that they are typically implemented for purposes other than industrial policy, such as the protection of human health. The 7 broad categories of intervention are listed below:

- **Export barriers** including export bans, tariffs and quotas, export licensing and other export-related trade barriers. An example is the export control measures targeting 30 drone-related products implemented by China on 9 January 2023.
- **Import barriers** including import bans, tariffs and quotas, import licensing and other import-related trade barriers, for example, the import licensing requirements on laptops, computers, and servers by India implemented on 11 January 2023.
- **Domestic subsidies** including tax rebates, grants, state loans and loan guarantees, price stabilization measures, production subsidies and other incentives to domestic production, for example, the financial grant of EUR 6.5 billion to compensate energy-intensive companies at risk of carbon leakage from higher fuel prices in Germany.
- **Export incentives** including tax-based export incentives, unit-based export subsidies, trade financing and other financial export promotion. For example, in September 2023, the Brazilian Development Bank (BNDES) provided two loans to aircraft manufacturer Embraer to support its export operations.
- **Foreign Direct Investment** measures including entry and ownership requirements as well as FDI screening decisions, for example, the measure adopted by Russia on 17 January 2023 grants authorization for certain companies to exclude the votes of shareholders from “unfriendly” countries.
- **Procurement policies** covering changes to public procurement law or practice that may favor local suppliers such as the steps taken by the United States in March 2023, motivated by national security considerations, to favor domestic firms in government contracts for circuit boards.
- **Localization incentives or requirements** as well as public procurement localization measures, include, for example, the local content requirements in the US Inflation Reduction Act.

Table 1. Taxonomy of Specific Policy Instruments

Export barriers 1. Export ban 2. Export licensing requirement 3. Export quota 4. Export tariff quota 5. Export tax 6. Local supply requirement for exports 7. Export-related non-tariff measure, nes	**Import barriers** 1. Anti-dumping 2. Anti-subsidy 3. Import ban 4. Import licensing requirement 5. Import monitoring 6. Import quota 7. Import tariff 8. Import tariff quota 9. Internal taxation of imports 10. Import-related non-tariff measure, nes
Domestic subsidies 1. Capital injection and equity stakes (including bailouts) 2. Financial grant 3. In-kind grant 4. Tax or social insurance relief 5. Production subsidy 6. Interest payment subsidy 7. Loan guarantee 8. Import incentive 9. Price stabilization 10. State loan 11. State aid, nes 12. State aid, unspecified	**Export incentives** 1. Trade finance 2. Export subsidy 3. Tax-based export incentive 4. Financial assistance in foreign market 5. Other export incentive
Foreign Direct Investment measures 1. FDI: Entry and ownership rule 2. FDI: Financial incentive 3. FDI: Treatment and operations, nes	**Public procurement measures** 1. Public procurement access 2. Public procurement, nes
Localization content measures 1. Local content incentive 2. Local content requirement 3. Local operations incentive 4. Local operations requirement 5. Local value-added incentive 6. Public procurement localization 7. Localization, nes	**Others** 1. Anti-circumvention 2. Control on personal transactions 3. Controls on commercial transactions and investment instruments 4. Controls on credit operations 5. Foreign customer limit 6. Intellectual property protection 7. Labor market access 8. Post-migration treatment 9. Repatriation & surrender requirements 10. Special safeguard 11. Trade payment measure 12. Instrument unclear

Note: “nes” refers to “not elsewhere specified” and in this context “elsewhere” refers to the policy interventions specifically named as those tracked in the GTA database.

Other Variables in the H-NIPO Database

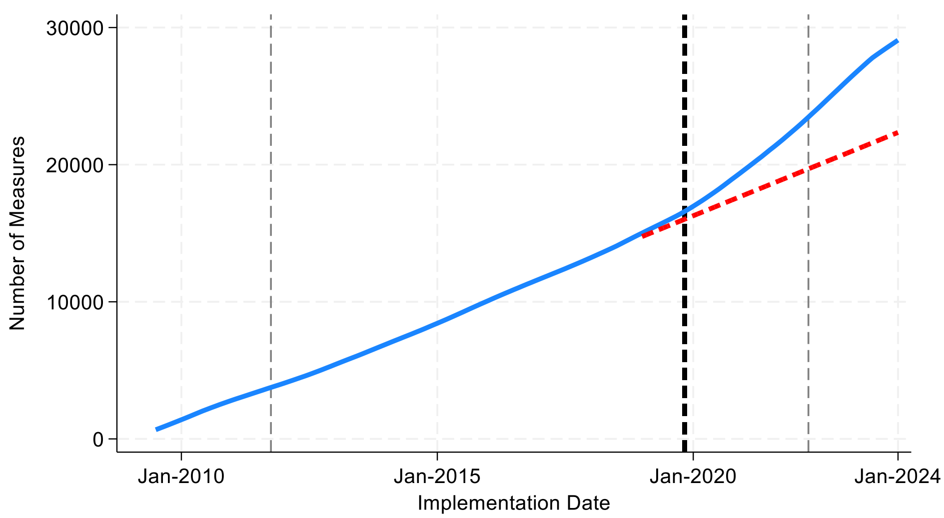
To provide a comprehensive and traceable inventory of interventions, the database records additional details on the level of government responsible for implementation, the targeted sectors, an assessment of the measures' relative treatment of domestic firms vis-à-vis foreign rivals (that is, whether they discriminate against foreign commercial interests), and other variables. This information is helpful for fully documenting the interventions and to aid researchers in combining them with other data sources related to the jurisdiction, timing, or targeted sectors and products (e.g., import and export data at the HS 6-digit level). Unlike the NIPO, the H-NIPO database does not record the values associated with subsidies, since this information has only been systematically collected by the GTA since 2023.

- **Intervention ID** and **Title**: the unique ID given to each entry in the GTA database and the title used in the GTA database.
- **Jurisdiction**: jurisdiction implementing the policy intervention or proposal.
- **Level of government implementation**: the NIPO database differentiates between measures or announcements of three different government levels or agencies: supra-national (announcement by supra-national bodies with binding consequences for its member states, including relevant International Financial Institutions), national (announcements made by central government, including relevant National Financial Institutions), and sub-national (announcements made by lower levels of government such as regional, state, provincial, and municipal governments).
- **Initial assessment on relative treatment of domestic and foreign commercial interests**: Each policy intervention is classified based on the likely effect of its implementation on the conditions of competition in the market most directly affected. Measures are deemed distortive if they generally discriminate against foreign commercial interests by restricting market access or by altering the conditions in favor of local firms. In contrast, liberalizing measures tend to enhance market access on a non-discriminatory (i.e., most favored nation) basis or improve the transparency of a relevant policy. Recall the emphasis of the GTA policy tracking initiative is on unilateral state intervention, not measures taken in the context of reciprocal trade accords.
- **Announcement, implementation, and removal date**: the issuance date of the policy intervention or proposal, the date the policy intervention entered into force according to the announcement text and the date the policy intervention is either withdrawn or fully replaced by another action respectively. The NIPO only includes measures either announced or implemented from 1 January 2023.
- **Targeted economic activity**: the database includes information on the affected HS codes at the 6-digit level (UN Harmonized System version 2012) and CPC sector codes at the 3-digit level (UN CPC codes, version 2.1) where available. For interventions that include product-level information, the associated sectors are selected based on the United Nations' correspondence table for CPC 2.1 and HS 2012. In all other cases, the sector code is chosen based on information from GTA according to the wording of the official source.
- **Source**: the sources documenting the policy intervention or proposal.

