

NBER WORKING PAPER SERIES

THE UNITED STATES AS AN ACTIVE INDUSTRIAL POLICY NATION

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Working Paper 34744
<http://www.nber.org/papers/w34744>

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
January 2026

The research is funded by our university research budgets only. We thank Sijia Li, Xinyu Guo, Jiawang Li, Hongxu Jiao, Yuxin Wang and Chong Chen for research assistance. We acknowledge helpful comments from Gary Hufbauer, Marc Melitz, Joseph Stiglitz, and seminar/conference participants at the Hong Kong Monetary Authority, the University of Chinese Academy of Sciences, the CF40 Forum, and the New Thinking in Industrial Policy Conference in Columbia University. We are responsible for all remaining errors. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

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NBER Working Paper No. 34744
January 2026
JEL No. F1, H20, H4, K20

ABSTRACT

We document and characterize a new history of U.S. federal-level industrial policies by scanning all 12,167 Congressional Acts and 6,030 Presidential Orders from 1973 through 2022. We find several interesting patterns. First, contrary to a common perception, the United States has always been an active industrial policy nation throughout the period, regardless of which party is in power, with 5.4 laws and 3.4 Presidential Orders per year on average containing new industrial policies. Second, we identify roughly 300% more instances of industrial policies than those in the Global Trade Alert (GTA) database during 2008-2022, despite using essentially the same definition. Third, industrial policies in practice are as likely to be justified by national security as by economic competitiveness. Fourth, many U.S. industrial policies incorporate design features that help mitigate potential drawbacks, such as explicit expiration dates and pilot programs for emerging technologies. Finally, based on stock market reactions and firm performance, the identified policies are recognized as economically significant in shifting resource allocations.

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I . Introduction

This paper documents a new history of U.S. national industrial policies for the period 1973-2022. We use a leading large language model (LLM) to scan all 12,167 Congressional Acts (CAs) and 6,030 Presidential Orders (POs) to identify policies that satisfy the standard definition of industrial policy during this period and characterize their salient features. Compared to the Global Trade Alert (GTA) database commonly relied upon to identify industrial policies in more recent years (e.g., Juhász et al. 2025), our data start 35 years earlier. For the recent period that overlaps with GTA, we find about 300% more instances of industrial policies in Federal laws and Presidential Orders than those identified in GTA.

Research on industrial policies in the United States and elsewhere has attracted an enormous amount of attention. A standard narrative in the literature is that the United States (and other advanced countries) has recently “renewed” its interest in industrial policy. For example, in introducing a collection of essays on industrial policy by Dani Rodrik, Bradford DeLong, Pinelopi Goldberg, and Raghuram Rajan in September 2024, Project Syndicate editors write: “After a decades-long love affair with laissez-faire policies, many governments – notably in developed countries – are increasingly seeking to shape their economies through tariffs, subsidies, public procurement, and more.”¹ Our new database challenges such a characterization. Instead, we show that the United States has been a persistently active industrial policy nation.

Our new database leverages recent advances in large language models. Reading the 18,197 Congressional Acts and Presidential Orders would have taken a human research assistant about a year and a half working continuously to accomplish and would still be prone to errors due to fatigue or boredom. Instead, we use ChatGPT-4o to perform this task by using a sequence of filters to pick out documents that contain new industrial policies.

Second, for the years 2001 and 2021, we conduct a human expert audit of the AI results. In particular, we ask three human experts (trained graduate students) to read through all 508 laws and presidential orders in these years and compare their independent judgements with the results of the AI process. All 508 negatives (not

1. <https://www.project-syndicate.org/onpoint/what-kind-of-industrial-policy-works>

industrial policy) identified by AI are confirmed to be negative by the experts; none of the negatives identified by AI were identified as positive by the experts. In other words, there were no false negatives in our pilot sample. On the other hand, some of the documents identified by the AI as industrial policies are judged to be false positive by the human experts with an overall false positive rate of 6.3%. The overall accuracy of the AI procedure = (correctly identified negatives + correctly identified positives) / total cases = $(508+18)/560 = 93.9\%$.

Third, if our purpose were to perform statistical analysis on the effects of industrial policies, the AI-generated database on U.S. industrial policies would appear satisfactory, given the Type I and Type II error probabilities reported above. As we wish to provide a new database on U.S. industrial policies, we go one step further by having the graduate student experts review all the cases identified as positive (possible industrial policies) by the AI, representing approximately 8.6% of the 18,197 documents. This process yields our final baseline database (representing roughly 2.5% of the total universe of the policy documents). We exclude the false positive cases through this extra step. This yields our baseline database of U.S. industrial policies over these 50 years. From the set of policies that pass the filters, we systematically extract policy attributes at the product-keyword level—specifically the policy goals, the timing variables (sunset month and duration), and the policy tools. The database we will release includes document identifiers and metadata; keyword and industry mapping; standardized policy attributes; and manual classification flags.

Note that we use a conventional definition of industrial policy but apply a conservative reading to construct the baseline sample. We define industrial policies as the use of government policy tools to purposefully alter the economic structure in a way that deviates from market outcomes under *laissez-faire*. Such a definition is standard (Rodrik 2004). We apply the definition conservatively by excluding policies aimed at public health and basic education from the set of industrial policies following the existing literature (Juhász et al. 2025; Evenett et al. 2024). We also exclude policies lacking an explicit “buy America” or “buy American” requirement; routine government appropriations; simple renewals of prior policies without significant new provisions; Free Trade Agreements (FTAs); policies primarily aimed at deregulation or at removing existing interventions; policies where the primary objective is ambiguous or focused on other areas such as environmental protection or education; and certain agricultural price

supports tied to temporary measures like disaster relief. We also exclude industrial policies that appear to be simple continuations of existing policies (such as those in annual budget bills). Our conclusion that the United States has always been an active industrial policy nation is reached after applying this conservative filter to select industrial policy documents. We are aware that some of the excluded policies could conceivably be regarded as industrial policies by other scholars, our data appendix also lists these policies to facilitate broader research.²

Our new USIP Database reveals a number of interesting findings. First, unlike the standard narrative in the existing literature that suggests a retreat from industrial policies in the decades before the recent renewal of interest, we find that the U.S. has been consistently active in promulgating industrial policies throughout our sample period of 1973-2022, regardless of which political party is in power. Indeed, every Congressional session and every president has enacted some new industrial policies. Our baseline dataset identifies a total of 267 laws and 187 Presidential Orders containing new industrial policies. This amounts to more than 9 new industrial policy directives (laws or presidential orders) per year on average.

Second, in contrast to the economics literature that emphasizes economic rationales for industrial policy such as economies of scale or positive externalities, we find that the industrial policies in practice are commonly justified by national security considerations. Indeed, they account for more than half of all industrial policy laws and presidential orders, including defense security (21%) and supply chain security/resilience (30%), respectively. In comparison, industrial policies explicitly justified by broadly defined economic competitiveness account for 37% of the total.

Third, there are some distinctive differences in the tools of industrial policies favored in Presidential Orders relative to those in the Congressional Acts. POs often resort to tariffs as a key instrument, whereas CAs tend to use direct instruments such as subsidies or tax reductions. In this sense, President Trump's use of tariffs to alter the economic structure is not an anomaly in the context of U.S. industrial policy history.

Fourth, we have uncovered features of U.S. industrial policies that may help mitigate their efficiency costs (such as protecting an infant industry that never matures). Importantly, a non-trivial fraction of U.S. industrial policies contain an expiration date

2. They are flagged as "Broadly Defined Industrial Policies" in the data appendix.

(about 59%) with an average duration of approximately four years, and many policies establish pilot programs.³ A smaller set of industrial policies contain a conditional trigger, e.g., government procurement of US-made products, only if the domestic price is no more than 125% of the international price level.⁴ Such features are not commonly discussed in the literature on industrial policies. In light of the frequent skepticism about the efficacy of industrial policies, it is noteworthy that many U.S. industrial policies in practice have these features that may help to mitigate efficiency losses.

While we do not assess whether these industrial policies have raised U.S. welfare, we conduct a market test of whether the industrial policies identified by our procedure are considered important by financial markets in shifting resource allocation. Our stock-market event-study analysis shows that the industrial policies in our database exert significant positive effects on stock returns around the dates of policy introduction, passage, and signing.⁵ The abnormal returns are not only statistically significant but also economically large. Further, firm performance indicators—total revenue, net income, and assets—rise notably following these policies. Policies with longer durations (more than 4 years) exhibit greater impact, whereas shorter-duration policies still matter but are roughly half the magnitude. The effect of national security-oriented industrial policies is as strong as that of economic competitiveness-oriented policies.

Finally, we compare our dataset to the Global Trade Alert (GTA) database. Our database begins 35 years earlier (1973 vs. 2008), and for the overlapping period between the two databases (2008-2022), it identifies approximately 300% more U.S. industrial policies under the same conservative criteria. We find that GTA could overcount industrial policies because it lists legislative proposals that ultimately failed to pass. Conversely, all the enacted industrial policies in GTA are also contained in our database. While we do not include federal department actions in our database, our stock price reaction analysis suggests that those department actions are likely captured by the

3. For example, a *pilot* design appears in S.1283 (Federal Nonnuclear Energy R&D Act of 1974), which authorizes demonstration projects to test and accelerate the commercial applications of new energy technologies on a limited, experimental basis.

4. H.R.2959 includes a conditional clause requiring that contracts for procurement of extra high voltage (EHV) power equipment be awarded only if domestic manufacturers offer a suitable product at a price not exceeding 125 percent of the most competitive foreign bid, and Proclamation 6301 imposes a special import quota on upland cotton if domestic prices exceed a specified threshold.

5. The introduction date is when a member of Congress introduces a proposal in the chamber; the passage date marks when the legislation is approved by both chambers of Congress; and the signing date is when the act is signed by the President. For Presidential Orders, only the signing date is available since these orders are typically published immediately upon release.

laws or presidential orders on which they are based. Indeed, those department actions not explicitly traceable to a CA or a PO do not produce a significant stock price reaction. We also find that those industrial policies identified in our database but missed by GTA do trigger a significant stock price reaction (even during 2008-2022). In other words, financial market participants appear to expect that these policies will significantly affect resource allocation.

We make five contributions to the literature. First, we provide a new comprehensive record of U.S. national industrial policies from 1973 to 2022. Our dataset identifies 300% more industrial policy documents than the commonly used GTA database during 2008-2022 in addition to having 35 extra years of data prior to 2008.

