Industrial Policies and Innovation: Evidence from the Global Automobile Industry

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Abstract

This paper examines the impact of industrial policies (IPs) on innovation in the global automobile industry. We compile the first comprehensive dataset linking global IPs with patent data related to the auto industry from 2008 to 2023. We document a major shift in policy focus: by 2022, nearly half of all IPs targeted electric vehicles (EV)-related sectors, up from almost none in 2008. In the meantime, there has been a clear technological transition from internal combustion engine (GV) technologies to EV innovations. Our analysis finds a positive relationship between policy support and innovation activity. At the country level, a one-standard-deviation increase in five-year cumulative EV-targeted IPs is associated with a four-percent rise in new EV patent applications. Firm-level analyses (using OLS, IV, and PPML) indicate that a ten-percent increase in EV financial incentives received by automakers and EV battery producers leads to a similar four-percent increase in EV innovations. We confirm the importance of path dependency in the direction of technology change in the automobile industry but find no evidence that EV-targeted IPs stimulate innovation in GV technologies.

Keywords: Industrial Policy, Innovation, Patent, Electric Vehicle

JEL Classification: L52, L62, O31, Q48

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1 Introduction

Industrial policies (IPs) have gained renewed interest among major economies over the past decade as they navigate challenges such as climate change, supply chain disruptions, and geopolitical tensions (Juhász et al., 2022; Juhász et al., 2024). Central to many of these policies is the automobile industry, which is undergoing a pivotal transformation driven by global efforts to combat climate change. Electrifying the transportation sector, along with a cleaner electricity grid, is increasingly seen as a crucial pathway for curbing carbon emissions (Crabtree, 2019).[1] As a result, many countries have set ambitious electric vehicle (EV) adoption goals, with Norway targeting 100% EV sales by 2025, the Netherlands by 2030, and the U.S. and China aiming for 50% and 40% by 2030, respectively. In pursuit of these targets, governments worldwide have enacted a range of IPs, such as purchase subsidies, to promote the growth of the EV and EV battery industries.

Despite the rapid expansion of the EV sector and widespread policy initiatives across the world, there is limited understanding of how these policies affect innovation within the global automobile industry. A major empirical challenge is that constructing quantitative measurements for IPs that are comparable across countries is difficult due to their complexity. Juhász et al. (2022) developed a text-based approach applied to a harmonized global industrial policy dataset (Global Trade Alert database), opening a promising new avenue in this literature. Another challenge lies in measuring firm-level innovation incentives associated with IPs, as government policies rarely specify how firms are differentially affected by sector-level policies.

Our study fills this gap by compiling a comprehensive database of global IPs and patents for the automobile industry. To overcome the difficulties in measuring IPs at the country-industry level, we employ two distinct approaches. First, we quantify the number of IPs following Juhász et al. (2022). Specifically, we rely on a pool of over sixty thousand policy documents worldwide from 2008 to 2023 from the Global Trade Analysis database and use Natural Language Processing techniques to identify both financial and non-financial IPs separately from non-IP

[1] Since the debut of the Chevrolet Volt and Nissan Leaf as the first mass-market EV models in the U.S. in late 2010, the EV market has grown annually by over 50%. By 2023, global new passenger EV sales reached 14.2 million units, accounting for 15.8% of the new passenger vehicle market.

policies. Second, we focus on a particular type of IPs in the automobile industry: EV purchase incentives. We compile a country-by-product level subsidy database for the global automobile industry. The automobile industry is especially suited to this approach, as the recent global push for transportation electrification has led to marked differences in EV incentives across countries. A unique feature of these purchase incentives is that they are often tied to vehicle attributes, generating significant variation across vehicle models and firms that have also changed dramatically over time.

To assess innovation, we use patent data from 1980 to 2023, sourced from PATSTAT Global. Using International Patent Classification (IPC) codes, we categorize vehicle-related patents into three distinct groups: patents specific to internal combustion engine vehicles (often referred to as gasoline vehicles or GVs); patents specific to EVs; and general patents, applicable to both GVs and EVs. We compile two separate datasets for our analysis: one at the country-IPC-year level, aggregating global patent filing records by applicant countries, and the other at the firm level, tracking patents applied for and held by major automakers and EV battery suppliers. We track patent activities of battery suppliers due to their close connections with EV producers.[2]

Our empirical analysis evaluates the impact of IPs on patent applications and grants within the global automobile industry, with a focus on EV-related IPs and EV-related patents that capture innovations in green technologies. We present two sets of empirical results based on different levels of data aggregation. First, we analyze the relationship between country-level patent numbers and the cumulative number of past IPs implemented in the countries. We treat the lagged number of IPs as exogenous to EV innovation after controlling for lagged EV patent stocks, the stringency of environmental regulations, country-IPC fixed effects, and year fixed effects. We demonstrate that our results are robust to alternative measures of both IPs and patents.

Second, building on the country-level analysis, we further investigate the impact of a specific type of IP: EV purchase incentives or consumer subsidies. Financial incentives are among the

[2]In 2023, battery costs account for approximately 30% of the total cost of EVs. The EV business is also the largest market for battery suppliers. For instance, for the largest battery supplier, CATL, the EV segment accounts for over 67% of its total business revenue, according to its 2024 semi-annual report. Sources: https://www.statista.com/statistics/797638/battery-share-of-large-electric-vehicle-cost and https://www.catl.com/uploads/1/file/public/202408/20240801093040_9d1b5kf7sc.pdf.

most commonly used IPs for EVs. Global public spending on consumer EV subsidies reached $30 billion in 2021 (IEA, 2022). Using the firm-level data, we examine how these EV subsidies influence patent applications by automakers and battery suppliers. Our empirical design leverages subsidy variation across vehicle models within a country as well as variation in subsidy intensity across countries. Automakers and battery suppliers that sell more EVs in heavily subsidized markets experience greater exposure to the financial incentives. By comparing patenting activities between firms with higher subsidy exposure and those with lower exposure, we quantify the elasticity of patenting activities with respect to financial incentives. To address concerns that total subsidies a firm receives depend on its EV sales, which may not be exogenous to its EV innovating activities, we construct simulated sales from a BLP-style demand model (Berry et al., 1995) using only exogenous demand shifters. Each firm's subsidy exposure from the simulated sales serves as a valid instrumental variable.

Using both the Poisson pseudo maximum likelihood (PPML) and linear panel models with a rich set of fixed effects, our country-level analysis shows that a one-standard-deviation increase in five-year cumulative IPs targeting the EV industry is associated with a four-percent increase in the number of new EV patents filed. The implied EV innovation elasticity with respect to EV IPs is about 0.1. Trade and subsidy-related IPs exhibit stronger correlations with innovation than other types of IPs. Leveraging variation in EV subsidies at the country-by-model level, our firm-level analysis based on the IV strategy indicates that a ten-percent increase in total EV subsidies received by automakers and battery suppliers leads to a four-percent increase in EV innovation. However, we find no evidence that EV IPs affect innovation for gasoline vehicle technologies.