Structural Trends in Global Industrial Policy: 2009-2023

This section presents a set of stylized facts derived from the new H-NIPO dataset, emphasizing key patterns in the use of trade distorting industrial policies observed over time and documenting structural breaks. The focus is on the cumulative number of implemented distortive polices, rather than liberalizing ones, because they make up 85 percent of policies recorded in the database and are recently at the center of a heated policy debate around their potential to create negative spillovers and difficult trade-offs. Moreover, the preponderance of international rules and agreements exist to govern the use of distortive policies. The aim is to highlight shifts in motives behind these policies, potential changes in their strategic focus, and the main instruments they employ, both across time and income groups. These descriptive insights set the stage for a more granular econometric investigation in the next section.

Figure 1: 2020 marks a turning point in industrial policy activity

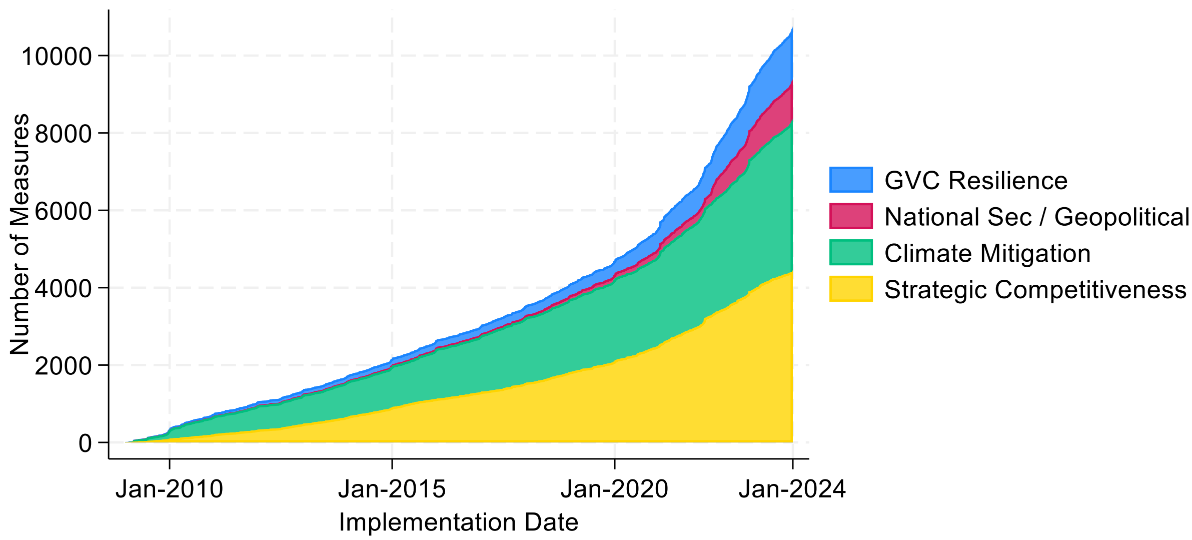


Note: Cumulative stock of measures.

We first investigate how trade distorting industrial policies have evolved since the GFC and identify November 2019 as the most statistically significant breakpoint, marking an acceleration of policy activity (Figure 1). The hypothetical continuation of the pre-breakpoint trend is plotted in red, with actual policy activity markedly above this trend. The breakpoint is determined by a supremum Wald test to detect structural breaks in time series. The test evaluates all feasible breakpoints over 2009-2023 subject to minimum sample requirements on either side, which constrains the analysis within the bounds indicated by the vertical grey lines. Similar breakpoints emerge around 2020 when studying the time series for different income groups (advanced economies and emerging market and developing economies excluding China), policy motives (competitiveness, climate, GVC resilience, and national security), and instrument categories (subsidies, trade restrictions, and localization measures). A caveat is that Chinese firm-level data exhibit excessive volatility due to annual reporting cycles and are excluded from the breakpoint analysis.

This finding provides evidence that the COVID-19 pandemic and concerns around supply chain dependencies on geopolitical distant partners that emerged at this time were important triggers in the shift in the use of industrial policies worldwide. Finally, the new trend of heightened industrial policy activity extends beyond the health emergency, as the number of new interventions did not diminish as countries started exiting the pandemic.

Figure 2: New industrial policies with LLM-assigned motive

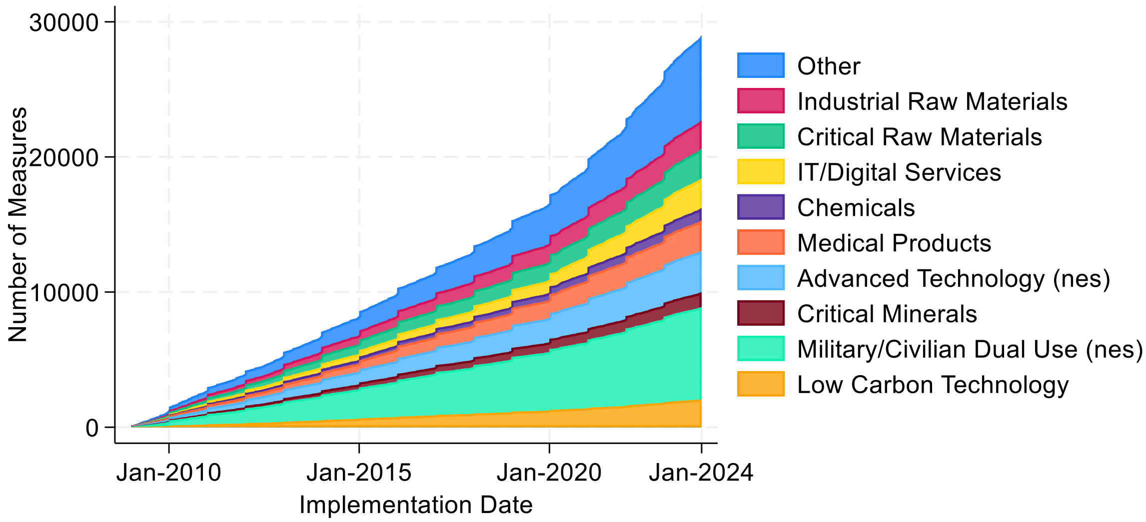


Note: Cumulative stock of measures. For measures with multiple motives, each motive is given equal weight.