Second, we find that the US has always been an active industrial policy nation, which differs from the conventional view. We also find that national security rationale is as often invoked by proponents of the industrial policies as economic rationale. So the recent attention to national security is not new in this regard.

Third, we uncover features of US industrial policies not commonly discussed in the existing literature but might potentially explain why industrial policies are not as inefficient as some of the political economy literature would have suggested. They include an explicit expiration date for more than half of the industrial policy documents and programs that are explicitly designed to address the “missing pioneer” problem (Hausmann and Rodrik 2003; Wei, Wei, and Xu 2021). Furthermore, a small subset of them has a shutdown mechanism for gross inefficiency. For example, having “buy American” requirement but only if the domestic price is no more than 125% of the international price. Future research could look into circumstances in which such clauses are introduced into the policy.

Fourth, we show that these U.S. industrial policies have tangible economic consequences, influencing resource allocation and industry dynamics. As noted by Lane (2020), the earlier empirical literature often relied on aggregate correlations that conflated effective promotion with rent-seeking; modern analysis requires credible identification strategies to isolate the effects of industrial policy. Our event-study analysis shows significant positive stock market reactions to the announcement of conservatively defined industrial policies. Complementing this, our firm-level difference-in-differences analysis indicates that targeted firms experience significant increases in key performance indicators, including total revenue, net income, and total

assets, following policy implementation. We find significant positive effects, consistent with the recent wave of rigorous empirical evidence (Criscuolo et al. 2019; Lane 2025).

Finally, we contribute to the literature applying textual analysis to legal documents. Recent studies have utilized natural language processing to examine the relationship between legislative output and economic growth (Ash, Morelli, and Vannoni 2025), analyze policy diffusion and polarization (DellaVigna and Kim 2025), or track the nationalization of lawmaking (Angelucci, Ash, and Longuet-Marx 2023). We broaden the source material by including Presidential Orders in addition to Congressional Acts and focus on constructing a new history of Federal level industrial policies.

II . Database Construction

II.A. Source Material

We begin with all 12,167 Congressional Acts (hereafter CAs) passed by the U.S. Congress⁶ and 6,030 Presidential Orders⁷ (hereafter POs, including 2,397 executive orders, 2,983 memoranda, and 650 substantive proclamations⁸) from January 1973 to December 2022, and apply a series of sequential filters. Note that ceremonial presidential proclamations⁹ were already excluded from the count of substantive proclamations.

II.B. Industrial Policy Identification Flow Chart

Our process uses three AI filters,¹⁰ as summarized in Table I. The first is a product or industry name filter. To qualify, documents need to contain names of specific industries or products. For example, the CHIPS and Science Act of 2022 passes this filter because it explicitly mentions semiconductors and other industries. Indeed, it

6. We programmatically retrieved bill summary text and core metadata (titles, sponsors, dates, bill identifiers, and URLs) from Congress.gov to construct the initial universe of Congressional Acts used in this study.

7. The American Presidency Project (APP), founded by the University of California, Santa Barbara (see Peters and Woolley 2017, for a description).

8. We distinguish (i) substantive proclamations, which contain operative provisions with legal, administrative, or economic effects (e.g., modifying tariff schedules, setting import quotas, invoking emergency authorities, allocating public lands); and (ii) ceremonial proclamations, which are honorific or commemorative (e.g., designating days, weeks, or months) and contain no operative mandate. Only substantive proclamations are counted as POs in our dataset; ceremonial proclamations are excluded ex ante.

9. An example of an excluded ceremonial proclamation would be a declaration of a particular calendar date in honor of a person or an event. They are judged to be irrelevant for industrial policy on an ex-ante basis.

10. The exact prompt used for these three stages appears in Appendix D, Prompt Table.

contains a total of 45 specific product or industry names. In comparison, the Federal Trade Commission Reauthorization Act¹¹ does not pass this filter as no specific industry or product is mentioned. Policies primarily aimed at redistribution or general social welfare are also excluded by our filtering process.¹² Consequently, 3,158 Congressional Acts and 1,628 Presidential Orders survive this filter.

The second is a purpose and intensity filter. For a document to qualify, it must explicitly favor or discourage certain economic activities and specify a clear direction of effect (promotion or restraint), rather than adopting a neutral or indirect stance. It must purposefully induce a change in the economic structure that a laissez-faire economy would not produce. For example, the CHIPS and Science Act passes this filter as it cites enhancing semiconductor supply-chain resilience and economic competitiveness as its concrete goals. Phrases such as “provides funds to support” in the law also make explicit the direction of the intended change in the economy. In comparison, documents with no reference to either supporting or restricting industry development are excluded by this filter. For example, the Mobile Telecommunications Procurement Act clarifies tax jurisdiction rules and sourcing rules but appears to be otherwise neutral rather than explicitly promoting or restricting the mobile telecommunication sector.¹³ The AI model concludes that this act does not pass the purpose and intensity filter. 1,607 CAs and 638 POs are left after this filter.

The third is a commercial entity and broad scope filter. The intended direct beneficiaries of a qualified policy must involve a range of commercial entities. In other words, the scope of the policy cannot be too narrow to cover a single firm by name or a single narrow geographic region within the country. The CHIPS and Science Act passes this filter as it aims to promote an entire commercial industry (semiconductor industry) and is not restricted to any particular region or firm. In comparison, the National Aeronautics and Space Administration Act of 2005 is excluded by this filter as it does not mention specific commercial activity in the act.¹⁴ We acknowledge that

11. H.R. 3553 — *Federal Trade Commission Reauthorization Act of 1996*. <https://www.congress.gov/bill/104th-congress/house-bill/3553>.

12. We systematically exclude policies primarily targeting service industries (e.g., financial activities - ISIC K, Real estate activities - ISIC L, Administrative activities N, education - ISIC P, human health - ISIC Q, etc.). This refinement ensures our focus on documents whose industry keywords pertain to Agriculture (ISIC A), Mining and Quarrying (ISIC B), Manufacturing (ISIC C), and Electricity Supply (ISIC D).

13. H.R. 4391 — *Mobile Telecommunications Sourcing Act*. Link: <https://www.congress.gov/bill/106th-congress/house-bill/4391>.

14. S. 1281 — *National Aeronautics and Space Administration Authorization Act of 2005*. Used as a Step 3 counterexample: the act concerns NASA authorization and activities and does not specify commercial industry

policies promoting NASA can indirectly benefit certain U.S. firms and industries. We also recognize that whether a policy document that benefits a single firm or a single narrowly defined geographic region constitutes an industrial policy could be debated. Therefore, our filter means that we apply a conservative interpretation of an industrial policy that may err on the side of excluding documents that might qualify under a more lenient definition of industrial policy. 1,024 CAs and 542 POs are left after this filter.

II.C. Audit by Human Experts of a Two-Year Subsample

To assess the accuracy of these AI filters, we conducted a human-expert audit using the entire set of 560 Congressional Acts and Presidential Orders in two calendar years (2001 and 2021). Specifically, we asked three economics graduate students who understand the concept of industrial policy to review all the documents in these two years and provide their independent judgment on whether a given document contains a new industrial policy.

The experts confirmed that all 508 documents flagged by the AI filters as non-industrial policies indeed contained nothing that would satisfy our definition of an industrial policy. This means our approach yields no false negatives in the sample. Conversely, among the 52 documents identified as industrial policies by the AI, 18 were confirmed as having new industrial policies. Hence, the false positive rate (the share of true negative cases that are wrongly labeled as positive) equals 34 out of $(560-18)=542$ true negative cases, or 6.27%. The overall accuracy rate equals $(508 \text{ correctly labeled negative cases} + 18 \text{ correctly labeled positive cases}) / 560 \text{ total cases} = 93.9\%$.

The human experts may judge a case to be a false positive for a variety of reasons. First, a congressional act may pass all three filters and indeed contain an industrial policy but represent a renewal of the same policy from a previous act. This can occur in many appropriations laws. Second, the law may implement or confirm a free trade agreement. Third, a Congressional Act or a Presidential Order may represent a partial or total reversal of a previous industrial policy by specifying a termination, withdrawal, or reduction in incentives to an industry. Fourth, certain agricultural price-support programs appear small in scale or short in duration.

beneficiaries; hence it fails the commercial/broad-scope criterion. Link: <https://www.congress.gov/bill/109th-congress/senate-bill/1281>.

Our guiding principle is to be conservative in designating laws and presidential orders that promulgate new industrial policies. For this reason, we exclude these cases from our baseline set of U.S. industrial policies. At the same time, we recognize that other researchers might regard some of these cases as industrial policy laws/orders. We therefore include many of them in our database with a notation indicating they fall outside our definition of conservatively defined industrial policy.

Using the knowledge from our audit exercise of 2001 and 2021, we returned to refine our database for the entire 50-year history. We experimented with codifying rules using ChatGPT prompts that could help reduce the false positive cases. While we did indeed succeed in reducing false positive cases, we found that the new rules also tended to create false negative cases.

As our objective is to produce an accurate history of U.S. industrial policies for the 50-year period, we chose a somewhat labor-intensive route – retaining the set of filters that produces some false positive documents but virtually no false negative cases, and removing the false positive documents at a later stage using human experts to manually review all 1,024 CAs and 542 POs. As these documents represent only 8.6% $[(1024+542)/18197]$ of the original laws and presidential orders, the three AI filters still saved approximately one and a half years of human research assistants’ time.

II.D. Full Data Review and Presentation of the Final Database

We conducted a review by human experts of all documents in the 50-year history that have passed the three AI filters with the aim of excluding false positives. This resulted in a final database of conservatively defined industrial policies — 267 CAs and 187 POs in total.

We report our industrial policy database in Appendix B. We affix standardized characteristics (“tags”) to each document including (a) a unique key identifying the document type (Federal law or Presidential Order) and the effective date, (b) whether it satisfies a conservative interpretation of industrial policy, and (c) product or industry names mentioned in the policy document and their corresponding 4-digit ISIC codes.

We also report a rich set of policy attributes extracted or inferred from the policy documents. They include (a) stated policy goals, (b) whether it contains an explicit expiration date and the duration of the policy, (c) intended direction of the policy (i.e., to encourage or discourage certain economic activities) as determined by the AI, (d)

whether the targeted products by the policy represent a substantial portion of the output in the corresponding 4-digit ISIC code as determined by human experts, and (e) special features (whether it is intended as a pilot program, whether it contains conditional support, or whether it is a specific trade measure). In all cases, we also include the key words or key sentences from the policy document that lead to the labeling.