Furthermore, we examine how knowledge stocks in different vehicle technologies influence innovation pathways. We confirm the significance of path dependency and knowledge spillovers in automotive innovation. Specifically, knowledge stocks related to the same fuel type facilitate the generation of new patents in the same country, while knowledge stocks of different fuel types hinder this process. In other words, firms with more extensive experience in EV-related technologies tend to innovate more rapidly and produce new EV patents faster. One implication of this finding is that the positive effects of IPs are self-reinforcing due to path dependence, suggesting that the marginal return of IPs in promoting EV innovation will be larger in the long run. Therefore, when assessing the costs and benefits of IPs, it is crucial to adopt a long-term perspective.

Our paper contributes to four strands of literature. First, it adds to the body of work on the economics of the EV market, particularly regarding the effects of government policies on EV diffusion. A growing literature evaluates the impact of consumer subsidies and charging access on EV adoption across countries (Barwick et al., 2023; Li et al., 2017, 2021; Muehlegger and Rapson, 2022; Springel, 2021). These studies show that both consumer subsidies and charging availability have been key determinants in the first decade of EV diffusion, with federal subsidies explaining up to 60% of EV sales in China, Norway, and the U.S. in the short run. Our study extends this literature by examining the impact of IPs on firm innovation, focusing on the supply side of the EV market. While Barwick et al. (2024a) analyzes the effect of EV subsidy design on firms' vehicle attribute choices, it does not explore innovation. The positive impact of IPs on innovation, when translated into improved product quality, has the potential to amplify demand in the long term.

Second, this paper contributes to the rich and growing literature on IPs. As argued by Juhász et al. (2024), earlier studies were largely correlational, regressing firm or sectoral outcomes (such as total output, revenue, employment, imports and exports, and sometimes productivity) on available measures of industrial policy (Noland and Pack, 2003; Pack and Saggi, 2006). Recently, a wave of new studies has leveraged natural or quasi-experimental variation in historical contexts to derive plausibly causal estimates of industrial policy effects on these outcomes (Juhász, 2018; Lane, 2024). In addition to these reduced-form studies, another strand of literature uses a model-based approach (such as general equilibrium models in macroeconomics and trade, or partial-equilibrium models in IO) to examine the effects of IPs on targeted and related industries, the aggregate economy, and sometimes welfare assessments (see Harrison and Rodríguez-Clare (2010) for a review). Whether reduced-form or model-based, few studies examine the effect of IPs on innovation.[3] Our study contributes to this literature by exploring how IPs affect innovation in both targeted and upstream industries.

[3]There is a small but growing literature on the impact of IPs on quality upgrading (Bai et al., 2024). See Verhoogen (2023) for a review.

Third, our study contributes to the literature on policy-induced innovation in clean technologies. Theoretical studies (Acemoglu et al., 2012, 2016) emphasize the importance of policy interventions in steering innovation toward clean technologies, helping to avoid prolonged and costly transitions. Empirical evidence supports the effectiveness of various policy tools in fostering green innovation, including subsidies (Banares-Sanchez et al., 2024; Wei et al., 2023), emissions trading schemes (Calel and Dechezleprêtre, 2016), carbon taxes (Cheng et al., 2021), and fuel-efficiency and CO_2 emission standards (Gessner, 2024; Rozendaal and Vollebergh, 2024). Similarly, Newell et al. (1999), Popp (2002), and Aghion et al. (2016) show that changes in energy prices, influenced by policy interventions, shape the pace and direction of technological change, with higher energy prices driving innovation in energy-efficient technologies. Our paper adds to this literature by providing a comprehensive analysis of industrial policies and showing how these policies, including subsidies and trade policies, impact innovation in EV technologies across countries. Additionally, we conduct a firm-level analysis, examining how global EV manufacturers' and battery suppliers' differential exposure to financial incentives in key markets influences innovation, accounting for path dependence based on their past innovation trajectories.

Lastly, the paper contributes to the small but growing literature that attempts to detect and measure industrial policies, which are often opaque and difficult to quantify. Juhász et al. (2022) is the first study to utilize the Global Trade Alert (GTA) database to examine the count and nature of IPs (e.g., subsidies, tariffs, non-financial interventions) across countries. Evenett et al. (2024) is a follow-up study using the GTA to analyze more recent industrial policies. One limitation of the GTA is that the database generally lacks complete information on the size and magnitude of government interventions. We provide two different IP measures. Our first measure closely follows the methodology of Juhász et al. (2022), which is based on recent advances in machine learning. Our second measure relies on data we have collected over the years, reporting financial subsidies and non-financial incentives provided by central governments targeting EVs. One advantage of our second measure is that the total amount of financial subsidies provided by central governments varies over time and across firms, offering rich variation often absent in other studies that rely solely on IP counts.

The paper is organized as follows. Section 2 describes the database and outlines our data construction procedure. Section 3 presents key descriptive patterns of IPs in the global automobile industry and patent data. Sections 4 and 5 provide country-level and firm-level empirical evidence on the effects of industrial policies on EV innovation. Section 6 concludes the paper.

2 Data

This section outlines how we compile a comprehensive dataset of global IPs and patents for the automobile industry. The procedure described here can be applied to other industries. Additional details on data construction are available in the Online Appendix.

2.1 Measuring IP using Global Trade Alert Database

For the country-level analysis, we measure industrial policies using the GTA database.[4] The raw data include over sixty thousand government policy statements from November 2008 until October 2023. Each policy statement is identified by a State Act ID and an Intervention ID, where a state act represents an announcement by a government body, and an intervention is a specific policy contained in that announcement. The key fields in the GTA data include policy identifiers (State Act and Intervention IDs), the implementing country and affected countries, the date of announcement, affected products classified by a six-digit Harmonized System (HS) code (a global product classification system), and, most importantly, a description of the policy.

Identify and Measuring IPs. We define IPs as policies with explicit or implicit goals of altering the composition of economic activities and apply Natural Language Processing (NLP) techniques to classify these policies, following Juhász et al. (2022). A policy must meet two criteria to be classified as an IP: (1) it is a goal-oriented state action aimed at shifting the composition of economic activity; (2) it is administered at a national level.

Each policy in the GTA database is accompanied by a concise description text, with an average length of 82 words.[5] To distinguish IPs from other policies, we use these descriptions to manually label a training dataset consisting of 1,023 policies, categorizing each policy as

[4]One caveat of the GTA database is that it is designed to track policies with international impact, especially those following a beggar-thy-neighbor approach. Therefore, policies that exclusively affect domestic firms and markets, as well as subnational policies, are sometimes not included in the GTA database.