We then explore the information on the motives associated with trade distorting industrial policies to study how governments around the world may justify their interventions and how these patterns have changed over time. Figure 2 illustrates the subset of trade distorting measures for which our LLM methodology has identified an associated motive. It reveals several notable patterns. First, strategic competitiveness and climate change mitigation were predominant motives behind industrial policies following the GFC. As discussed in the Introduction, this is consistent with the push for "green recovery" and "green jobs" espoused both in the United States and Europe over this period, and a trend which has been persistent since then, with China, US, and EU leading the way in green subsidies. In contrast, motives such as national security, geopolitical concerns, and supply chain resilience have only picked up steam in more recent years, particularly in the post-pandemic period. This temporal pattern coincides with the intensification of US-China trade tensions which started taking shape with the Obama administration's "Pivot to Asia" strategy and intensified with the 2018-19 tariff escalation. The COVID-19 pandemic drew further attention to the resilience of supply chains in certain critical products.

Figure 3 shows which strategic sectors are targeted by trade distorting industrial policies over time. It reveals that the majority of trade distorting measures in the dataset meet the inclusion criterion of targeting products from one or more of the predefined lists of strategic sectors (Figure 3 splits measures targeting more than one list equally among them). The data points to a large share of measures targeting military/civilian dual use products and various advanced technologies, as well as their upstream inputs, such as critical minerals, chemicals, and industrial materials like steel and aluminum.

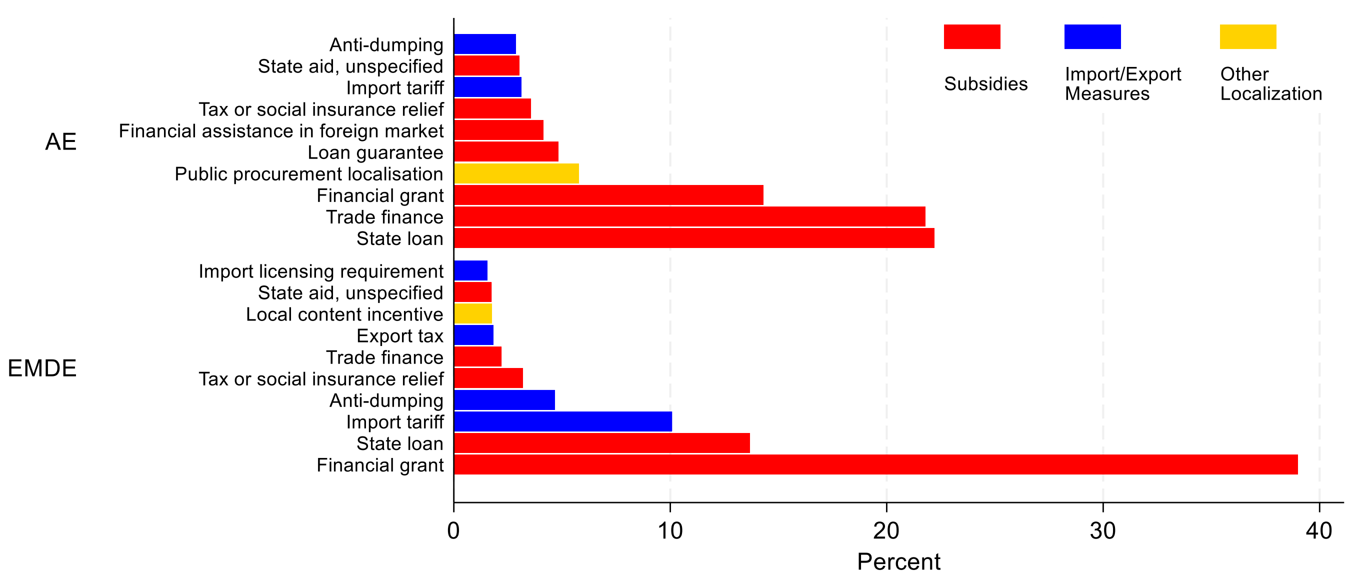
Figure 3: New industrial policies by sector



Note: Cumulative stock of measures. For measures with multiple sectors, each sector is given equal weight.

Surprisingly, low carbon technology products do not account for a prominent share despite climate mitigation being a prominent motive. This is explained by the large share of climate motivated measures that target energy intensive industries that are not low carbon products (e.g., steel and aluminum). This is because the expected improvements in efficiency of these sectors will have a large impact on emissions. Although no great shifts in the target products have occurred between 2009 and 2023, we find that policies targeting critical minerals and industrial raw materials have played a more salient role in recent years.

Figure 4: Trade distortive industrial policy instruments by income group

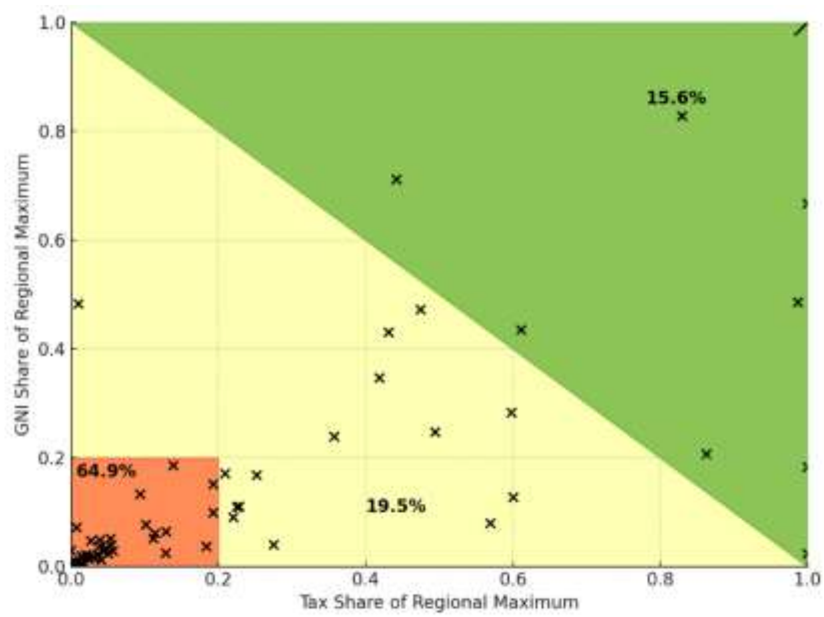


The main instrument for conducting industrial policy is subsidization, but there are key differences between how AE and EMDE governments subsidize (Figure 4). Financial grants are the most common instrument among EMDEs, while the bulk of subsidies in AEs employ state loans and trade finance. There are also important differences across income groups in their use of other instruments besides subsidies. Public procurement localization measures are more commonly used among AEs (accounting for over 5 percent of all trade distorting industrial policies), while import restricting measures play an important role in EMDEs (18 percent of all trade distorting industrial policies).