III. Salient Features of the US Industrial Policies

III.A. Basics

Figure I, Panel A displays the time series of the count of U.S. industrial policy documents, separated into Congressional Acts Industrial Policies (CAIPs, black bars) and Presidential Orders Industrial Policies (POIPs, grey bars) for each two-year congressional session from 1973 to 2022. An important takeaway is the consistent presence of new industrial policy laws and presidential orders throughout the entire 50-year period. Congress enacts new industrial policies in nearly every session, and every President promulgates some new industrial policies. This pattern challenges a common narrative that the U.S. experienced a long dormant period before the recent renewed interest in industrial policy. Over the 50-year period, we identify a total of 267 laws and 187 presidential orders containing new industrial policies. This amounts to more than 9 new industrial policies per year in this period. As noted earlier, these counts already reflect a conservative interpretation of the industrial policy definition (e.g., by excluding policies contained in trade agreements with partner countries, or policies that are applicable only to a single firm or a single geographic region).

There are two relative peaks. The first and most pronounced peak occurred during the 1977-1980 sessions, when about 100 industrial policy documents, chiefly through congressional acts, were promulgated. A second peak emerged more recently after 2017, driven predominantly by Presidential Orders.

Figure I, Panel B shows that while Congressional Acts were the more frequent source of industrial policy before the 2010s, Presidential Orders have become more important over time, especially after 2017. As shown in Table II, in terms of presidential actions, the use of Presidential Orders to enact industrial policy has been most concentrated in the three most recent congressional sessions in our dataset. The 115th and 116th congressional sessions, corresponding to the first Trump administration,

recorded POIP ratios of 8.50% and 10.60%, respectively. The subsequent 117th session, corresponding to the first two years of the Biden administration, shows a similarly high ratio of 9.61%. These three figures represent the highest POIPs ratios in our entire 50-year sample period. In contrast, the two Bush administrations—George H.W. Bush and George W. Bush—show the lowest level of activity in this regard.

While both parties enact industrial policies, those Congressional sessions when the Democrats control both chambers exhibit more activities (15 CAIPs per year versus 7 per year when both chambers are under Republican control).

III.B. The Role of National Security in the USIP

Based on the text of the documents, we classify the goals of industrial policies as stated in the documents into five categories: (a) security/resilience of supply chains, (b) national defense, (c) economic competitiveness, (d) climate change/environment, and (e) others or no explicit goals identified. Note that (a) and (b) may also be grouped under a common heading of “national security,” as the term is sometimes used. A given document can cite more than one goal.

In Table III, we tabulate the count and frequency of the industrial policy documents based on their primary and secondary goals. Domestic competitiveness (37.0%) and security of supply chains (29.5%) are the leading two types of primary goals, followed by national security (20.9%). If we use “national security” to group together “security of supply chains” and “national defense,” then “national security” (51.1%) accounts for more than half of all laws or presidential orders containing new industrial policies. Only 8.2% of the laws/orders containing industrial policies list “climate” or “environmental” as the primary goal.

On the other hand, 73.6% of the laws/orders have “economic competitiveness” as either a primary or secondary goal. In comparison, 24.2% and 58.2% of the total, respectively, have “national defense” and “security of supply chains” as either the primary or the secondary goal. Finally, 26.0% have “climate” or “environmental” as either the primary or the secondary goal. “Defense security” is often invoked on its own (as can be seen from the closeness of the corresponding numbers in Columns 3 and 5), whereas “supply chain security” and “economic competitiveness” are often mentioned in conjunction with other objectives.

To summarize, a notable finding is that industrial policies in practice are at least

as likely to be justified on national-security grounds (either “national defense” or “supply security”) as on economic-competitiveness or environmental grounds.¹⁵ Indeed, there has been a significant rise in the use of national security as a rationale for industrial policy since 2017.¹⁶

In terms of policy tools used to support industrial policies, we see a notable difference between laws and presidential orders (as reported in Appendix Table B.1). In particular, tariffs or other trade policy tools are heavily favored in Presidential Orders, invoked in 57.8% of the POIPs, compared to only 16.1% of the CAIPs.

In CAIPs, firm subsidies, tax measures, and customer subsidies are employed in 20.6%, 9.4%, and 8.6% of the cases, respectively. In comparison, the POIPs exhibit a significantly lower propensity to use the same tools (9.1% for firm subsidies, 1.1% for tax measures, and 4.3% for customer subsidies).

Such differences in the relative usage of the tools are perhaps not surprising: Congress has delegated the authority to make trade policies to the President, who can often announce or change tariffs or enter a trade agreement with a foreign country without prior consultation with Congress. In contrast, Congress retains its constitutional authority to adjust tax and revenue policies.

III.C. Comparison with Industrial Policies in the GTA Database

Our database has 35 extra years (1973-2007) of coverage compared to the GTA, since the latter only starts in 2008. We now compare the industrial policies identified by our method and those in the GTA during the overlapping period of 2008-2022.

We begin by extracting US industrial policies from the GTA using the same three filters. From GTA’s descriptions, we identified 26 distinct Federal laws and 17 Presidential Orders that contain industrial policies.¹⁷ The cross-verification results are summarized in Appendix Table B.2. Out of the 46 CAIPs in our database, the GTA has missed 29 of them. Out of the 89 POIPs, the GTA has missed 72 of them.

15. We do not investigate the theoretical reasons why security is a primary determinant of US policy making. One possible reason is that security concerns likely reflect zero-sum thinking among countries. For studies on the effects of zero-sum thinking in US policy making, please see Sahil Chinoy, Nathan Nunn, Sandra Sequeira, and Stefanie Stantcheva, "Zero-Sum Thinking and the Roots of U.S. Political Differences".

16. See Appendix Figure B.1 for additional information.

17. There are also 141 Federal departmental regulations in the GTA that could not be traced to a specific CA or PO. Our subsequent stock-price event studies suggest that these departmental actions do not generate significant abnormal returns.

In comparison, all 17 Presidential Orders containing industrial policies in the GTA database are also in our database. Eight Congressional bills in the GTA are not in our database. Upon closer investigation, we find that all of them are legislative proposals that have never become law¹⁸.

To summarize, in addition to having an extra 35 years of data, our database is also substantially more comprehensive and accurate in its coverage of enacted national industrial policies during 2008-2022. While the GTA misses more than half of the laws and a majority of Presidential Orders that contain new industrial policies, our database does not appear to miss any that are in the GTA.

Our database also provides more comprehensive textual information. The average text length for Congressional Acts in our database is 7,558 words, while Presidential Orders average around 1,965 words—both substantially longer than the 204-word average in GTA descriptions. This additional detail enables a more precise classification of policies, as well as a richer understanding of their potential economic implications.

IV. Do Industrial Policies Shift Resource Allocation Significantly?

IV.A. Stock Price Reactions

We use the stock price reactions to assess whether the promulgation of these industrial policies is regarded by the financial market as economically meaningful, i.e., capable of altering the payoffs of the policy-targeted activities relative to others. Specifically, we measure cumulative abnormal returns (CARs) of the stocks in the policy-targeted industries over 3-day, 7-day, and 11-day windows. In the baseline case, we focus on those industrial policies that would in theory have a non-negative effect on the firms.¹⁹ Note that this exercise is different from an assessment of the welfare effect of the policies, which we leave for future research. Conversely, if the policies identified by our procedure were just white noise, we would not expect to see any significant

18. Our subsequent stock price analysis suggests that these eight bills are not regarded by stock market participants as significant in terms of generating abnormal returns.

19. The excluded policies are mostly environmental policies that regulate emissions, which account for less than 10% of the overall industrial policy documents. Specifically, we restrict the baseline event-study sample to policies where *ip_impact* = 1 and *isic4_substantial_share* = 1. The first condition isolates supportive policy shocks to targeted firms. The second condition excludes policies with an ambiguous or narrowly targeted impact. For example, if a law's product keywords refer to a narrow niche such as "low-emission steel manufacturing," its applicability to the broader steel sector (ISIC Rev.4 2410) is unclear, and it would be coded as *isic4_substantial_share* = 0. In contrast, if the keywords were simply "Steel" or "Steel Manufacturing," the policy would be coded as *isic4_substantial_share* = 1 and included in our sample.

stock price reactions.

We extract stock price data for U.S. companies listed on NYSE, AMEX, or NASDAQ from 1973 to 2022 from the Wharton Research Data Services (WRDS) database. Following the practice of a typical event-study using stock prices, we exclude companies in the financial, insurance, and real estate sectors (SIC codes 60-69). We further restrict the sample to firms that are continuously listed and not subject to trading halts on *each* relevant event date (introduction, passage, and signing) for the corresponding U.S. industrial-policy measure.

For CAIPs, we use three event dates: the date when the eventual law was first introduced as a bill (the introduced date), the passage date in Congress, and the effective date (which is usually the date of presidential signature). For POIPs, the event date is the date when it is signed and announced. Daily abnormal returns for stock i (AR) are calculated using a market-adjusted model:

$$AR_{i,t} = R_{i,t} - R_{m,t} \quad (1)$$

where $R_{i,t}$ is the daily raw return of firm i on day t and $R_{m,t}$ is the market return on day t . All event windows are centered on event date 0. The CARs are calculated as

$$CAR_i[-T, T] = \sum_{t=-T}^T AR_{i,t} \times 100 \quad (2)$$

where $CAR_i[-T, T]$ denotes the abnormal returns of firm i accumulated in the event window $[-T, T]$. For any CA or PO that contains new industrial policies, multiple listed firms may be in the affected industries. In that case, our dependent variable will be the equally-weighted average of the CARs of the affected firms.

The regression results are presented in Table IV. For CAs containing new industrial policies, a significantly positive stock price response is observed following the introduction of the legislative bill that eventually becomes law (Column 1). For the event window $[-1, +1]$, the prices of the affected stocks go up by 0.601% (not annualized) on average, which is economically significant. We see even bigger price movement when we use $[-3, +3]$ or $[-5, +5]$ as the event window. This suggests that stock market investors believe that the industrial policies embedded in such legislation will alter the economic payoffs to the affected firms in a significant way.

We also see positive stock price reactions when we use other event dates, such as the passage of the law in the Congress (0.276% for the $[-1, +1]$ event window) or the presidential signature on the law (0.306%). The existence of the additional CARs at the

second and third milestones (Columns 2 or 3) reflects uncertainty over whether any given bill introduced in either the Senate or the House will eventually become a law. It is important to know that, since the President can sign legislation into law very quickly after it passes Congress, the last two events can often, though do not always, overlap.