[5]The first and third quartiles of the description length are 30 and 99 words, respectively.

either IP or non-IP. This training set represents 1.6% of the total policy sample. We then train a supervised machine learning (ML) model using the training dataset. We experimented with a range of candidate models, including Logistic Regression with L2 regularization, Random Forest, XGBoost, Recurrent Neural Network (RNN), and a pre-trained Large Language Model (BERT). Logistic regression with L2 regularization provides the best prediction performance. The model has a precision rate of 95% for non-IPs and 84% for IPs.[6] We then apply the model to the full GTA database to predict which policies should be labeled as IPs. Details on labeling training data, NLP techniques, ML model training, validation, and performance are discussed in Appendix B. Using this approach, the cleaned data for this study consists of 3,385 unique IPs related to the automobile market.[7]

Classification and Aggregation. Each IP in the GTA database is associated with at least one affected product and its 6-digit HS product code. To measure fuel type-specific IPs, we categorize all IPs into three mutually exclusive groups based on the fuel type of the affected products: those impacting the production cycle of EVs (EV IPs), those impacting the production cycle of internal combustion engine vehicles (GV IPs), and those impacting both EVs and GVs (general IPs). We use the HS codes of the affected products instead of the text description to classify IPs by fuel type because other electrification-related sectors, like battery cells and electricity generation, can also influence the EV industry through technology spillovers (Dugoua and Dumas, 2024). This approach accounts for cases where an EV IP does not explicitly reference "electric vehicles" but nonetheless impacts the EV industry. Appendix Table A.1 tabulates the HS codes assigned to EV, GV, and general categories, and those three categories are mutually exclusive. Appendix Table A.2 provides examples of IPs and details on the classification procedures.

Next, we aggregate the data to construct the number of IPs at the country-fuel type level. A challenge with aggregation is that a single IP could affect multiple countries and products, with the affected products differing across countries and spanning various fuel types.[8]

[6]This means that when a policy is classified as non-IP, the model is correct 95% of the time, while for policies classified as IP, it is correct 84% of the time.

[7]In the regression analyses in Sections 4 and 5, we drop 839 IPs without explicitly affected countries and drop an additional 139 IPs designed to limit the development of targeted sectors.

[8]For example, the IP implemented by the US Bureau of Industry and Security (State Act ID: 64760 and Intervention ID: 104901) affected China's product HS-850134 ("Electric motors and generators: DC, of an output exceeding 750W"), classified as an EV-related HS code, as well as product HS-870891 ("Radiators and parts"), classified as a general HS code. Additionally, the same

In our aggregation, we count each IP once per fuel type, regardless of the number of affected countries or products within that category. Figure 1 illustrates this approach with an IP impacting two EV-related products in Country 1, one EV and one GV product in Country 2, and one EV product along with two general products in Country 3. We consolidate the four EV-related entries across countries into a single EV IP for the implementing country.[9] The same method applies to GV and general IPs, resulting in three IP observations for this policy. This reflects the broad policy scope, as a single IP can affect both green and traditional sectors. Thus, each unique State Act ID and Intervention ID may appear up to three times in the regression analysis if it impacts multiple fuel types. This approach allows us to measure the number of distinct IPs impacting each fuel type within a country, which we later use to analyze the relationship between patenting activity and the number of IPs affecting each fuel type.[10]

Our empirical analysis focuses primarily on EV IPs, given their current prominence and their pivotal role in the green transition. We also assess how GV IPs impact innovation. Since general IPs make up a relatively small share of all IPs (19%), we omit this category from our analysis. Appendix Figure A.1 displays the number of IPs identified in our data by each policy category, as defined by GTA, separately for EV IPs and GV IPs. The most common policy categories are financial grants, trade finance, state loans, and loan guarantees.

2.2 Measuring IP using Country-by-Model EV Subsidy

In the firm-level analysis, we measure industrial policies using firm-level EV subsidies. We utilize a database of model-level EV subsidies compiled for 13 countries from 2013 to 2020. These countries account for approximately 95% of global EV sales.[11] The data are organized at the country-year-EV model level, based on a wide range of policy documents covering various financial incentives, including direct consumer subsidies, acquisition and ownership tax credits, income tax credits, and sales tax exemptions. To ensure comparability across countries, only central or federal subsidies are included. A unique aspect of these financial incentives is that

policy also affected Vietnam's product HS-842131 ("Machinery: intake air filters for internal combustion engines"), classified as a GV-related HS code.

[9] In Section 4, we also present results using alternative IP measures that consider the number of affected countries and products.

[10] Using this approach, the original 3,385 unique IPs become 5,090 IP-fuel type combinations.

[11] The 13 countries include Austria, Canada, China, France, Germany, Japan, the Netherlands, Norway, Spain, Sweden, Switzerland, the United Kingdom, and the United States.

they are often based on vehicle attributes (such as propulsion type, driving range, and battery characteristics). We apply the criteria outlined in each policy document to the attributes of every EV model to calculate the vehicle-model-level subsidies. The final subsidy variable is the sum of all types of financial incentives for a given country-model year. Full details on data sources and the construction procedure are provided in Appendix Section D.

Aggregating subsidies across EV models allows us to calculate each automaker's subsidy exposure. Additionally, we observe the battery supplier for each EV model and measure the financial incentives these suppliers encounter by calculating the subsidies that their downstream EV automakers receive from EV sales. This approach provides a measure of indirect subsidy exposure for battery suppliers. Note that only a portion of these indirect subsidies is transferred to battery suppliers, depending on the pass-through rate; therefore, this should be interpreted as a measure of subsidy exposure rather than actual subsidies received. Our log specification in the empirical analyses in Section 5 ensures robustness to variation in the pass-through rate.

2.3 Patents Data: PATSTAT Database

To measure innovation in the automobile industry, we use patent data from the European Patent Office (EPO)'s PATSTAT database, which records patent applications received and patents granted by all patent offices. We treat all patent applications within the same DOCDB family[12] as a single invention or technology. All applications within a DOCDB family are considered to share identical technical content. A single invention is often associated with multiple IPC codes.[13] We classify each IPC code into three mutually exclusive categories: EV, GV, and general technologies.[14] EV technologies are applicable to the EV production process, such as circuit arrangements for monitoring or controlling batteries, electric power supply for auxiliary equipment, and the arrangement or mounting of electrical propulsion units. GV technologies are relevant to GV production, while general technologies can be applied to both EV and GV

[12] DOCDB is the EPO's master documentation database. A DOCDB patent family is a collection of patent documents considered to cover a single invention.

[13] The IPC codes describe the technical area of an invention. In the PATSTAT database, an IPC code (e.g., B60W 10/08) consists of five fields: section (B), class (60), subclass (W), group (10), and subgroup (08). To reduce the number of IPC codes used in estimation, we consolidate IPC codes using the first three fields: section, class, and subclass. The list of consolidated IPC codes is shown in Appendix Table A.3.

[14] For this study, we retain DOCDB families that have at least one patent application with an EV, GV, or General IPC code.

production. Appendix Table A.3 lists all the IPC codes used in this study for EV, GV, and general patents.

As with GTA data, PATSTAT also contains duplicates.[15] For each DOCDB family, there may be patent application filings at different patent offices (authorities), with each filing potentially associated with multiple IPC codes.[16] Next, we discuss the procedures for aggregating the patent data for country-level and firm-level regression analyses, respectively.