Interestingly, AEs and EMDEs have converged in their use of policy instruments over time. Between 2009-2023, the share of subsidies in AEs decreased from 84 to 75 percent and rose in EMDEs from 56 to 71 percent. The share of trade measures increased from 3 to 8 percent in AEs but decreased from 27 to 18 percent in EMDEs. Localization policies increased from 7 to 8 percent in AEs and 2 to 6 percent in EMDEs.

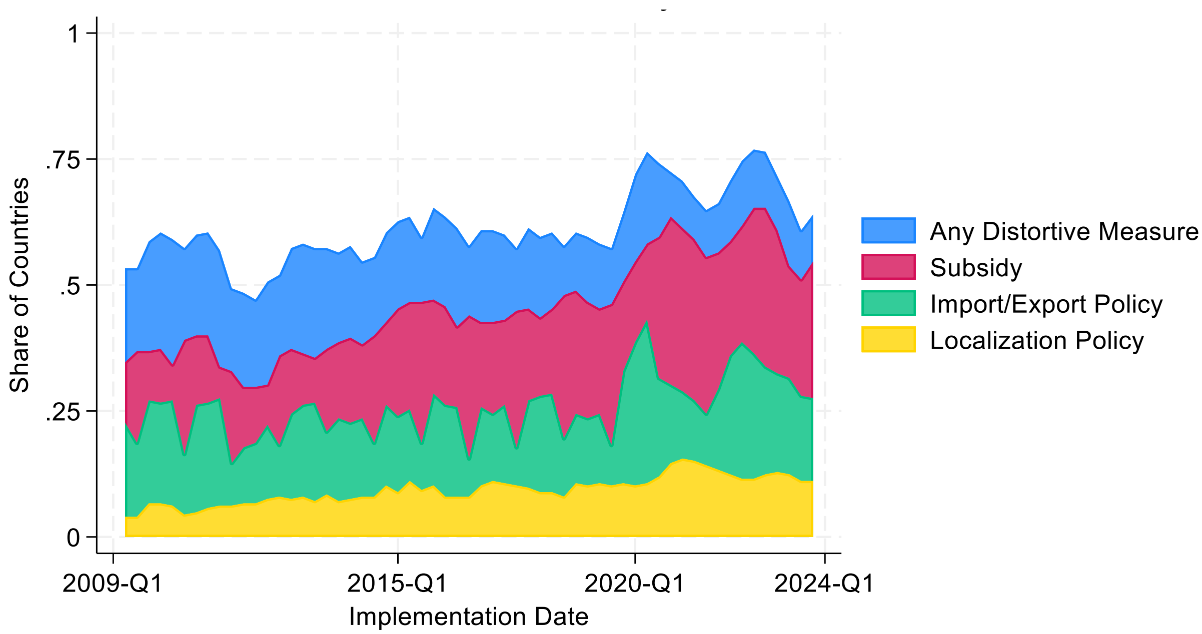
The dataset reveals shifting patterns of the use of policy instruments across the various motives over the sample period between 2009-2019 and 2020-2023 (see Annex IV Table A1 for the complete table). Little has changed in the design of climate motivated measures, with domestic subsidies remaining the dominant policy instrument throughout, used in 89 percent of cases before 2020 and 92 percent thereafter. By contrast, measures motivated by national security or geopolitical concerns have seen major changes, with export barriers accounting for only 7 percent of measures before 2020 and 22 percent after, while the share of localization or public procurement dropped from 30 to 9 percent, the share of import barriers from 28 to 11 percent, and the share of FDI measures from 24 to 11 percent—measures in the 'other' category rose from 5 to 37 percent indicating the rising popularity of unconventional instruments (see Table 1 for the taxonomy of such measures). Measures motivated by supply chain resilience also rely mostly on domestic subsidies, at 82 percent before 2020 and 76 percent after, with a notable increase in the share of export barriers from 3 percent to 13 percent. Finally, measures with a strategic competitiveness motive saw an increase in their reliance on domestic subsidies from 63 percent to 75 percent and a decrease in the use of export subsidies from 27 percent to 11 percent.

Figure 5: Opportunity cost of industrial subsidies decreases with tax revenue and market size



The temptation to favor certain commercial activities may differ across economies, based on the amount of resources available to governments and local market size. Governments with relatively larger tax bases compared to neighbors may find provision of corporate subsidies more attractive. States with large domestic markets may feel they can demand private sector investors to source more locally. Using the World Development Indicators database, we assembled data for 77 economies' tax bases and GNI, relative to regional peers (last year available). Figure 5 reveals that nearly two-thirds of economies had relatively small tax bases and market sizes, raising the opportunity cost of corporate subsidies and blunting the likely effectiveness of localization measures. Conversely, only 16 percent of economies in this sample (in the green area) had larger markets (regionally speaking) and states with potentially deep pockets. Another 20 percent of economies in this sample (in the yellow area) may be tempted to compete with big regional rivals but they do so at a structural disadvantage.

Figure 6: The share of jurisdictions employing trade distortive policies has increased



Note: Quarterly shares of jurisdictions can take values 0-1 for each instrument separately. Three-quarter moving average.

Finally, in Figure 6 we explore what changes have occurred at the extensive margin among the 75 NIPO jurisdictions being monitored. We find that the share of jurisdictions deploying trade distorting industrial policies has increased from around 56 percent in 2009 to 63 percent in 2023, reaching up to 75 percent in 2020 and 2022. This change is most notable for subsidies: in 2009 only 36 percent of countries employed trade distorting subsidies while in 2023 this had risen to 59 percent. Import and export measures have remained relatively stable throughout between 26 and 32 percent, while localization policies have doubled from 6 percent to 12 percent.

Interestingly, the high share of AE jurisdictions employing subsidies has further increased from 81 to 90 percent, reaching 100 percent in 2020, the year of the COVID-19 pandemic. Import and export restrictions were used by 19 percent of AEs in 2009 and the share increased to 35 percent in 2023, with a peak of 74 percent in 2020. The use of localization policies has also increased, with 6 percent of AEs employing them in 2009 rising to 16 percent by 2023. Among EMDEs, the share of jurisdictions employing subsidies is lower than among AEs but has also risen, from 36 to 57 percent, reaching 66 percent in 2020. The share of EMDEs employing import and export restrictions has stayed level at 57 percent with a peak of 77 percent in 2020, while the share using localization policies exhibited a modest increase from 18 to 23 percent.