Presidential Orders, for which only signing dates are observed, also generate large and statistically significant CARs. For example, for the $[-1,+1]$ event window, the stock prices of the affected firms go up by 0.496% relative to the market as a whole. This means that financial market investors believe that the industrial policies embedded in presidential orders can also alter resource allocation in an economically significant way.

We provide additional analysis in Appendix Table B.3. Specifically, when we sort industrial policies by stated rationales (national defense, supply-chain resilience, and economic competitiveness), we find positive and statistically significant stock price reactions in each category. Notably, stock market investors regard those policies based on national security as equally important in terms of affected firms' future financial payoffs as those based on economic competitiveness.

We investigate whether the perceived strength of industrial policies varies over time. In Appendix Figure B.2, we perform the stock market event studies by presidential tenure. We see no obvious trend in the size of the abnormal returns. In other words, judged by financial investors' reactions, industrial policies in the earlier decades are regarded as significant as their more recent counterparts.

IV.B. A Market-test Comparison between our USIP and GTA Databases

We apply a market test to compare our US industrial policy history data with the industrial policies extracted from the GTA database during 2008-2022.

There are three categories of industrial policies: those common in both datasets, those identified by our method but missed by the GTA, and those in the GTA but not in ours. Unsurprisingly, we generally see positive stock price reactions to industrial policies identified by both our approach and the GTA database (Panel A of Appendix Table B.4). Importantly, for the industrial policies in our database but missed by the GTA, we see strong and significant stock price reactions (Panel B of Appendix Table B.4). In fact, in 7 out of 12 cases, the point estimates are larger for this category of industrial policies than for those common to both databases. In other words, the large number of industrial policies missed by the GTA database are economically significant

policies as judged by financial market participants.

Finally, for the small number of industrial policies in the GTA but not in our database, we find that the CARs are indistinguishable from zero (Panel C of Appendix Table B.4). This finding is consistent with our earlier discussion that the extra industrial policy cases in the GTA are either bills that appear in news but fail to become law in the end, or departmental regulations that cannot be traced to a specific CA or PO. Those documents are not regarded by financial market participants as significant enough to alter the cash flows of potentially affected firms.

IV.C. Impact on Firm Performance

We estimate the impact of industrial policies in our database on the affected firms' subsequent performance, such as revenue and real income. We adopt the staggered difference-in-differences (DiD) approach proposed by De Chaisemartin and D'Haultfœuille (2020), which traces the dynamic responses and mitigates possible biases from heterogeneous treatment timing and effects.

We focus on those policies that in theory would have a non-negative effect on the affected firms. We summarize the key results on the affected firms' revenue, net income, and total assets, all in logarithms, in Panels A–C, respectively, in Figure II.

Across all these dimensions, we see that the treated firms grow significantly faster than their counterparts in the control group. The relative gains typically emerge in the first year following the industrial policy enactment, and the gap over the control group widens in the subsequent two years. By the time they reach a peak in the third year, both the revenue and the net income of the affected firms are about 10% higher than would otherwise be the case, and the assets are greater by about 5% on average. The positive and significant effects of the industrial policies on the affected firms' fundamentals validate the expectation of financial market investors as revealed in the previous stock price analysis.

In Panels D and E, we see that the effects of the policies rationalized by defense security or supply-chain security have economically significant effects on the affected firms' real fundamentals (log revenue). In Panels F and G, we also find that the industrial policies that are designed for a shorter duration (such as those lasting fewer than four years) have a more muted real effect (log revenue) than those designed to last longer (including those without an explicit expiration date).

V. Conclusion

We document a new database on the history of U.S. federal-level industrial policies from 1973-2022 (USIP Database for short) by analyzing all 18,197 U.S. Congressional Acts (CAs) and Presidential Orders (POs) during the 50-year period. The historical database will be made publicly available upon the publication of the paper.

Using a conventional definition of industrial policy but interpreted conservatively (to exclude recurrent policies or policies affecting only one region or one firm), we identify 454 CAs or POs (267 CAs and 187 POs) that contain new industrial policies. These policies are spread over the sample period, regardless of which political party controls the White House or Congress. This means that the United States has been an active industrial policy nation at least throughout the last half century. Furthermore, national defense, as opposed to the economic competitiveness emphasized in the economics literature (such as scale economies and productivity spillovers), has always been featured prominently as a rationale for industrial policies in practice. Along these dimensions, recent industrial policies do not represent a structural break.

The skepticism about industrial policies held by some economists is partly due to political economy considerations — even when a given policy can be justified initially on efficiency grounds, it can in practice outlive its initial usefulness or be exploited by self-interested firms or politicians. For example, once an industrial policy is in place, vested interest groups might emerge endogenously and do their best to keep the policy in place even if it becomes unwarranted by subsequent information.

With such considerations in mind, we uncover features of the actual US industrial policies that may have limited the downsides of industrial policies. First, about 59% of all industrial policy laws or orders have an explicit expiration date. Second, several policies are explicitly enacted on an experimental or pilot basis. This may be interpreted as addressing a “missing pioneers” problem (Hausmann and Rodrik 2003; Wei, Wei, and Xu 2021). Third, a small number of industrial policies offer help to U.S. firms with a conditional trigger—for example, “Buy America” provisions that apply only if the domestic price is no more than 125% of the international price. The government support will be withdrawn if the inefficiency is too large. Future research could look into why and how these guardrails are put in place and whether they indeed serve to limit potential inefficiencies associated with the industrial policies.

Compared to the U.S. industrial policies extracted from the GTA database, our database covers a significantly longer time period (by extra 35 years). For the overlapping period (2008-2022), our database identifies approximately three times as many industrial policies as the GTA. Our stock price analysis suggests that those policies missed by the GTA are regarded as economically significant by financial market investors. Our database lays the foundation for many future research projects. For example, one may look into the determinants and consequences of actual industrial policies.

Our event study confirms that the introduction, passage, and signing dates of CAIPs—and the signing dates of POIPs—consistently generate significantly positive abnormal returns. This indicates that financial market participants perceive these policy events as materially affecting firm performance and resource allocation. A comparison with the GTA database shows that we capture three times as many industrial policies in our database as in the GTA.

We find not only a positive and significant stock price reaction to the enactment of the industrial policies, but also real growth in revenue and real income of the affected firms in subsequent years.

In sum, we have provided a new and comprehensive history of U.S. federal-level industrial policies during 1973-2022. The United States has been an active industrial policy nation. But the database also reveals a number of interesting features that have not received sufficient attention in the existing literature, such as an explicit expiration date for a large number of the policies. Such history should be a useful foundation for future research on the causes and consequences of U.S. industrial policies.

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TABLES AND FIGURES

TABLE I Identification of US Industrial Policies Through Filters

Filter Name	Count of Congressional Acts (CAs)	Count of Presidential Orders (POs)
	After Each Filter	After Each Filter
Initial Document Count	12,167	6,030
Step 1: Product or Industry Name Filter	3,158	1,628
Step 2: Purpose and Intensity Filter	1,607	638
Step 3: Commercial and Broad Scope Filter	1,024	542
Step 4: Human Expert Review Filter	267	187

Notes. This table summarizes the filtering process used to construct the USIP Database 1973-2022.

TABLE II: US Industrial Policy Documents by Congressional Sessions

1973–2022

Congress Session	Year	President (Party)	Senate Majority Party	House Majority Party	CAIPs Total	POIPs Total	CAIPs Ratio (%)	POIPs Ratio (%)
93rd	1973-1974	Richard Nixon (R)	D	D	6	6	1.04	3.35
94th	1975-1976	Gerald Ford (R)	D	D	9	7	1.37	3.35
95th	1977-1978	Jimmy Carter (D)	D	D	29	15	4.58	4.34
96th	1979-1980	Jimmy Carter (D)	D	D	33	16	5.38	5.39
97th	1981-1982	Ronald Reagan (R)	R	D	10	3	2.48	1.52
98th	1983-1984	Ronald Reagan (R)	R	D	13	7	1.88	4.12
99th	1985-1986	Ronald Reagan (R)	R	D	7	8	1.06	4.06
100th	1987-1988	Ronald Reagan (R)	D	D	21	7	2.95	2.87
101st	1989-1990	George H. W. Bush (R)	D	D	17	0	2.62	0
102nd	1991-1992	George H. W. Bush (R)	D	D	13	2	2.20	0.73
103rd	1993-1994	Bill Clinton (D)	D	D	13	3	2.80	0.91
104th	1995-1996	Bill Clinton (D)	R	R	8	4	2.40	1.37
105th	1997-1998	Bill Clinton (D)	R	R	3	3	0.76	1.21
106th	1999-2000	Bill Clinton (D)	R	R	9	15	1.55	5.17
107th	2001-2002	George W. Bush (R)	D	R	5	2	1.34	0.79
108th	2003-2004	George W. Bush (R)	R	R	15	0	3.11	0
109th	2005-2006	George W. Bush (R)	R	R	6	0	1.28	0
110th	2007-2008	George W. Bush (R)	D	D	12	0	2.54	0
111th	2009-2010	Barack Obama (D)	D	D	6	4	1.73	1.72
112th	2011-2012	Barack Obama (D)	D	R	6	6	2.18	3.12
113th	2013-2014	Barack Obama (D)	D	R	7	0	2.05	0
114th	2015-	Barack	R	R	2	1	0.61	0.46

	2016	Obama (D)						
115th	2017-2018	Donald Trump (R)	R	R	6	21	1.46	8.50
116th	2019-2020	Donald Trump (R)	R	D	5	30	1.59	10.60
117th	2021-2022	Joe Biden (D)	D	D	6	27	1.54	9.61
Total	1973-2022				267	187	2.10	2.93

Notes. CAIPs and POIPs refer to the counts of Congressional Acts and Presidential Orders containing Industrial Policies, respectively, identified as containing conservatively-defined industrial policies in our USIP Database. The CAIPs Ratio is the number of CAIPs divided by the total number of Congressional Acts enacted in the same session, multiplied by 100. The POIPs Ratio is the number of POIPs divided by the total number of substantive Presidential Orders (Executive Orders, Memoranda, and substantive Proclamations) issued in a given congressional session, multiplied by 100. Party affiliations: D = Democrat, R = Republican. Political control data and total policy counts are based on official records and established databases (e.g., Congress.gov, presidency.ucsb.edu). The last row (labeled as “total”) shows aggregate counts for 1973-2022 and the period average ratios.