Patent Count by Country-IPC-Year For the country-level analyses, we follow Aghion et al. (2016) and consider only the "triadic" patents, which refer to inventions filed at all three major patent offices: the United States Patent and Trademark Office (USPTO), EPO, and the Japan Patent Office (JPO). Triadic patents are considered to have higher quality as they involve higher filing costs and reflect the applicant's view that the technology has broader applicability.

A patent is defined as a unique combination of the DOCDB Family ID, application authority (e.g., EPO), inventor's residence country (e.g., China), and IPC code (e.g., B60L). In the example illustrated in panel (a) of Figure 2, patent applications based on a single invention are filed in three patent offices and span five IPC codes, with IPC 1 appearing in all offices. For the country-level analysis, we retain these seven entries as separate records. Thus, they appear as seven distinct DOCDB family-application authority-IPC patents.[17] Our cleaned dataset includes 82,206 unique DOCDB families and 357,067 DOCDB family-application authority-IPC patents. Appendix Section C provides additional details on the construction of the patent dataset.

We then aggregate the DOCDB family-application authority-IPC patent data by the applicant's country of residence, earliest filing year, and IPC codes. Panel A of Table 1 presents summary statistics for this country-IPC-year level data. The final dataset includes 67 countries, spans the years 2008 to 2020, and covers five IPC codes (at the section-class-subclass level) for EV-related patents, nine for GV patents, and fifteen for general-purpose patents. The average

[15] A patent filing often lists multiple inventors. We consolidate the inventors by their country of residence and retain one entry per country.

[16] For example, a patent applied for by Daimler Group was classified as F02D 41/22 in the US Patent Office, which refers to "Safety or Protective Devices for Electrical Control of Supply of Combustion Engines" and is categorized as a "GV" patent. A patent for the same invention was classified as B60W 10/02 in the Japan Patent Office, referring to "Control of Driveline Clutches" under "Control Systems Specially Adapted for Hybrid Vehicles," and categorized as an "EV" patent.

[17] We show later that our findings remain consistent if we instead count each unique DOCDB family-IPC code combination as a patent.

number of new patents filed per country-IPC-year is 7.24 for EV patents, 2.2 for GV patents, and 6.78 for general-purpose patents.

Micro Data: Firm-Level Panel Data When constructing the firm-level panel data, the aggregation method is less granular, as we do not distinguish between IPC codes within the same fuel type due to the relatively small number of patents per firm for a given IPC code. In this context, a patent is defined by a unique combination of DOCDB Family ID, application authority (e.g., EPO), and fuel type (e.g., EV). Panel (b) of Figure 2 illustrates how we consolidate patent filing records. In the example, we merge two EV IPC filing records under the first application authority and two general IPC filing records under the third application authority. As a result, we count the seven data entries as five firm-fuel type patents: three EV patents (one for each office), one GV patent, and one general patent.

We use a list of 92 automaker groups (e.g., VW Group) and 45 battery suppliers (e.g., CATL) as compiled by Barwick et al. (2024b). Of the 137 firms on these lists, 124 are matched with at least one patent application. For automaker groups, we include patents owned not only by the parent firm directly but also by their major subsidiary brands (e.g., patents owned by the VW Group include those filed by Audi). The firm-level data spans from 2013 to 2020, with further details provided in Appendix Section D.

For firm-level patent counts, we do not restrict to triadic inventions for two reasons. First, the number of firms in our analysis is relatively small, and we aim to retain as many firms as possible with non-zero patent application records. Second, the triadic constraint would require us to omit patents held by Chinese automakers and EV battery suppliers that are filed solely at the Chinese Patent Office, potentially underrepresenting a key player in the EV market. Nonetheless, to ensure consistency with the country-level analysis and the previous study by Aghion et al. (2016), we report firm-level analyses using only triadic patents in Section 5.3 and demonstrate that the results remain robust.

2.4 OECD EPS Database

Environmental policies and regulations could impact EV innovation, so we include them as control variables. To measure the scope and magnitude of environmental regulations, we use the Environmental Policy Stringency (EPS) Index compiled by the OECD.[18] The raw data include the overall EPS index and subcategory-specific scores (e.g., market-based instruments, technology support policies) on a 0-5 scale, with 5 indicating the highest policy stringency. The OECD calculates the overall EPS index as a weighted average across all subcategories. We use this overall EPS index in our analysis. For non-OECD countries, we set the index to zero and interact it with a non-OECD dummy.

3 Descriptive Patterns: Industrial Policies and Patents

We begin by outlining key data patterns of industrial policies and innovation in the global automobile industry. It is important to note a distinction between the counts of IPs and inventions presented here and those in Sections 4 and 5. The regression analyses in Sections 4 and 5 examine how fuel type-specific IPs impact related patents, so we count IPs by fuel type (allowing the possibility that one IP may be counted in multiple fuel type categories depending on its policy scope). Similarly, we count an invention as multiple patents if it is filed under different fuel type IPC codes. In contrast, in this section, we refer to the original counts of unique policies (State Act ID and Intervention ID) and unique inventions (DOCDB family ID) to avoid duplication.[19] The qualitative patterns remain similar if we instead use fuel type-specific IP and patent counts.

3.1 IPs in the Automobile Industry

Figure 3 illustrates the trend in new automobile-related IPs from 2008 to 2022. The bar plot, using the left axis, represents the annual count of new policies, while the line plot, using the right axis, depicts the proportion of IPs specifically targeting EVs.[20] Following the 2008 global financial crisis, the number of IPs increased steadily from fewer than 100 in 2009 to over 300

[18] Source: *EPS Database*. Last accessed in September 2024.
[19] In other words, we focus on inventions here, while the empirical analysis sections focus on patents filed based on these inventions.
[20] A policy is labeled as "EV-targeted" if more than 50% of the affected country-products pertain to EVs.

by 2022. Meanwhile, the share of EV-targeted IPs jumped from nearly zero in 2008 to nearly 50% by 2022. This upward trend reflects the global shift toward electrifying the transportation sector and underscores the increasing emphasis on supporting EVs in recent policy initiatives.

Figure 4 shows the top 20 countries by cumulative automobile-related IPs during the same period. Countries are ranked by their total number of IPs, with black diamonds indicating the share of policies specifically targeting EV-related sectors. Developed countries dominated IP implementation post-2008, with the U.S. leading in the number of policies. This aligns with the findings by Juhász et al. (2024). One concern is that the GTA database may over-represent U.S. policies, possibly due to better data accessibility. For comparison, Appendix Figure A.2 presents the cumulative number of non-IPs in the GTA database. Countries like Brazil and China have the highest non-IP policy counts, followed by the U.S. The distribution (histogram) of non-IP policy counts is more balanced across nations. These patterns suggest that U.S. over-representation might not be a major issue and support the observation that the U.S. indeed uses IPs more extensively than other countries.