Determinants of Industrial Policy Use

In this section, we explore empirically the role of certain hypothesized drivers of trade distortive industrial policies at the country-product level, and how these change over time, to shed light on what is behind the aggregate trends and structural break observed in the previous section. Our aim is to investigate how market dynamics, including concentration and comparative advantage, changes in geopolitics, and the historical use of industrial policies both at home and abroad, have had an impact on governments' choices of allocating support to certain industries, and how the influence of these factors has changed over time.

We run a series of ordinary least squares regressions employing granular fixed effects to gauge the correlates of changes in trade distortive industrial policies at the county-product level and explore their changing relevance over time by comparing different sub-periods. In what follows, the dependent variable is the change in implemented measures at the level of individual jurisdictions c and the specific product categories p (at the six-digit HS subheading level) which they target. The benchmark specification is given in Equation (1):

$$\Delta IPMeasures_{c,t,p} = \alpha_{ct} + \gamma_{pt} + \theta_{cp} + \boldsymbol{\beta}\, \boldsymbol{X_{p,c,t-1}} + \varepsilon_{c,t,p} \qquad (1)$$

Here the explanatory variable $\boldsymbol{X_{p,c,t-1}}$ includes hypothesized forces driving industrial policies, such as market dynamics, including concentration and comparative advantage, changes in geopolitics, and the historical use of industrial policies both at home and abroad (Evenett et al., 2024).

Specifically, these include (a) exposure of a country's imports to geopolitical rivals, which might threaten their security of supply; (b) exposure of a country's exports to industrial policies by other countries targeting the same product, which aims to capture the tit-for-tat nature of industrial policy; (c) a Herfindahl–Hirschman index (HHI) of a country's import concentration of the given product, capturing both the risk of relying on a limited number of foreign suppliers but also the dearth of competition which is associated with price volatility and high markups; (d) separately the change and level of a country's (Balassa) revealed comparative advantage (RCA) in a given product, that is, presence in the global markets, indicating both external competitiveness and the global size of a given sector, potentially associated with its lobbying power; (e) the stock of past industrial policies, indicating both the current level of advantages and the proclivity of the government to bestow them on a given sector.

The construction of each control variable is as follows. First, to measure geopolitical exposure, we construct a new variable that leverages the database by Bailey, Strezhnev, and Voeten (2017) who derive a time-varying ideal point distance (IPD) between countries based on their voting patterns in the UN General Assembly. This means that a pair of countries is more distant from a geopolitical perspective when IPD is higher. We then construct an import-weighted measure of geopolitical distance (*GPD*) at the product level as follows:

$$GPD_{p,c,t-1} = \sum_{j \in J} \frac{M_{j,c,p,t-1}}{M_{c,p,t-1}} IPD_{j,c,t-1}$$

Where M represents imports, *j* is in an index of the exporter country, *c* is the importer country, and *p* is the targeted product. Thus, the GPD variable captures how reliant country *c* is on imports of product *p* from geopolitical distant countries.

The exposure to industrial policies by other countries targeting the same product is constructed as the weighted sum of trade distortive industrial policies targeting product *p* introduced by all countries except *c,* where the weights are the export share of other countries except *c* in global markets. More precisely, we measure the export-weighted industrial policy measures by other countries as:

$$XWIP_{p,c,t} = \sum_{j \neq c} \frac{X_{j,p,t}}{\sum_{j \neq c} X_{j,p,t}} IP_{j,p,t}$$

where X represents exports.

The HHI for a country's imports of product *p* is simply:

$$HHI_{p,c,t} = \sum_{j \in J} \left(\frac{M_{j,c,p,t}}{\sum_{j \in J} M_{j,p,t}} \right)^2$$

The Balassa RCA index of country *c* in product *p* is computed as:

$$RCA_{p,c,t} = \frac{X_{c,p,t}}{\sum_j X_{j,p,t}} \bigg/ \frac{X_{c,t}}{\sum_j X_{j,t}}$$

where $X_{c,t}$ represents aggregate exports of country *c* in year *t.*

We begin by documenting the evolving relevance of each correlate of changes in industrial policy use. To do so, we estimate equation (1) for rolling six-year subperiods. Table 2 reveals several interesting facts. Most importantly, the structural break we had observed around 2020 in the aggregate data is also present at the country-product level and there are significant shifts (sign reversals) in the coefficients of some of the key explanatory variables around the year 2020. Notably, geopolitical exposure has a significant negative coefficient until the 2012-2018 period, after which it turns insignificant, and then positive and significant in recent years. This implies that countries had previously eschewed targeting measures at products imported from their rivals but in recent years have reversed course and increased support to exactly these products. This is consistent with the geopolitical derisking narrative in the wake of the COVID-19 pandemic and Russia's War in Ukraine. A similar sign shift occurs between 2014-2020 and 2015-2021 for the coefficient on export exposure to other countries' industrial policies. In particular, until the 2014-2020 period there was a negative correlation between the change in industrial policy use in a given country and export-weighted industrial policy measures introduced by other countries for a given targeted product. This pattern flipped after the 2015-2021 period, when, on average, countries are more prone to introduce industrial policy measures in products where large exporters have a large stock of measures in place. This is suggestive of a tit-for-tat dynamic which can potentially lead to globally inefficient subsidy competition in certain products.

Import concentration has a consistently positive and significant sign in all periods, consistent with either efforts to de-risk vulnerable supply chains or to support highly oligopolistic "high rent" industries. While changes in RCA are not statistically significant, the level of RCA is significant for recent periods and also exhibits a sign reversal between 2014-2020 and 2016-2022. We find evidence that in the initial years countries supported products with a more prominent export presence, often established industries with lobbying power, but have recently switched to targeting sectors and products whether they are relatively uncompetitive, or which are new for them. This finding could reflect several forces. It could be the result of more countries adopting “new” industrial policies aiming to enter high-tech industries previously the purview of a handful of advanced economies. At the same time, and potentially related, the shift occurred at a time when countries sought to develop larger GVC resilience and geopolitical alliances were being redrawn, forces that could have geared countries towards targeting previously uncompetitive products with the goal of becoming competitive in the medium term.

Finally, a significant sign reversal from negative to positive occurs between the periods 2012-2018 and 2014-2020 for the coefficient of the stock of existing industrial policies. This implies that, while in the past countries slowed the introduction of new industrial policies as their stock grew, in recent years there is growing support for industries where there is already a large industrial policy footprint. Thus, countries are now concentrating more support to previously targeted sectors, all else equal. This is consistent with the structural break around 2020 in the aggregate time series, pointing to heightened overall activity.