TABLE III: Policy Rationale as Cited in the Policy Documents

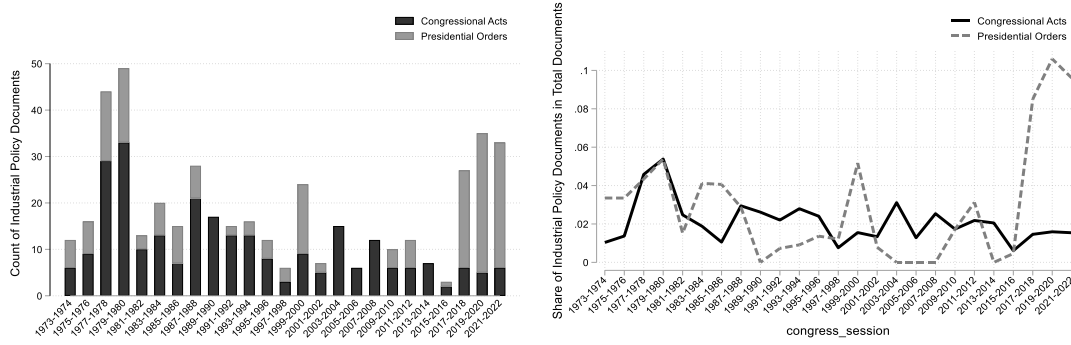
Goal Category	Primary Goal (Count)	Primary Goal Share (% of documents)	Either primary or secondary goal (Count)	Either primary or secondary goal share (% of documents)
Defense Security	95	20.93	110	24.23
Resilience/Security of Supply	134	29.52	264	58.15
Domestic Competitiveness	168	37.00	334	73.57
Climate Change Mitigation and Environmental Objectives	37	8.15	118	25.99
Not Mentioned / Others	20	4.41	67	14.76

Notes. This table summarizes the stated goals of U.S. industrial policies in terms of primary objectives and additional mentions. “Share (% of documents)” uses the total number of distinct documents as the denominator ($N = 454$). “Either primary or secondary goal” categories are non-mutually exclusive; shares need not sum to 100%. “Primary Goal” shares are mutually exclusive and sum to 100% (subject to rounding). The primary goal is identified at the keywords and ISIC-code level: for each document we aggregate goal tags across all keywords and assign as the primary designation the category with the largest aggregate count.

**TABLE IV: Stock Price Reactions to Laws or Presidential Orders
Containing Industrial Policies**

	(1)	(2)	(3)	(4)
	Congressional Acts			Presidential Orders
Event Window	Introduction Date	Passage Date	Effective Date	Sign Date
[-1,+1]	0.601*** (0.069)	0.276*** (0.064)	0.306*** (0.063)	0.496*** (0.068)
[-3,+3]	1.101*** (0.101)	0.369*** (0.096)	0.601*** (0.098)	0.743*** (0.098)
[-5,+5]	1.444*** (0.125)	0.523*** (0.121)	0.769*** (0.122)	0.864*** (0.118)
Obs.	5,677	5,677	5,677	5,083

Notes. This table reports the cumulative abnormal returns (CARs) of the treated firms around industrial policy events identified by our USIP Database. The event windows are centered on key dates: for CAIPs, we use the introduced date, passed date, and signed date; for POIPs, we use the signed date. Only firms that satisfy the continuous-listing condition on all three dates are included. The estimation windows are [-1,+1], [-3,+3] and [-5,+5] days around the event date. Standard errors are provided in parentheses below the coefficients. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

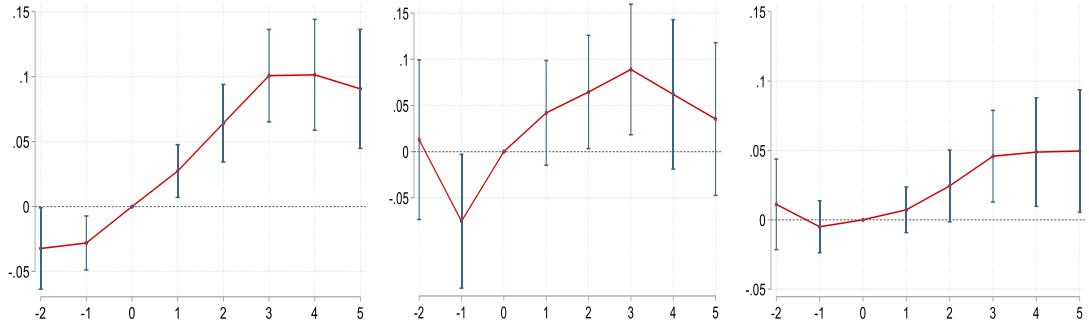


(A): the Number of CAIPs and POIPs

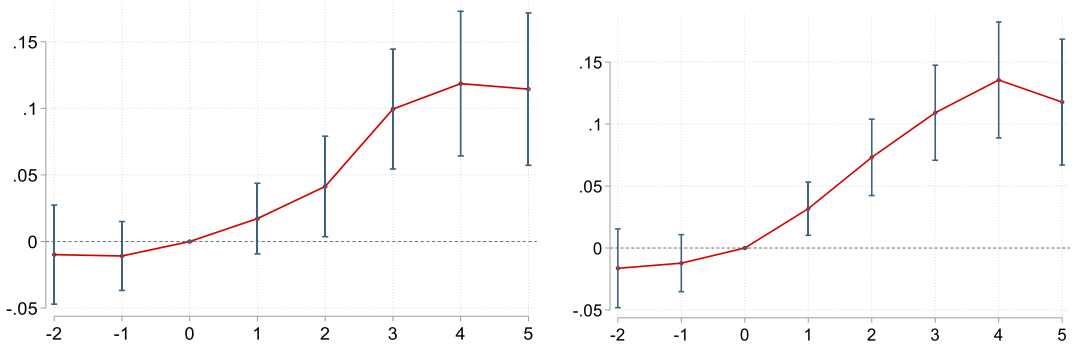
(B): Proportion of CAIPs and POIPs

FIGURE I Trends in CAIPs and POIPs (1973-2022)

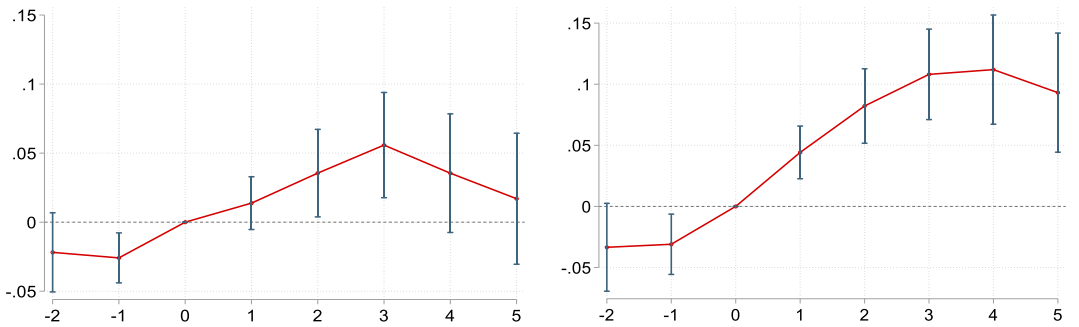
Notes. Panel A shows the number of CAIPs and POIPs from 1973 to 2022, highlighting two peaks: 1978-1980 and 2018-2022. Over time, the number of CAIPs has decreased, while that of POIPs has risen, indicating a shift towards using presidential orders for industrial policy. Panel B illustrates the ratio of CAs and POs containing industrial policies to total documents. The POIPs ratio has surged, especially after 2010, while the CAIPs ratio remains stable, suggesting that the overall rise in industrial policies is driven by increased POIP use.



(A) Total Revenue (in log) (B) Net income (in log) (C) Total asset (in log)



(D) Goal = Defense Security (log revenue) (E) Goal = Supply Security (log revenue)



(F) Short Duration: < 4 years (log revenue) (G) Long Duration: ≥ 4 years (log revenue)

FIGURE II Effects of the Industrial Policies on the Treated Firms' Real Variables

Notes. We implement the heterogeneity-robust dynamic staggered difference-in-differences estimator proposed by De Chaisemartin and D'Haultfoeulle (2020), on a firm-year panel. Confidence bars are 95%, and standard errors are clustered at the firm level. Outcomes shown in panels are log-transformed. The baseline event-study sample is restricted to $ip_impact = 1$ and $isic4_substantial_share = 1$.

Appendix A: Choice of AI model

We choose ChatGPT-4o over alternative AI tools such as Bidirectional Encoder Representations from Transformers (BERT) used in Juhász et al. (2025) for several reasons. First, the average length of the text of a Congressional Act is 7,558 words, whereas that for a Presidential Order is 1,965 words. While BERT has a word limit of 460 words per input,²⁰ and would have required significant computational resources, GPT-4o can handle up to 96,000 words,²¹ and hence is better suited for analyzing lengthy legislative text without segmentation errors. Second, GPT-4o as a generative AI can “understand” economics and law much better than most machine learning tools including BERT. ChatGPT scores at the 91st percentile for microeconomics and the 99th percentile for macroeconomics on the Test of Understanding in College Economics (TUCE) (Geerling et al. 2023) and outperforms 90% of the candidates on the uniform bar examination (Katz et al. 2024). While BERT requires fine-tuning for specific domains like FinBERT and LegalBERT,²² GPT-4o covers both fields comprehensively, making it more efficient. Third, GPT-4o's multitask capabilities allow us to extract multiple elements (e.g., product keywords, ISIC codes, policy scope) using a single model, significantly reducing the need for separate datasets and models. In comparison, BERT would have required extensive annotation for each sub-step. For these reasons, we use the GPT-4o model for all tasks.²³

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20. The model has a limit of 512 tokens, and 100 tokens might represent about 80-90 words, depending on the complexity and vocabulary of the text, so this limits the range from 410 to 460 words.

21. GPT-4o has a limit of 128,000 tokens, and in GPT-4 models, a token is roughly equivalent to 0.75 words in English, so this limits the input to approximately 96,000 words.

22. See <https://arxiv.org/abs/1908.10063> and <https://arxiv.org/abs/2010.02559> for the introduction of these two models.

23. We specify the parameters to minimize AI hallucination and maximize consistency (obtaining the same or similar answers when asking similar questions in different trials): Temperature = 0 (minimum randomness, focused and deterministic output), Top_p = 0 (high probability token selection), and Seed = 22 for reproducibility.