When it comes to the proportion of EV-targeted IPs among all automobile IPs, the U.S. ranks lower than European countries. This is consistent with the comparatively lower EV adoption rate in the U.S. (IEA, 2024). Many European countries, including France, Finland, and Poland, have over 50% of their automobile IPs targeting EV-related sectors, aligning with their ambitious zero-emission vehicle transition plans and strong focus on decarbonizing the automobile sector.

Emerging economies such as Russia, Brazil, India, and China have also implemented a considerable number of IPs in the automobile industry. The scope of IPs in these countries tends to be broader, affecting more countries and products compared to those in developed economies. When weighted by the number of affected countries and products, India, Brazil, Russia, and China rank first, second, third, and sixth, respectively, in terms of total IPs implemented. For this reason, we conduct robustness analyses in Section 4.3, where the IP regressions are weighted by the number of affected countries and products. Unlike developed economies, the industrial policies in these countries appear less focused on EVs, possibly reflecting a continued emphasis on labor-intensive advantages in traditional internal combustion engine manufacturing. Surprisingly, Japan ranks low in both total and EV-targeted IPs, despite the fact that Japanese companies, such as Toyota, hold the majority of EV patents. Results are robust to omitting Japan in the country-level analyses (Section 4.3).

3.2 Firm Subsidies

Appendix Figure A.3 highlights the top ten automotive firms in Panel (a) and battery firms in Panel (b) ranked by total subsidies received. The gray bar represents the total subsidy for each firm, while the black dots with numbers indicate the average subsidy. The top ten firms are well distributed across major countries. Subsidies are highly concentrated, with 48.2% of total subsidies received by the top four firms in the automobile industry (Tesla, Renault-Nissan Group, BYD Auto, and VW Group) and 58.6% of total subsidies received by the top three firms in the battery industry (Panasonic, LG Energy Solution, and CATL).

3.3 Innovations: the Transition to Green Technology

We now examine the global development of green technology over the past four decades. We focus on the number of *inventions*, identified by unique DOCDB family IDs, as this provides a more accurate picture of overall technological innovations than patent counts (which depend on the IPC codes and number of countries filed). To highlight the development of EV-specific green technology (as opposed to dual-purpose technologies), we define an EV invention as one whose IPC codes across all patent filings fall exclusively within the EV category (see Appendix Table A.3 for a list of EV-related IPC codes). Similarly, we define a GV invention as one whose IPC codes exclusively belong to the GV category. If an invention has IPC codes from both the EV and GV categories, it is classified as a general invention.

Figure 5 displays the number of newly granted inventions from 1980 to 2018, separately for EV inventions by a solid black line (left axis), GV inventions by a dashed dark grey line (left axis), and general inventions by a dash-dot light grey line (right axis).[21] The figure reveals a clear technological shift from GV technologies to EV technologies, especially after 2000. Newly granted inventions were predominantly focused on GV technologies before 2010, with rapid growth occurring from the 1990s through 2010. The number of GV-exclusive inventions peaked

[21] It takes time for patents to be included in the PATSTAT database. The number of inventions post-2018 is considerably lower due to right truncation and is not reported.

in 2011 and has since gradually declined. In contrast, EV-exclusive inventions worldwide have exhibited exponential growth since the mid-2000s, surpassing GV inventions in 2013. By 2020, the number of EV inventions had grown to three times that of GV inventions. General inventions applicable to both EVs and GVs have mostly grown steadily over the past four decades, though they appeared to peak in 2016 and have since started to trend downward. These patterns align with the growing number of EV-related policies in the last decade, as shown in Figure 3. Figure A.4 indicates similar trends when innovation is measured by the number of patents, as used in the subsequent regression analysis.

Panel (a) of Appendix Figure A.5 shows the top ten countries with the highest cumulative EV inventions, with Japan holding 36% of global patents. The U.S. and Germany follow in second and third places. Panel (b) displays the top ten countries for EV inventions granted in 2019, with Japan and the U.S. still in the lead, while China ranks third for EV inventions granted that year.

EV patent holdings at the firm level are highly concentrated. In the automotive sector, Toyota Group, Honda, and the Renault-Nissan Alliance hold the majority of EV-related patents. For EV battery suppliers, Samsung, LG Energy Solution (both based in South Korea), and China-based Contemporary Amperex Technology Co., Limited (CATL) lead in patent holdings. Specifically, the top three automakers account for 74% of all EV inventions filed by automakers, and the top three battery suppliers represent 77% of those filed by battery suppliers.

4 Country-level Analysis on Industrial Policies

This section examines the effect of IPs on innovation using country-IPC-year regressions. We focus on the effect of EV IPs on EV patents in our main specification, but we also consider GV patents and general patents in robustness checks. The data is at the country-IPC-year level, where the country of a patent is defined by the inventor's residence country. As outlined in Section 2.3, one patent is defined as a unique combination of DOCDB Family ID, application authority, inventor's residence country, and IPC code.

4.1 Empirical Strategy

We use the number of new EV patents applied for and granted as a measure of green technology innovation in the automobile industry. We employ two estimation strategies. The first strategy is a linear panel regression model with fixed effects, and the second is the PPML method, which is commonly used for discrete outcomes. Given the large number of zero patent counts at the country-IPC-year level, PPML is better suited to handle zero values effectively.

Linear Panel Regression The linear panel regression model with fixed effects is specified as follows:

$$\ln(Y_{clt}) = \alpha_1 \, IP_{c,k,t-1} + \alpha_2 \, EPS_{ct} + \alpha_3 \, \ln(Cum.\,Patent_{c,l,t-1}) + \tau_c + \tau_l + \tau_t + u_{clt}, \tag{1}$$

where Y_{clt} is the count of new patents applied for by inventors residing in country c, IPC code l, and year t. To address zero patent counts, we use a modified logarithm as suggested in Chen and Roth (2024) and other transformations, such as $\ln(Y+1)$ and the inverse hyperbolic sine.[22]

$IP_{c,k,t-1}$ denotes the cumulative measure of IPs implemented in country c related to technology type k by year $t-1$. Each IPC code l is associated with a specific technology type $k \in \{\text{EV, GV, General}\}$. The main specification uses the five-year cumulative number of IPs, as IPs may be effective for a limited period post-implementation. We also use the total cumulative number of IPs launched since 2008 as a robustness check. Additional controls include the OECD's environmental policy stringency index that captures country c's regulatory efforts, EPS_{ct}, and the cumulative knowledge stock in country c in IPC code l up to year $t-1$, $Cum.\,Patent_{c,l,t-1}$, which accounts for path dependence in technology innovation as well as the scope for innovation capacity (Aghion et al., 2016). All explanatory variables are normalized and divided by their standard deviation. The remaining controls are τ_c, τ_l, and τ_t, which are country, IPC, and year fixed effects, respectively.