Table 2: The Evolving Relevance of Correlates of Industrial Policy

	Dependent variable: Change in industrial policies implemented								
	2009-2015	2010-2016	2011-2017	2012-2018	2013-2019	2014-2020	2015-2021	2016-2022	2017-2023
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Import-weighted geopolitical distance (t-1)	-0.0588***	-0.0588***	-0.0253**	-0.0292**	-0.0109	-0.0237	0.0038	0.0433***	0.0298**
	(0.0159)	(0.0159)	(0.0128)	(0.0129)	(0.0186)	(0.0197)	(0.0166)	(0.0166)	(0.0129)
Export-weighted IPs by other countries (t-1)	-0.3109***	-0.3109***	-0.4165***	-0.2170***	-0.1430**	-0.3767***	0.1588***	0.4197***	0.4523***
	(0.0361)	(0.0361)	(0.0341)	(0.0497)	(0.0669)	(0.0833)	(0.0312)	(0.0390)	(0.0342)
HHI of product p imports (t-1)	0.0688***	0.0688***	0.0403*	0.0465**	0.0646***	0.0613***	0.0849***	0.0950***	0.0879***
	(0.0266)	(0.0266)	(0.0207)	(0.0186)	(0.0223)	(0.0230)	(0.0212)	(0.0208)	(0.0198)
Change in RCA (t-1)	0.0003	0.0003	0.0011	0.0006	-0.0000	0.0001	-0.0002	0.0003	0.0019
	(0.0011)	(0.0011)	(0.0009)	(0.0006)	(0.0006)	(0.0006)	(0.0005)	(0.0006)	(0.0012)
RCA (t-1)	0.0031	0.0031	0.0019	0.0009	0.0011	0.0024**	-0.0010	-0.0055***	-0.0085**
	(0.0021)	(0.0021)	(0.0015)	(0.0010)	(0.0010)	(0.0011)	(0.0009)	(0.0021)	(0.0037)
Count of IPs (t-1)	-0.2807***	-0.2807***	-0.2663***	-0.3001***	-0.0152	0.2994***	0.2338***	0.2218***	0.1517***
	(0.0116)	(0.0116)	(0.0129)	(0.0164)	(0.0182)	(0.0248)	(0.0099)	(0.0137)	(0.0106)
Constant	3.8127***	3.8127***	4.4505***	3.4263***	1.7646***	2.1995***	-2.4010***	-5.2770***	-5.7818***
	(0.2241)	(0.2241)	(0.2417)	(0.3508)	(0.5178)	(0.7545)	(0.3413)	(0.4727)	(0.4508)
Observations	431,940	431,940	585,660	717,911	809,519	906,567	1,001,571	1,045,223	1,067,533
R-squared	0.7219	0.7219	0.6613	0.5461	0.4315	0.5501	0.5590	0.6218	0.6727
Country-Product FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Country-Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Product-Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3 presents a more granular look at the benchmark results by interacting each of the key variables with a dummy variable capturing the country’s income group.[18] Column (1) shows the aggregate results over the full sample period (2009-2023). Given the large number of variables with sign reversals over time that we identify in Table 1, it is not surprising that several key variables are not statistically significant in this aggregated sample.

[18] We use the April 2025 IMF WEO definition for Advanced Economies (AE) and Emerging Market and Developing Economies (EMDE).

Table 3: Differences in the Correlates of Industrial Policy Changes Across Income Groups

	Dependent variable: Change in industrial policies implemented		
	All	Pre-2020	Post-2020
	(1)	(2)	(3)
Import-weighted geopolitical distance (t-1) x EMDE	-0.0134	-0.0366***	-0.0219
	(0.0199)	(0.0141)	(0.0186)
Import-weighted geopolitical distance (t-1) x AE	-0.0182	0.0493***	0.0336**
	(0.0139)	(0.0176)	(0.0150)
Export-weighted IPs by other countries (t-1) x EMDE	0.0452**	-0.1577***	0.0170
	(0.0209)	(0.0384)	(0.0280)
Export-weighted IPs by other countries (t-1) x AE	0.0444**	-0.1029**	0.0218
	(0.0208)	(0.0402)	(0.0278)
HHI of product p imports (t-1) x EMDE	0.0502	0.0906***	0.0003
	(0.0399)	(0.0283)	(0.0295)
HHI of product p imports (t-1) x AE	0.0910***	0.0559**	0.0685***
	(0.0249)	(0.0251)	(0.0236)
Change in RCA (t-1) x EMDE	-0.0007	0.0002	-0.0031***
	(0.0006)	(0.0012)	(0.0011)
Change in RCA (t-1) x AE	0.0013**	0.0014*	0.0026**
	(0.0006)	(0.0008)	(0.0010)
RCA (t-1) x EMDE	-0.0008	0.0001	0.0027
	(0.0011)	(0.0016)	(0.0021)
RCA (t-1) x AE	0.0004	-0.0006	-0.0012
	(0.0010)	(0.0013)	(0.0013)
Count of IPs (t-1) x EMDE	0.0651***	-0.0140	-0.3427***
	(0.0050)	(0.0104)	(0.0080)
Count of IPs (t-1) x AE	0.2754***	-0.5953***	0.1860***
	(0.0035)	(0.0296)	(0.0033)
Constant	-1.0689***	3.3103***	0.2191
	(0.2177)	(0.2355)	(0.3854)
Observations	1,521,000	731,139	781,747
R-squared	0.6118	0.6240	0.8938
Country-Product FE	YES	YES	YES
Country-Year FE	YES	YES	YES
Product-Year FE	YES	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Columns (2) and (3) present results for pre- and post-2020 respectively. The first key takeaway from comparing the two columns is that the negative coefficient of geopolitical exposure for EMDEs switched from significant to insignificant, while it remains positive and significant for AEs in both periods. This suggests that in Table 1 the aggregate result showing the coefficient of geopolitical exposure turning from negative to positive is driven predominantly by the dynamics in EMDEs. On the other hand, we find no differences by income class for the coefficient of export exposure to other countries' industrial policies, which turns from negative to insignificant post-2020. These results are not driven by differences in the stock of pre-existing policies between geopolitically important and other sectors, given these are controlled for in the regressions. Concentration of imports is positive but no longer significant for EMDEs in the second period, indicating less attention to supply chain derisking or oligopolistic sectors.

Different from the aggregate regressions, the change in RCA is positive and significant for AEs but for EMDEs it is positive and insignificant in the first period and negative and significant in the second period. This implies AEs have consistently targeted sectors where their competitiveness is on a growing path, but EMDEs have switched to targeting sectors where competitiveness is sliding. The level of RCA is consistently insignificant for each income class.

Turning to the stock of pre-existing domestic industrial policy measures, we observe that the coefficient for EMDEs is consistently negative and significant in the second period, while the coefficient for AEs turns from negative and significant to positive and significant. This implies that the aggregate results in Table 1 that point to a switch from deceleration to acceleration and growing concentration of industrial policies are driven predominantly by AEs.