Appendix B: Supplementary Tables and Figures

TABLE B.1 Policy Tools in CAIPs and POIPs

Tools	CAIP	Percent	POIP	Percent
Firm Subsidy	55	20.60%	17	9.09%
Tax Measures	25	9.36%	2	1.07%
Credit and Loan Policies	74	27.72%	15	8.02%
Trade Policies	43	16.10%	108	57.75%
Public Procurement	83	31.09%	57	30.48%
Sector-specific Infrastructure	66	24.72%	42	22.46%
Sector-specific Training	32	11.99%	22	11.76%
Customer Subsidies	23	8.61%	8	4.28%
Local Supply Chain Requirements	36	13.48%	28	14.97%
Regulatory Measures	136	50.94%	84	44.92%
Others	45	16.85%	16	8.56%

Notes. Percentages are calculated within the set of CAIPs and within POIPs that pass our filters; because a single policy may deploy multiple tools, column totals can exceed 100%. “Trade Policies” include tariffs and non-tariff measures, whereas “Tax Measures” exclude tariffs, consistent with our classification. Entries in bold mark tool categories where CAIPs and POIPs exhibit relatively large differences in usage.

TABLE B.2 Comparisons with Industrial Policies in GTA, 2008–2022

Document Type	Matched (Both databases flag as enacted)	Missed by USIP (GTA flags enacted; USIP not enacted)	Missed by GTA (USIP flags enacted; GTA not flagged)	USIP Enacted (Total)
Congressional Acts (CAs)	17	0	29	46
Presidential Orders (POs)	17	0	72	89
All (CA + PO)	34	0	101	135

Notes. This table cross-checks our USIP database against GTA flags for enacted industrial policies during 2008–2022. *Matched* refers to items both sources flag as enacted; *Missed by GTA* refers to enacted items in USIP not flagged by GTA. The column labeled *Missed by USIP* would capture cases flagged as enacted by GTA but not by USIP; after manual validation, we find the eight such items are legislative proposals that never passed, i.e., GTA misclassifications, so the true Missed by USIP equals 0.

**TABLE B.3 Event Study Cumulative Abnormal Returns (CARs)
by Declared Goals and Announcement Date**

	(1)	(2)	(3)	(4)
		CAIP		POIP
Estimation Window	Introduced Date	Passed Date	Sign date	Sign Date
Panel A: IP Goal: Defense Security				
[-1,+1]	0.663*** (0.158)	0.093 (0.136)	0.165 (0.126)	0.552*** (0.103)
[-3,+3]	1.465*** (0.232)	-0.050 (0.197)	0.078 (0.198)	0.746*** (0.155)
[-5,+5]	2.420*** (0.281)	-0.251 (0.254)	0.461* (0.246)	0.661*** (0.188)
Obs.	1,501	1,501	1,501	1,977
Panel B: IP Goal: Supply Security				
[-1,+1]	0.503*** (0.095)	0.287*** (0.088)	0.511*** (0.087)	0.426*** (0.079)
[-3,+3]	1.284*** (0.140)	0.026 (0.128)	0.854*** (0.134)	0.752*** (0.115)
[-5,+5]	1.633*** (0.171)	0.162 (0.159)	1.082*** (0.166)	0.816*** (0.139)
Obs.	2,787	2,787	2,787	3,670
Panel C: IP Goal: Domestic Competitiveness				
[-1,+1]	0.476*** (0.084)	0.349*** (0.081)	0.367*** (0.079)	0.445*** (0.077)
[-3,+3]	0.962*** (0.124)	0.537*** (0.121)	0.721*** (0.124)	0.658*** (0.111)
[-5,+5]	1.213*** (0.153)	0.700*** (0.152)	0.904*** (0.154)	0.912*** (0.135)
Obs.	3,979	3,979	3,979	3,937

Notes. This table reports average cumulative abnormal returns (CARs, percentage points) around industrial-policy announcement dates identified in the USIP Database. Event windows are trading days relative to the announcement ($t=0$) and include [-1,+1], [-3,+3], and [-5,+5]. For CAIPs we report three event anchors (introduced, passed, signed); for POIP we report the signed date. Standard errors are in parentheses; *, **, *** denote 10%, 5%, 1% significance levels, respectively. *Obs.* gives the number of policies–firm observations used for each column in the corresponding panel.

**TABLE B.4 Comparing Our Data with GTA in
Event Studies (CARs of Industrial Policy Announcements)**

Estimation Window	(1)	(2)	(3)	(6)
	CAIP			POIP
	Introduction Date	Passed date	Sign Date	Sign date
Panel A: Both Our Database and GTA Identified IP (2008-2022)				
[-1,+1]	0.108 (0.204)	0.826*** (0.293)	0.806*** (0.244)	0.303* (0.164)
[-3,+3]	0.134 (0.296)	-0.052 (0.377)	0.619 (0.392)	-0.307 (0.232)
[-5,+5]	-0.954** (0.389)	1.748*** (0.450)	1.142** (0.469)	0.463 (0.326)
Obs.	181	181	181	578
Panel B: Our Database-Unique Identified IP (2008-2022)				
[-1,+1]	1.479*** (0.264)	0.603** (0.235)	0.020 (0.211)	0.609*** (0.113)
[-3,+3]	1.939*** (0.366)	0.957*** (0.336)	0.544* (0.308)	1.232*** (0.180)
[-5,+5]	3.580*** (0.474)	1.524*** (0.459)	0.518 (0.363)	0.848*** (0.205)
Obs.	610	610	610	1,904
Panel C: GTA-Unique Identified IP (2008-2022)				
[-1,+1]	/	/	0.001 (0.073)	/
[-3,+3]	/	/	0.080 (0.109)	/
[-5,+5]	/	/	0.018 (0.137)	/
Obs.	/	/	4,621	/

Notes. This table compares CARs for industrial-policy events in 2008–2022 across sources. Panel A uses events identified by both databases; Panel B uses USIP-only events; Panel C uses GTA-only events, which consist of departmental regulations not traceable to a specific CA or PO and eight proposals that ultimately did not pass. For these GTA-unique items, the GTA database does not record introduction or passage dates (nor PO signed dates); therefore, we use the GTA-recorded *announced date* as the event date ($t=0$) to compute CARs in Panel C. Event windows are [-1,+1], [-3,+3], and [-5,+5] trading days; standard errors are in parentheses; *, **, *** denote 10%, 5%, 1% significance levels, respectively.

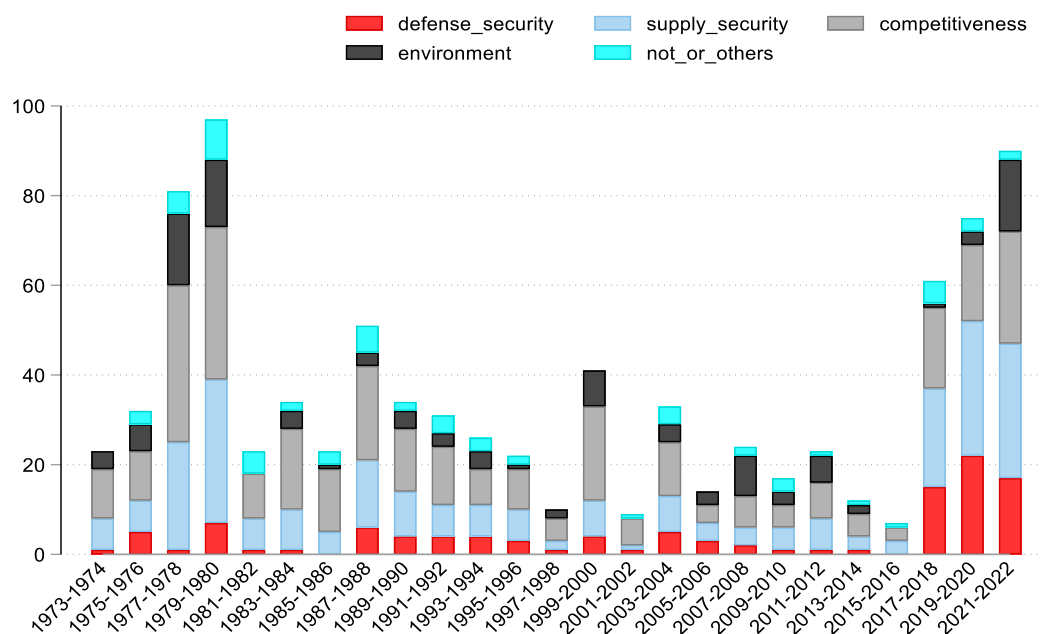


FIGURE B.1 The Evolution of Stated Industrial Policy Goals, 1973-2022

Notes. The chart displays the count of documents associated with each policy goal. As a single industrial policy document can be tagged with multiple goals (e.g., both Defense Security and Domestic Competitiveness), the total height of the stacked bar in each period (the sum of all goal-document occurrences) may exceed the total number of unique industrial policy documents.

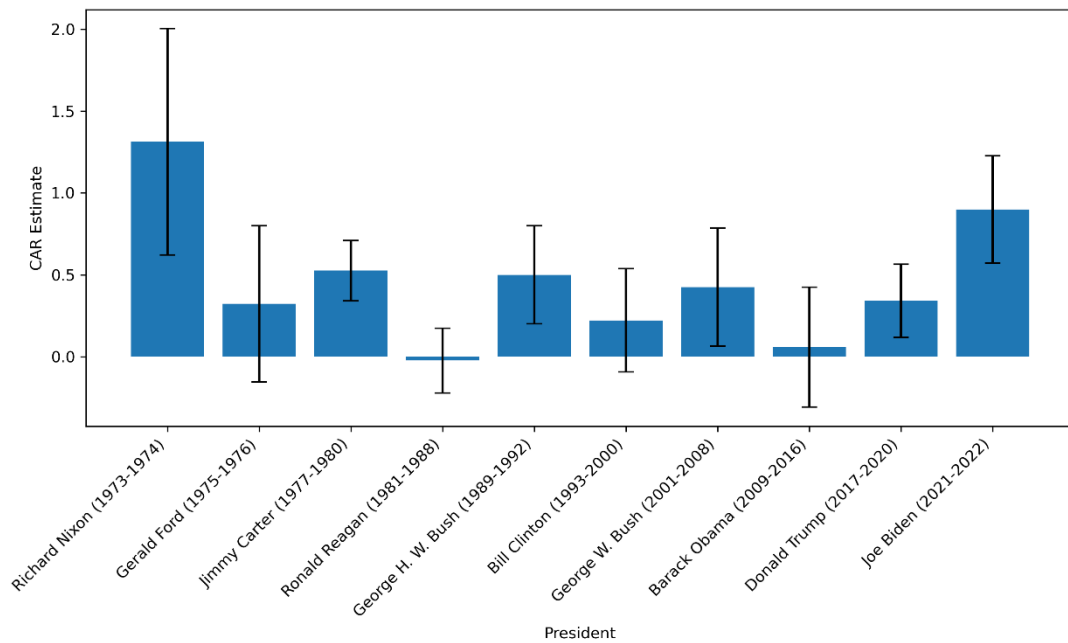


FIGURE B.2 Mean CARs by Presidential Tenure for Industrial Policy

Notes. Bars plot the mean CARs for all CAIP and POIP whose *sign_date* falls within each president's tenure. Error bars are 95% confidence intervals. CARs are computed as described in the empirical methodology; the figure pools events within a presidency and reports the mean effect by tenure.