[22] The modified logarithm in Chen and Roth (2024) is $m(y) = \ln(y)$ if $y > 0$ and $m(y) = -x$ if $y = 0$. Chen and Roth (2024) suggest using $x = 1$ or 3. We use $x = 1$. The interpretation is that the effect of moving y from 0 to 1 is valued the same as a 100 log-point effect on the intensive margin (e.g., the same as the effect from $\ln(a)$ to $\ln(b)$ where $\ln(b) - \ln(a) = 1$).

PPML Method Our preferred specification is based on the PPML model, which is widely used in scenarios where the outcome variable includes many zeros (Silva and Tenreyro, 2010). As an extension of Poisson regression, PPML provides a flexible and robust approach to modeling count data.[23] The PPML model can be summarized as:

$$\begin{aligned}\mathbb{E}\left(Y_{clt} \mid X_{clt}\right) &= \exp\left(\lambda_{clt}\right) \\ &= exp\left(\beta_1\, IP_{c,k,t-1} + \beta_2\, EPS_{ct} + \beta_3 \ln(Cum.\, Patent_{c,l,t-1}) + \tau_c + \tau_l + \tau_t\right)\end{aligned}$$

Here, X_{clt} includes the same control variables and fixed effects as before. The coefficients β measure the semi-elasticity of the expected patent counts with respect to the independent variables. For example, the coefficient of $IP_{c,k,t-1}$ indicates the percentage change in the expected patent counts when $IP_{c,k,t-1}$ increases by one standard deviation. The log-likelihood function is:

$$\mathcal{L}\left(Y_{clt} \mid X_{clt}\right) = \sum_{c,l,t}\left[Y_{clt} \cdot \left(\lambda_{clt}\right) - \exp\left(\lambda_{clt}\right)\right] + \text{constant}$$

4.2 Baseline Estimation Results

Figure 6 graphically depicts the estimation results of Equation (1). It shows the residualized binned scatter plot of the effects of EV IPs on the number of applied patents, using the method proposed by Cattaneo et al. (2024). The black circles and solid fitted line represent EV patents, while the gray diamonds and dashed fitted line represent GV patents. Two main patterns emerge. First, there is a clustering of data points near the origin, reflecting that a large proportion of the sample (country-IPC-year) has no new patent applications, requiring methods that account for zero outcomes. Second, there is a clear positive relationship between EV patents and cumulative EV IPs, while no such relationship is observed for GV patents and EV IPs. This suggests that EV IPs incentivize research and innovation in clean vehicle technologies without spillover effects on non-targeted GV technologies. Appendix Figure A.6 shows similar patterns in the raw data

[23] While PPML is derived from Poisson regression, it does not require the variance of the dependent variable to equal its mean. Specifically, PPML estimation focuses on correctly estimating the mean of the dependent variable and does not require the variance to follow a particular distribution. It relies only on the conditional mean assumption from the Poisson regression framework without assuming the full Poisson distribution for the dependent variable. Even when the dependent variable does not follow a Poisson distribution, PPML still produces consistent and unbiased parameter estimates.

without any covariates included.

Table 2 reports the baseline results for the country-level analyses. We include country, IPC, and year fixed effects across all columns. Results are robust with Country-by-IPC fixed effects, as shown in Appendix Table A.4. Columns (1) and (2) use OLS estimation, where the dependent variable is the modified logarithm suggested by Chen and Roth (2024) to address zero values. Column (1) uses the full sample with 4,355 observations, while Column (2) includes only observations with at least one patent count, reducing the sample size to 738. The coefficients indicate that a one standard deviation increase in 5-year cumulative EV IPs is associated with a 4.5% increase in EV patents overall and a 3.2% increase on the intensive margin. Appendix Table A.5 shows that these results are robust to alternative transformations of the outcome variables (e.g., log of 1 plus the number of EV patents, inverse hyperbolic sine of the patents).

Columns (3) to (6) report results from the PPML estimation, where the dependent variables are the number of EV patents applied in Columns (3) to (5) and EV patents granted in Column (6). Note that the number of observations is smaller for the PPML model than for OLS because PPML only includes country-IPC pairs with positive patents in at least one year.[24] Column (3) uses the full sample and is our preferred specification, while Column (4) includes only observations with a positive number of EV patents applied, capturing the intensive margin.

The coefficients across columns indicate a positive and statistically significant effect of IPs on innovation in the global EV industry. Specifically, a one standard deviation increase in 5-year cumulative EV IPs is associated with a 3.9% increase in the number of EV-related patents in the full sample (Column (3)) and a 4.0% increase in the subsample with at least one patent (Column (4)). Both effects are statistically significant at the 1% level. In contrast, the EPS variable is generally insignificant across columns. These patterns suggest that the number of new EV patents applied for is likely driven by industrial policies specifically targeted at the automobile industry rather than by broader environmental regulations.

The coefficient estimate on the lagged cumulative patents granted is significantly positive, ranging from 0.2 to 0.5. This suggests that a 1% increase in cumulative EV patents in the past would lead to 0.2 to 0.5% more new EV patent filings, indicating a strong path dependency in

[24]The observations that are dropped—with zero patents throughout—can be safely discarded as they provide no useful information (Correia et al., 2019).

EV innovation. This path dependence, along with inherent differences across countries (captured by country-fixed effects), accounts for a substantial proportion of the observed variation in EV technology innovation across countries.

Column (5) includes both the 5-year cumulative EV and GV IPs. As explained in Section 2.1, we limit the regression sample to IPs that are beneficial to the country of implementation (i.e., EV IPs are likely to provide direct incentives to the domestic EV sector, while GV IPs are likely to benefit the domestic GV sector). The negative effect of GV IPs on EV-related innovation demonstrates that IPs targeting the GV sector tend to inhibit domestic automobile market electrification. This confirms that directed policy support is crucial for fostering innovation in target technologies and diverting research away from untargeted technologies.[25] Meanwhile, the coefficient on EV IPs, when controlling for GV IPs, is positive and becomes three times as large as the baseline (Column (3)). This suggests that GV and EV IPs are negatively correlated, conditional on controls and fixed effects, making our preferred specification likely to provide a lower-bound estimate. Column (6) uses the number of granted EV patents as the outcome variable, with the coefficient estimate closely resembling the baseline, suggesting that EV IPs have similar impacts on both patent applications and patent grants.

4.3 Robustness Checks and Discussions

Table 3 presents robustness checks and extends the baseline result from Column (3) of Table 2 by examining heterogeneity among different types of IPs. Both the dependent variable (new patents applied) and the empirical specification (PPML with the full sample) are the same as the baseline. Column (1) uses lagged total cumulative EV-targeted IPs, and the coefficient is larger than the baseline: a one-standard-deviation increase in lagged cumulative IPs (48 policies) is associated with an 11.2% increase in the number of EV-related patents.[26] Column (2) augments the baseline 5-year cumulative IP measure by weighting it by the number of affected products. This measure reflects policy intensity rather than just the count; the greater the number of products affected by an IP, the broader its scope. We find that the augmented IP measure (incorporating the number of affected products) leads to larger effects on EV innovation – the

[25] This pattern is consistent when using OLS estimation instead of PPML, as shown in Appendix Table A.5.