Table 4. Correlates of Industrial Policy Dynamics, by Stated Motive

Dep. Var.	Change in Climate IPs		Change in Competitiveness IPs		Change in Nat. Sec. and GVC Res.			
	Pre-2020	Post-2020	Pre-2020	Post-2020	Pre-2020	Post-2020	Pre-2020	Post-2020
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Import-weighted geopolitical distance (t-1)	0.0022	0.0073***	0.0015	0.0003	0.0006	0.0066**	0.0003	0.0078**
	(0.0034)	(0.0023)	(0.0037)	(0.0018)	(0.0010)	(0.0027)	(0.0014)	(0.0036)
Export-weighted IPs by other countries (t-1)	-0.0030**	-0.0118***	-0.0071***	-0.0133***	0.0107***	0.0036**	0.0151***	-0.0009
	(0.0015)	(0.0020)	(0.0015)	(0.0018)	(0.0014)	(0.0014)	(0.0022)	(0.0022)
HHI of product p imports (t-1)	0.0079	0.0142***	0.0144**	0.0029	0.0001	0.0022	-0.0002	0.0012
	(0.0056)	(0.0045)	(0.0061)	(0.0034)	(0.0013)	(0.0046)	(0.0019)	(0.0057)
Change in RCA (t-1)	0.0000	-0.0001	-0.0002	-0.0007***	-0.0000	0.0006*	-0.0001	0.0008*
	(0.0003)	(0.0002)	(0.0003)	(0.0002)	(0.0000)	(0.0003)	(0.0001)	(0.0005)
RCA (t-1)	-0.0000	0.0006*	0.0003	0.0010***	-0.0001	-0.0002	-0.0001	0.0002
	(0.0004)	(0.0003)	(0.0004)	(0.0003)	(0.0001)	(0.0004)	(0.0001)	(0.0005)
Count of Climate IPs (t-1)	-0.4357***	-0.1971***						
	(0.0107)	(0.0087)						
Count of Competitiveness IPs (t-1)			-0.4565***	-0.2805***				
			(0.0092)	(0.0102)				
Count of Nat. Sec. and GVC Res. IPs (t-1)					-0.4106***	0.3702***	-0.5078***	0.3306***
					(0.0208)	(0.0153)	(0.0280)	(0.0189)
Constant	0.2807***	0.2630***	0.3290***	0.2925***	-0.0568***	0.0052	-0.0821***	0.0700**
	(0.0111)	(0.0261)	(0.0115)	(0.0240)	(0.0093)	(0.0191)	(0.0148)	(0.0291)
	All Products	All Products	All Products	All Products	All Products	All Products	Intermediate goods	Intermediate goods
Observations	731,139	781,747	731,139	781,747	731,139	781,747	433,563	470,150
R-squared	0.5813	0.5462	0.5828	0.5061	0.5192	0.6737	0.5147	0.6703
Country-Product FE	YES	YES	YES	YES	YES	YES	YES	YES
Country-Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Product-Year FE	YES	YES	YES	YES	YES	YES	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4 explores how the benchmark results differ across policies associated with various motives identified by the LLM. From the four original motives, we combine national security and supply chain resilience (NS/GVC) due to the smaller number of these measures. For this combined motive, however, we run additional regressions with a narrower sample of only intermediate products, potentially more affected by supply chain motives.[19]

We find that geopolitical exposure becomes positive and significant in the post-2020 period for climate and NS/GVC motives but not for competitiveness. For NS/GVC, this holds both for all products and the subsample of intermediate products. For exposure of exports to other countries' industrial policies, we find negative and significant coefficients in both periods for climate and competitiveness motives but a positive and significant coefficient for NS/GVC, indicating that the aggregate sign reversal identified in Table 1 is driven by this latter motive.

Changes in RCA in the post-2020 periods have positive and significant coefficients for NS/GVC but negative and significant coefficient for competitiveness. This implies that countries apply more NS/GVC motivated

[19] Intermediate products are defined as those HS six-digit codes associated with BEC codes 111, 112, 21, 22, 31, 322, 42, and 53.

measures in sectors of growing competitiveness, while the reverse is true for competitiveness motivated measures—countries apply more such measures when losing comparative advantage. These results appear to validate the accuracy of the classification algorithm. On the other hand, the coefficient of the level of RCA post-2020 is positive and significant for climate and competitiveness motivated measures only. This implies that even though on aggregate RCA has in recent years implied less support, measures motivated by climate and competitiveness run counter to this trend.

Finally, the stock of past industrial policy measures has a negative and significant association with industrial policies motivated by climate and competitiveness in both periods, whereas for NS/GVC motivated measures (for both all products and intermediate products) this turns from negative to positive post-2020, implying an increasing concentration of such measures.

Conclusions

In this paper, we introduce a historical extension of the New Industrial Policy Observatory (NIPO) dataset that reveals new stylized facts about the post-GFC industrial policy landscape. Notably, 2020 marks a structural shift with increased resort to industrial policy in both AEs and EMDEs. Competitiveness and climate remain the most frequent motives throughout, consistent with the objective of a green recovery from the GFC, but new-style industrial policies motivated by supply chain resilience, national security, and geopolitical concerns begin to emerge around 2020. Subsidies are the main policy instrument in both AEs and EMDEs, and the share of countries implementing them has risen markedly since the GFC. Trade measures are more commonly deployed by EMDEs.

Empirical results reveal that 2020 also marks a reversal for key determinants of the number of interventions affecting a given product: exposure to geopolitically distant trading partners turns from negatively correlated to positively correlated, consistent with calls for derisking. Similarly, the correlation with industrial support by other countries and the stock of domestic industrial policies turns positive, consistent with renewed tit-for-tat dynamics and an increased sectoral concentration of policies. Revealed comparative advantage, on the other hand, switches from a positive to a negative correlation (a pattern that appears to be driven by AEs) implying a shift in focus to less established sectors on the global market. Additional more granular results point to EMDEs driving the shift towards increasing use of industrial policies based on geopolitical exposure, while the acceleration and increased concentration of support to previously targeted sectors is driven by AEs. Moreover, we find that measures motivated by national security and supply chain resilience account for many of these observed shifts in behavior.

These historical data, in combination with the NIPO, which is continuously updated with new policies, are among the most comprehensive and longest running inventory of industrial policy interventions by states available to researchers. Future work should exploit the over 15-year time horizon to address some salient open questions in the literature, such as on the dynamic impacts of non-market interventions in shaping comparative advantage, the success of variously motivated measures in meeting their non-trade objectives, and crucially, whether industrial policies can be on net welfare improving, under certain conditions. Spillovers to other countries are also an important area of research and central to the current policy debates around WTO reform. We hope this research agenda can contribute to an informed policy discussion around the design of industrial policies, the circumstances under which they should be deployed, and how best to adapt the multilateral rules governing their use, such as on subsidies and trade restrictions.