Appendix C. The USIP (U.S. Industrial Policy) Database

This appendix provides the USIP Database used in this paper. A public release will be posted on the NBER website.

Appendix D. AI Filters and Variable-Extraction Prompts

Stage	Prompt
First Stage: Product / Industry Name Filter	#Role: You are an expert in the field of economic industrial classification. ##Background: Assist in extracting all "product keywords" from the provided text and categorize these into the International Standard Industrial Classification of All Economic Activities, Fourth Edition (ISIC ver4). You must identify the appropriate ISIC Rev.4 4-digit codes for each keyword, ensuring that these codes are relevant and exhaustive. Please help me extract all the “product keywords” in the text I sent you and then categorize these “product keywords” into the ISIC Rev.4 and find their corresponding 4-digit codes. If more than one 4-digit code applies, separate them with commas and sort by relevance. If there is no corresponding code, output “null”. If the text is too ambiguous to extract a defensible keyword or code, output “cannot decide”. For all tasks, proceed step-by-step. ##Instructions: For each "product keyword" extracted from the text: 1. product_keyword: Ensure that each 'product keyword' is no more than five words long and does not duplicate within the output. 2. ISIC ver4 code: Find the corresponding 4-digit ISIC ver4 code for each keyword. If multiple codes apply, list them separated by commas, sorted in descending order of relevance. If ambiguous, return “cannot decide”; if truly not

	classifiable, return “null”. Example 1: <i>Bill title:</i> CHIPS and Science Act of 2022 <i>Bill text:</i> This act provides funds to support the domestic production of semiconductors and authorizes various programs and activities of the federal science agencies. <i>Detected product keyword:</i> “Semiconductors” → <i>ISIC Rev.4:</i> 2610 (Manufacture of electronic components and boards), 2620 (Computers and peripheral equipment) <i>Note:</i> Multiple codes permitted; 2610 ranked higher by relevance. Example 2: <i>Bill title:</i> Federal Trade Commission Reauthorization Act <i>Bill text:</i> Federal Trade Commission Reauthorization Act of 1996 - Amends the Federal Trade Commission Act to authorize appropriations for FY 1997 and 1998 for the Federal Trade Commission. <i>Detected product keywords:</i> none (no concrete product/industry terms present) <i>ISIC Rev.4 codes:</i> null (no applicable 4-digit mapping)
B. Purpose & Intensity Filter	#Role: You are an expert in industrial policy in the field of economics and a jurist in the field of Acts of Congress and Presidential orders. ##Background: Strictly follow each given product_keyword in the product_keyword list: {product_keywords}, its corresponding ISIC code: {isic_code}, and the bill title: {bill title}. Analyze the industrial policy for each product_keyword in the given text. Your task is to analyze the industrial policy implications of each product_keyword in the bill text one by one, providing the results in a

	structured JSON format. For all the questions above, take a deep breath and work on this step-by-step. This is very important to my career. ##Instructions: For each product_keyword, you are to include the following information: 1. product_keyword: The value of the product_keyword contained in the list above. Create a row for each product_keyword. 2. IP_purpose: Evaluate if the bill contains an industrial policy purpose targeting the specific 'product_keyword' within the United States. Use 1 for yes, 0 for no, or “cannot decide” when the intent cannot be stably inferred. The assessment is based on: (A) Evaluate whether the policy support or restrict a domestic industry's performance, aiming at fostering growth, development, or competitive advantage, or limiting its operations for strategic reasons. (B) Exclusion Criteria: The industrial policy should not be primarily aimed at public welfare areas, including healthcare, education, consumer safety, foreign aid and sanctions, trade policies for diplomatic purposes, children, the handicapped, veterans, food safety, civil rights, emergency assistance, immigration, voting, religion, antitrust, social security, monetary policies, medal, mint, marine conservation, road safety, and other similar areas. If the bill's title or content explicitly focuses on these areas, even if it might impact a specific industry directly, it should not be considered as industrial policy. 3. IP_impact: Determine if the text explicitly mentions supporting or suppressing the development of the product_keyword. Assign one of the following four values: '1': if it explicitly mentions support; '-1': if it explicitly mentions suppression; '0': if it does not explicitly
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	mention either support or suppression, or if the effect is indirect (e.g., a study or recommendation); 'cannot decide': if the policy's effect is mixed within the industry associated with the ISIC code. For instance, a policy aimed at climate change may support a clean segment (such as electric vehicles within ISIC 2910) while adversely affecting a traditional segment (such as gasoline-powered vehicles), leading to a mixed or ambiguous net effect on the overall ISIC code industry. ##Example1 <i>bill title:</i> Chips and Science Act <i>bill Text:</i> This act provides funds to support the domestic production of semiconductors and authorizes various programs and activities of the federal science agencies. (Sec. 102) The act establishes and provides funding for the Creating Helpful Incentives to Produce Semiconductors (CHIPS) for America Fund to carry out activities relating to the creation of incentives to produce semiconductors in the United States. (Sec. 103) This section expands the financial assistance program relating to semiconductor incentives to include production of semiconductors and equipment and material related to production of semiconductors. The Department of Commerce shall establish within the financial assistance program an additional program that provides federal financial assistance to covered entities to incentivize investment in facilities and equipment in the United States for the fabrication, assembly, testing, or packaging of semiconductors at mature technology nodes. Answer: 1. product_keyword: 'Semiconductors'. 2. IP_purpose: Marking IP_dummy as '1' is justified since the bill provides direct support to the semiconductor
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	industry. This support aligns with the industrial policy criteria and does not fall into the excluded categories of public welfare. 3. IP_impact: Marking IP_impact as '1'. The phrase 'provides funds to support' clearly indicates an intention to promote the semiconductor industry. ##Example2 <i>bill title:</i> Technology-Related Assistance for Individuals With Disabilities Act of 1988 <i>bill Text:</i> Programs of National Significance - Part A: Study on Financing of Assistive Technology Devices and Assistive Technology Services for Individuals with Disabilities - Requires the National Council on the Handicapped to: (1) conduct a study and make recommendations to the Congress and the President concerning financing and other aspects of technology-related assistance, devices, and services. Answer: 1. product_keyword: 'Assistive Technology Devices'. 2. IP_purpose: Marking IP_dummy as "0" is correct. Although the text mentions financing measures to support this product, the bill's primary focus is on disability assistance. This falls within the exclusion criteria, specifically targeting sectors such as healthcare and disability services rather than constituting direct industrial policy. 3. IP_impact: The bill directs financing studies and recommendations, which implies indirect or attenuated support rather than clear and direct support. Therefore, we code this indirect positive impact as '0'.
C. Commercial & Broad-Scope Filter	#Role: You are an expert in industrial policy in the field of

	economics and a jurist in the field of Acts of Congress and Presidential orders. ##Background: Strictly follow each given product_keyword in the product_keyword list:{product_keywords}, and the bill title:{bill_title}. Analyze the industrial policy for each product_keyword in the given text. Your task is to analyze the industrial policy implications of each product_keyword in the bill text one by one, and providing the results in a structured JSON format. For all the questions above, take a deep breath and work on this step-by-step. This is very important to my career. ##Instructions For each product_keyword, you are to include the following information: 1. product_keyword: The value of the product_keyword contained in the product_keyword list above. Create a row for each product_keyword. 2. IP_scope: Determine the scope of this industrial policy. Use '1' if the policy covers all U.S. companies in the entire product industry, Use '0' if the policy is aimed at specific or individual entities producing the product, e.g., a policy issued by a state government that can only be applied to local companies. “cannot decide” if the scope cannot be determined from the text. 3. IP_target: Identify the type of entity targeted in the 'product_keyword' industry for which the policy is intended, including [private enterprises, research institutions, public institutions, others] (Multiple selections allowed). Select only from the listed options. If ambiguous, include “cannot decide”.
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	##Example1 <i>Bill title:</i> Chips and Science Act <i>Bill Text:</i> This act provides funds to support the domestic production of semiconductors and authorizes various programs and activities of the federal science agencies. (Sec. 102) The act establishes and provides funding for the Creating Helpful Incentives to Produce Semiconductors (CHIPS) for America Fund to carry out activities relating to the creation of incentives to produce semiconductors in the United States. (Sec. 103) This section expands the financial assistance program relating to semiconductor incentives to include production of semiconductors and equipment and material related to production of semiconductors. The Department of Commerce shall establish within the financial assistance program an additional program that provides federal financial assistance to covered entities to incentivize investment in facilities and equipment in the United States for the fabrication, assembly, testing, or packaging of semiconductors at mature technology nodes. Answer: 1. product_keyword: 'Semiconductors'. 2. IP_scope: Legislation typically aims for wide-ranging impact unless limitations are clearly stated. Therefore, in the absence of explicit restrictions, we assume the policy applies to all companies within the industry, leading to an IP_scope of '1'. 3. IP_target: The text explains that the bill focuses on covered entities to incentivize investment in facilities and equipment, and it also mentioned that the bill includes production of semiconductors and equipment and material related to production of semiconductors, semiconductor manufacturing and related activities in the U.S. are predominantly privately owned, and therefore the target of
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	the bill is [private enterprises]. ##Example2 <i>Bill title:</i> Inflation Reduction Act of 2022 <i>Bill text:</i> (Sec. 80003) In addition, the act provides funding to the BIA for a tribal electrification program that (1) provides electricity to unelectrified tribal homes through zero-emissions energy systems, (2) transitions electrified tribal homes to zero-emissions energy systems, and (3) provides home repairs necessary to install those systems. Funding for the program shall remain available through FY2031. Answer: 1. product_keyword: 'zero-emissions energy systems'. 2. IP_scope: Given the bill's focus is on electrification of tribal homes using zero-emissions energy systems, and it explicitly targets a very specific group (tribal homes) rather than the entire industry or all potential entities within it, an IP_scope of '0' is appropriate. 3. IP_target: The text describes the funding for the BIA and the supported product, zero-emissions energy systems, but the U.S. manufacturers of this product supported are both private firms and public institutions, so it should be labeled ['private enterprises', 'public institutions'].
D. Variable Extraction for Passed Items (Tools / Goals / Duration)	1.Prompt for tools prompt = f"" #Role: You are an expert in industrial policy in the field of economics and a jurist in the field of Acts of Congress and Presidential orders