[26] A one-standard-deviation increase in lagged five-year cumulative IPs corresponds to 27 policies.

coefficient estimate is 0.076 compared to 0.039 in the baseline.

Columns (3) to (5) in Table 3 examine three mutually exclusive categories of IPs: Trade, Subsidy, and Others. Trade- and subsidy-related IPs contribute to the positive overall effects on patents, with trade-related IPs being slightly more effective, while IPs in other categories do not appear to play a role. Column (6) uses the logarithm of 5-year cumulative IPs to estimate the elasticity of green innovations. The elasticity of new EV patent applications with respect to 5-year cumulative EV-targeted IPs is slightly less than 0.1, implying that at the country level, a 10 percent increase in cumulative IPs is associated with approximately a 1 percent increase in EV patents.

Appendix Table A.4 shows that the results are robust to alternative controls and different patent aggregation methods. Column (1) controls only for lagged five-year cumulative EV IPs, along with country and year fixed effects. Column (2) adds lagged knowledge stock and the EPS index, while Column (3) includes country-by-IPC fixed effects. Results are consistent across columns. Column (4) uses cumulative citations of granted patents, which directly measure the quality of innovation. The effect is about 0.5%, which is smaller than other outcome measures, partly because this is a stock variable rather than a flow variable. Column (5) shows that our findings are not sensitive to data aggregation methods; we count a patent as a unique combination of DOCDB Family ID-IPC code (aggregated across application offices). Both the magnitude and significance of the key parameter remain unchanged.

Appendix Table A.6 evaluates the impact of EV-targeted IPs on GV technology and on general technology applicable to both EV and GV. EV IPs are policies designed to foster automobile electrification and, in theory, should not advance GV technologies but may generate spillover benefits to general technologies, such as brake controls, wheels, and safety devices. Detecting positive effects on GV patents would raise concerns that the main findings could be driven by omitted confounding factors affecting the entire automobile industry. The null and marginally negative effects on GV patents in Columns (1) to (4) suggest that such concerns are unlikely to be significant. As expected, we find positive effects of EV IPs on general-purpose patents.

Appendix Table A.7 demonstrates that our findings are robust to several adjustments: dropping major EV patent holders (e.g., Japan), excluding China (where IPs might be harder to detect), eliminating countries that have never implemented IPs, and including only countries with at least one patent throughout the sample period.

5 Firm-level Analysis on the Effects of EV Subsidies

We have shown the positive effects of IPs on the innovation in the EV sector and that trade and subsidy-related IP policies are likely to be the primary policies at play. This section provides direct evidence of firms' responses to subsidy incentives in the context of the EV market. Barwick et al. (2023) shows that governments in many countries have provided large-scale financial subsidies to promote the electrification of the automobile industry.

5.1 Empirical Strategy

Our research design exploits variations in firm-specific subsidy exposure by combining global EV sales volumes and country-by-model-level incentives. Countries provide different purchase incentives based on their own green-vehicle transition plan as well as the criteria that apply to a vehicle's attributes, e.g., price, battery range, expected carbon reduction, etc. Intuitively, if an automaker sells more of its EVs to markets that provide higher per-model purchase subsidies (and tax credits), the automaker and its battery supplier would be more exposed to industrial policy. Similar to the country-level analyses in Section 4, we use both linear regressions (OLS and IV) and PPML methods in the firm-level analyses.

Linear Panel Regression. The linear panel regression specification is:

$$\ln(PAT_{it}) = a_1 \ln(Subsidy_{i,t-1}) + \underbrace{a_2 \ln(Stock^{ev}_{c,t-1}) + a_3 \ln(Stock^{gv}_{c,t-1})}_{A_{c,t-1}} + \tau_i + \tau_t + \varepsilon_{it} \tag{2}$$

where PAT_{it} is the number of EV-related patents applied by firm i in year t and headquartered in country c. We report the impact on GV and general patents in Section 5.3. $\ln Subsidy_{i,t-1}$ is firm i's subsidy exposure, which we measure in two ways. The main analyses use the total amount of subsidies received by firm i (in logarithm) in period $t-1$, which is a sales-weighted sum of subsidies across all of its EV models. The second measure (for robustness) is a sales-weighted average subsidy rate across all EV models by firm i in year $t-1$.

To account for path dependency where a firm's innovation activity is influenced by existing know-how, we construct technology stocks for EV and GV patents, $Stock^{ev}_{c,t-1}$ and $Stock^{gv}_{c,t-1}$, in firm i's headquarter country c.[27] The primary difference between our approach and that of Aghion et al. (2016) is that our technology stock includes both a firm's own knowledge stock and that of other firms in the same country. In other words, we consider technology stock on a broader scale without distinguishing between stocks owned by the firm itself and spillovers from other inventors in different firms within the same country. This approach is appropriate because the firms in our sample are all large conglomerates, and the sample size is relatively small.[28]

Instruments for Subsidy Exposure. One concern with our empirical strategy is that the sales variable used to construct a firm's total or average subsidy exposure could potentially be endogenous and correlated with its innovation activities.

We address this issue by constructing an instrumental variable. Specifically, we simulate sales using a BLP-style demand model to predict sales that are only explained by observed vehicle attributes and EV subsidies. The demand model is a random coefficients discrete choice model of EV demand, where potential buyers take into account both the post-subsidy EV price as well as vehicle attributes in their purchasing decisions. The simulated sales are taken from Barwick et al. (2024b), which has additional details. Then, we use the model-simulated sales to construct simulated subsidy exposure and use the latter as an IV for the observed subsidy exposure.

The idea behind this instrument is that the simulated subsidy exposure primarily reflects variation in EV subsidies combined with differential exposure of firms to these subsidies arising from exogenous reasons. For instance, simulated subsidy exposure will be higher for firms selling in jurisdictions with more generous subsidies, or firms offering EV attributes that are favored by attribute-based subsidies. Such variation is exogenous to firms' innovation activities.

PPML IV with a Control Function. Our second estimation procedure uses PPML to deal with zero outcomes. However, the 2SLS approach cannot be directly applied in a non-linear

[27]The patent stock is constructed using a perpetual inventory method with an annual patent depreciation rate of 0.2.
[28]Our main findings remain unchanged when distinguishing between own stock and spillovers from other firms.

model like PPML. Therefore, we combine PPML with IV using a two-stage control function approach proposed in Wooldridge (2015). Specifically, the lagged predicted estimation residual $\hat{u}$ from the first-stage regression of observed subsidy exposure on simulated subsidy exposure is included in the PPML estimation as an additional control:

$$\mathbb{E}\left(\ln PAT_{it} \mid X_{it}\right) = \exp\left(\lambda_{it}^{firm} + \zeta \cdot \hat{u}_{i,t-1}\right),$$

$$\lambda_{it}^{firm} = b_1 \ln Subsidy_{i,t-1} + A_{c,t-1} + \tau_i + \tau_t.$$

5.2 Baseline Regression Results

Figure 7 presents a binned scatter plot of the number of EV patents against total subsidies received by firm i, separately for automakers (black circles and solid black fitted line) and battery suppliers (diamond dots and dashed grey fitted line). The figure provides suggestive evidence of a positive correlation between the lagged total incentive exposure and the number of new EV patent applications (controlling for firm and year fixed effects and patent stocks). The pattern holds true for both automakers and upstream battery suppliers. The relation is likely to be non-linear, as the positive correlation is mainly driven by firms with relatively high total subsidies. No positive effects are detected for firms receiving modest subsidies. Appendix Figure A.7 shows such patterns remain robust without any covariates and become more salient for battery firms.