Annex I. Methodology for Global Trade Alert Data Collection

The GTA initiative documents credible announcements of meaningful and unilateral changes by governments that affect the relative treatment of foreign versus domestic commercial interests. The dataset begins in November 2008, the month of the first G20 Summit where government leaders stated their intention to eschew certain types of protectionism. The emphasis on unilateral policy changes is meant to distinguish such measures from those taken to implement regional, plurilateral, and multilateral trade agreements.

The foreign commercial interests considered by the GTA are trade in goods and services, investment as well as labor force migration. Over 60 different types of commercial policy intervention—including subsidies—affecting these cross-border commercial flows are documented. So as to avoid concerns that regulatory policy changes swamp the database, the GTA initiative does not track changes in Technical Barriers to Trade (TBT) and Sanitary and Phytosanitary Measures (SPS). These are covered by the WTO ePing SPS & TBT Platform.

Each GTA database entry provides information on the implementing jurisdiction, about the direction of the change (distortive or liberalizing), the announced policy instrument, its announcement date and, where available, implementation date as well as the sectors and products covered by the relevant government statement. Finally, for measures affecting cross-border trade in goods, the database entry includes the potentially affected trading partners which are identified based on official United Nations trade flow data.

Each database entry is based on the official statement by the responsible institution wherever possible. All database entries undergo a two-stage review process before publication. Each announcement documented by the GTA team includes at least one new and credible public declaration for change in market conditions at home or abroad. An announcement may involve several unilateral changes in policy interventions. As of this writing, over 60,000 policy interventions have been documented since the GTA initiative began.

For an intervention to warrant a new entry in the GTA database, the following seven conditions have to be satisfied:

1) Unilateral Action: the intervention shall be a deliberate action that tilts the playing field to benefit or harm foreign commercial interests. Interventions that are bi-, pluri- or multilaterally agreed are beyond the scope of this dataset.
2) Relative Treatment Test: the intervention must alter the relative treatment of domestic commercial interests vis-à-vis foreign competitors. Therefore, a measure is deemed distortive if it discriminates against foreign commercial entities in favor of at least one rival with operations in the implementing jurisdiction.
3) Meaningful Change: the intervention is likely to meaningfully change international commercial flows.
4) Credible Action: the intervention must be implemented already or its future implementation date is enacted and known.
5) Absence of uncontested higher motive: multilateral measures with a codified set of goals that are superior to the preservation of seamless international commerce are not included. Such codification can happen through international treaties, agreements or resolutions in the public domain.
6) One announcement, one entry: interventions with the same announcement are to be reported in the same GTA database entry.
7) GTA monitoring period: the meaningful change has to be announced on or after 1 November 2008.

Annex II. List of Jurisdictions in the Extended NIPO Database

The following 75 jurisdictions are actively tracked, although not all of them currently have measures recorded in the NIPO database:

Algeria	Argentina	Australia	Austria	Bangladesh
Belgium	Bolivia	Bosnia & Herzegovina	Brazil	Canada
Chile	China	Colombia	Croatia	Czechia
Denmark	East African Community	Ecuador	Egypt	Eurasian Economic Union
European Union	Finland	France	Germany	Ghana
Greece	Gulf Cooperation Council (GCC)	Hong Kong SAR	Hungary	Iceland
India	Indonesia	Ireland	Israel	Italy
Japan	Kenya	Malaysia	Mexico	Mercosur
Morocco	Mozambique	Nepal	Netherlands	New Zealand
Nigeria	North Macedonia	Norway	Pakistan	Peru
Philippines	Poland	Portugal	Qatar	Russia
SACU	Saudi Arabia	Serbia	Singapore	Slovakia
Slovenia	South Africa	Korea	Spain	Sweden
Switzerland	Taiwan Province of China	Thailand	Tunisia	Türkiye
Ukraine	United Arab Emirates	United Kingdom	United States	Viet Nam

Annex III. Classifying Industrial Policy Motives using a Large Language Model Ensemble Approach

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

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

Finally, as recent work by McCoy et al. (2020) points out, LLM performance can be unstable due to randomization during training. To address this issue, we employ an ensemble approach: we train RoBERTa ten times, each time with a randomly initialized classification head and a randomized batch order during training, and calculate the average probability to determine the final classification. This process is designed to enhance the robustness of our predictions. Below are details about our algorithm.

Algorithm in Detail

Step 0 – Model Construction. For each motive, we finetune RoBERTa by augmenting it with a custom classification head. RoBERTa generates 768-dimensional vector representations for each input token. We use the 768-dimensional hidden state as input to our classification head. The classification head consists of a fully connected layer (768 × 768), a GeLU activation function, a dropout layer (dropout rate: 0.1), and a final classification layer (768 × 2). A softmax function is applied at the output to generate probability distributions over the target classes. We perform full finetuning, allowing all model weights—including both RoBERTa’s pre-trained weights and the classification head’s weights—to be updated during training.

Step 1 – Training/Testing set split. We randomly split our labeled NIPO dataset into training and testing sets. We use a class-stratified 80% sample for training and reserve the remaining 20% for testing. This train/test split is performed each time of fine-tuning with a different seed number. The test dataset is withheld until the entire algorithm is complete, at which point we evaluate its performance. The result of this test is presented below.

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

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

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

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

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

Performance

The table below presents the average precision and recall across the 10 fine-tuned models, as assessed with the test datasets. While the algorithm performs best for policies without motive, it still achieves a precision above 80% for all motives and recall above 80% for three out of four motives, indicating strong overall performance.

	Strategic competitiveness		GVC Resilience		Geopolitical concerns or national security		Climate change mitigation	
	precision	recall	precision	recall	precision	recall	precision	recall
Without motive	0.95	0.93	0.97	0.98	0.99	0.99	0.97	0.97
With motives	0.80	0.83	0.83	0.75	0.90	0.93	0.84	0.87

Annex IV. Additional Descriptive Statistics

Table A1. Frequency of Policy Instrument by Stated Motive

Stated Motives	Policy Instrument	Share (%) 2009-2019	Share (%) 2020-2023
Climate Change Mitigation	Domestic subsidy	89	92
	Export barrier	0	0
	Export subsidy	6	3
	FDI	0	0
	Import barrier	0	0
	Localization or Procurement	5	5
	Other	0	0
National Security and/or Geopolitical Concern	Domestic subsidy	6	10
	Export barrier	7	22
	Export subsidy	0	0
	FDI	24	11
	Import barrier	28	11
	Localization or Procurement	30	9
	Other	5	37
Resilience/Security of Supply Chains (Non-food)	Domestic subsidy	82	76
	Export barrier	3	13
	Export subsidy	5	3
	FDI	0	1
	Import barrier	4	2
	Localization or Procurement	5	4
	Other	1	0
Strategic Competitiveness	Domestic subsidy	63	75
	Export barrier	0	1
	Export subsidy	27	11
	FDI	1	0
	Import barrier	4	7
	Localization or Procurement	5	6
	Other	0	0

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