	##Background: Strictly follow each given product_keyword in the product_keyword list: {product_keywords}, and the bill title: {bill_title}. Analyze the industrial policy for each product_keyword in the given text. Your task is to analyze the industrial policy implications of each product_keyword in the bill text one by one, and provide the results in a structured JSON format. For all the tasks above, take a deep breath and work on this step-by-step. This is very important to my career. ##Instructions For each product_keyword, you are to include the following information: 1.product_keyword: The value of the product_keyword contained in the product_keyword list above. Create a row for each product_keyword. 2.IP_tools: Identify the specific measures in the bill targeting the domestic 'product_keyword' industry, including [Firm Subsidy, Trade Policies, Tax Measures, Local Supply Chain Requirements, Credit and Loan Policies, Sector-specific Training, Sector-specific Infrastructure, Regulatory Measures, Public Procurement, Customer Subsidies, Others] (Multiple selections allowed). Select only from the listed options. Firm Subsidy: Direct financial subsidies from the government to enterprises. Trade Policies: Regulations affecting international trade through tariff (taxes on imports and exports) and non-tariff measures (quotas, standards, licensing). Tax Measures: Government adjustments in tax policies to promote or discourage specific industry activities, excluding tariff measures. Local Supply Chain Requirements: Policies encouraging
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	or mandating the use of domestically produced goods and services. Credit and Loan Policies: Government-backed financing options to support business operations and expansion. Sector-specific Training: Programs to enhance workforce skills and competencies. Sector-specific Infrastructure: Investments in physical and digital infrastructure to support industry growth. Regulatory Measures: Laws and regulations that directly impact industry operations. Public Procurement: Government policies prioritizing the purchase of domestic goods in public projects. Customer Subsidies: Policies to consumers to encourage the purchase of certain goods. Others: Any other actions not covered above. ##Example1 <i>Bill title:</i> Chips and Science Act <i>Bill Text:</i> This act provides funds to support the domestic production of semiconductors and authorizes various programs and activities of the federal science agencies. (Sec. 102) The act establishes and provides funding for the Creating Helpful Incentives to Produce Semiconductors (CHIPS) for America Fund to carry out activities relating to the creation of incentives to produce semiconductors in the United States. (Sec. 103) This section expands the financial assistance program relating to semiconductor incentives to include production of semiconductors and equipment and material related to production of semiconductors. The Department of Commerce shall establish within the financial assistance program an additional program that provides federal financial assistance to covered entities to incentivize investment in facilities and equipment in the
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	United States for the fabrication, assembly, testing, or packaging of semiconductors at mature technology nodes. Answer: 1.product_keyword: 'Semiconductors'. 2. IP_tools: Labeling the policy action as 'Firm Subsidy' is accurate, as the bill establishes and provides funding for the creating helpful incentives to produce semiconductors, representing a form of firm subsidy, therefore labeling ['Firm Subsidy']. ##Example2 <i>Bill title:</i> Omnibus Trade and Competitiveness Act of 1988 <i>Bill text:</i> Provides that the term "synthetic plastics materials" includes silicones whether or not such materials are solid in the finished articles. Places a duty on silicone resins and materials. Provides that the term "rubber" does not include silicones. Answer: 1.product_keyword: 'silicone resins'. 2. IP_tools: The text explicitly describes the imposition of tariffs on silicone resins and materials as a manifestation of trade policy. These measures directly affect the international terms of trade and competitiveness of the U.S. domestic silicone resins and materials industry by adjusting import tariffs, therefore labeling ['trade policies']. 2. Prompt for goals prompt = f""" #Role: You are an expert in industrial policy in the field of
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	economics and a jurist in the field of Acts of Congress and Presidential orders ##Background: Strictly follow each given product_keyword in the product_keyword list {product_keywords}, and the bill title: {bill_title}. Analyze the industrial policy for each product_keyword in the given text. Your task is to analyze the industrial policy implications of each product_keyword in the bill text one by one, and provide the results in a structured JSON format. For all the tasks above, take a deep breath and work on this step-by-step. This is very important to my career. ##Instructions For each product_keyword, you are to include the following information: 1. product_keyword: The value of the product_keyword contained in the product_keyword list above. Create a row for each product_keyword. 2. IP_goal: Identify the goal of this industry policy. It includes [Not Mentioned, Defense Security, Resilience/Security of Supply, Domestic Competitiveness in this Sector, Climate Change Mitigation and other Environmental Objectives, Others] (Multiple selections allowed). Select only from the provided options. - Not Mentioned: This category is chosen when the bill text or policy document does not explicitly state any industrial policy goals related to the product keyword. - Defense Security: This refers to policies aimed at protecting or enhancing the current or future defense security of a nation, ensuring that its defense capabilities and technologies remain robust against potential threats. - Resilience/Security of Supply: Focuses on ensuring the stability and security of supplies chains of critical non-food
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	products, aiming to prevent supply chain disruptions and enhance national resilience. - Domestic Competitiveness in this Sector: Pertains to measures designed to boost domestic industries' competitiveness or foster innovation. - Climate Change Mitigation and other Environmental Objectives: Encompasses policies aimed at environmental protection, reducing the impacts of climate change, or facilitating the transition towards a low-carbon economy. - Others: This category is reserved for motives or objectives that do not fit neatly into the aforementioned categories but are still significant considerations within the policy framework. ##Example1 <i>Bill title:</i> Chips and Science Act <i>Bill Text:</i> This act provides funds to support the domestic production of semiconductors and authorizes various programs and activities of the federal science agencies. (Sec. 102) The act establishes and provides funding for the Creating Helpful Incentives to Produce Semiconductors (CHIPS) for America Fund to carry out activities relating to the creation of incentives to produce semiconductors in the United States. (Sec. 103) This section expands the financial assistance program relating to semiconductor incentives to include production of semiconductors and equipment and material related to production of semiconductors. The Department of Commerce shall establish within the financial assistance program an additional program that provides federal financial assistance to covered entities to incentivize investment in facilities and equipment in the United States for the fabrication, assembly, testing, or packaging of semiconductors at mature technology nodes.
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	Answer: 1.product_keywords: 'Semiconductors'. 2. IP_goal: The identification of "Domestic Competitiveness in this Sector" as the IP_goal is also supported by the bill's emphasis on bolstering the competitiveness of the US semiconductor industry, therefore labeling ['Domestic Competitiveness in this Sector'].. ##Example2 Bill title: Inflation Reduction Act of 2022 Bill text: Part 2--Clean Fuels (Sec. 13201) The act extends through 2024 the income tax credit for biodiesel and renewable diesel used as fuel, the biodiesel excise tax credit, the alternative fuels tax credit, and the second generation biofuel producer tax credit. Answer: 1. product_keywords: 'alternative fuels'. 2. IP_goal: The extension of tax credits for alternative fuels under this section supports the policy's aim to mitigate climate change through the promotion of low-carbon energy sources, therefore labeling ['Climate Change Mitigation and other Environmental Objectives']. 3. Prompt for duration #Role: You are an expert in industrial policy in the field of economics and a jurist in the field of Acts of Congress and Presidential orders. ##Background:
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	Strictly follow each given product_keyword in the product_keyword list: {product_keywords}, and the bill title: {bill_title}. You will be provided with the bill text and the month/year the bill was signed (sign_month in MM/YYYY format). Your task is to identify or infer the sunset date (the month and year the policy ceases to have effect) and the total duration of the policy in months for each product_keyword in the bill text one by one, and provide the results in a structured JSON format. For all the tasks above, take a deep breath and work on this step-by-step. This is very important to my career. ##Instructions: - For each product_keyword, determine a “sunset_month” in MM/YYYY format. - If the text explicitly states a sunset date, use that date. - If not explicitly stated, infer the sunset date from contextual clues (such as references to a fiscal year or stated period of applicability). - If you cannot determine a sunset date at all, output "null". - Calculate the “duration(month)” of the policy’s effect in months. - If the exact start date is unspecified, assume the policy starts from the bill’s signing month. - If the sunset date was inferred, use that inferred date. - If no sunset date can be inferred, set duration(month) to "null". For all the steps above, take a deep breath and proceed step-by-step. This is very important to my career.
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	##Example1 Bill title: "H.R.2982 - An Act to suspend until the close of June 30, 1980, the duty on synthetic tantalum/columbium concentrate, and for other purposes." Bill text: "Amends the Tariff Schedules of the United States to suspend, until June 30, 1980, the customs duty imposed upon the importation of synthetic tantalum/columbium concentrate." Product keywords: "synthetic tantalum/columbium concentrate" Sign_month: "11/1977" Answer: 1. product_keyword: "synthetic tantalum/columbium concentrate" 2. sunset_month: "06/1980". sunset_reason: The text explicitly states that the duty suspension ends on June 30, 1980. 3. duration(month): "31". duration_reason: From November 1977 (assumed start) to June 1980 is about 31 months total (2 years and 7 months). ##Example2 Bill title: "S.1542 - Maritime Appropriation Authorization Act of 1975" Bill text: "Maritime Appropriation Authorization Act - Authorizes appropriations for fiscal year 1976..." Product keywords: "vessels" Sign_month: "11/1975" Answer: 1. product_keyword: "vessels" 2. sunset_month: "12/1976". sunset_reason: Although not
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	explicitly stated, fiscal year 1976 typically runs through the end of 1976, so December 1976 is the inferred sunset month. 3. duration(month): "12". duration_reason: Assuming it starts from November 1975 and covers the entire fiscal year 1976, that's effectively a policy lasting through December 1976, about 12 months in duration.
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