Table 4 reports the OLS and PPML estimates of Equation 2. Consistent with country-level analyses, we use the modified log proposed by Chen and Roth (2024) for OLS and the count of EV patents applied as the dependent variable for PPML.[29] The key explanatory variable is the log of total EV incentives received in the previous year. Therefore, the estimated coefficient is the elasticity of EV patent applications with respect to total subsidy. Different specifications across columns provide similar estimates of the elasticity: a ten percent increase in total subsidies will, on average, lift EV patent applications by 0.4 percent.[30]. The coefficients are statistically

[29] Appendix Table A.8 shows the results are not sensitive to alternative transformations of outcome variables when estimation using OLS methods.

[30] The elasticity using the sub-sample with only positive total subsidy is larger at 0.1: a ten percent increase in total subsidies raises patents by one percent.

significant at the 1% level, though the estimated elasticity is smaller than the clean technology elasticity to fuel prices in Aghion et al. (2016).

Knowledge stocks for both clean and dirty technology play a role. The effect of EV knowledge stock is significantly positive across all specifications, while the effect of GV knowledge stocks is negative (and significant in PPML specifications). Specifically, a ten percent increase in EV knowledge stock is associated with 5.4% more new EV patent applications in the following year, while a ten percent increase in GV knowledge stock reduces patent applications by 3.4-3.8% based on the PPML estimates. The patterns confirm strong path dependence in automobile technology, consistent with Aghion et al. (2016). As a result, IPs are likely to have stronger effects in the long run than in the short run.

Table 5 reports IV estimates (Columns (1) and (2)) and PPML estimates with a control function (Columns (3) and (4)). Columns (1) and (3) use the full sample, while the other two columns focus on the sample with positive patents. The estimated elasticity of EV patents with respect to subsidy exposure is about 0.04 across all specifications and similar in magnitude to those in Table 4. This suggests that endogeneity in subsidy exposure, if present, is unlikely to be driving our results.

5.3 Robustness Checks and Discussion

Table 6 presents robustness checks by examining different samples and explanatory variables. Columns (1) and (2) use the automakers and battery suppliers separately. The innovation elasticity is slightly larger for battery firms. This could reflect that EV sales are more critical for battery firms, as gasoline-powered vehicles still account for a substantial source of revenue among many automakers in our sample. Column (3) uses the average incentive per vehicle (i.e., the subsidy rate) instead of total EV incentives. The elasticity of EV innovation with respect to the EV subsidy rate is approximately 0.066, slightly higher than the elasticity for total subsidies. Column (4) considers total EV incentives over the past three years, where the effect is somewhat smaller. Column (5) uses the five-year cumulative IP count from the GTA database but weighs it by a firm's EV sales in that implementing country. The innovation elasticity w.r.t sales weighted IPs is 0.08, similar to the country-level elasticity at 0.09 reported in Table 3.

Appendix Table A.9 uses only "Triadic" patents, which are considered to have higher quality. Even though we lost about half of the firms due to the lower number of included patents, the results remain robust. Appendix Table A.10 separates firms' own knowledge stock from the knowledge stock of other firms in the same country in Column (1) and excludes the top three largest automakers in Column (2) and the top three battery suppliers in Column (3). Results are robust to these alternative specifications.

6 Conclusion

Despite skepticism from mainstream economics, industrial policies (IPs) have gained increasing popularity globally in recent years. In this study, we examine the role of IPs in accelerating transportation electrification through innovation. We first compile a comprehensive database of IPs and patents in the global automobile industry. IPs are most prevalent in developed countries, and there is a clear global transition toward clean technology innovation.

Our empirical analyses document a positive effect from both the count of EV-targeted IPs and consumer EV incentives on the number of EV patents applied for and granted. We confirm the importance of path dependence in technological changes within the automobile industry, suggesting that the positive effects of IPs will be self-reinforcing and grow over time. We do not find evidence of spillovers from EV-related IPs onto innovation in GV technologies, indicating that the impact of fuel type-targeted IPs is directional. The extent to which induced innovation has been adopted in EV production and its subsequent impact on EV diffusion are important questions for future research.

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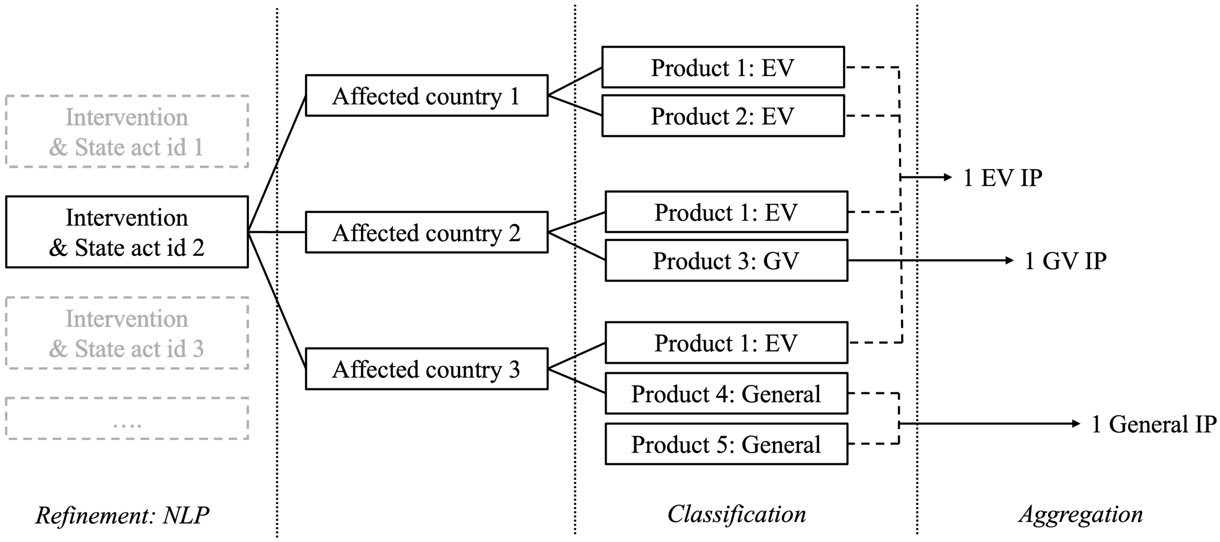
Figures

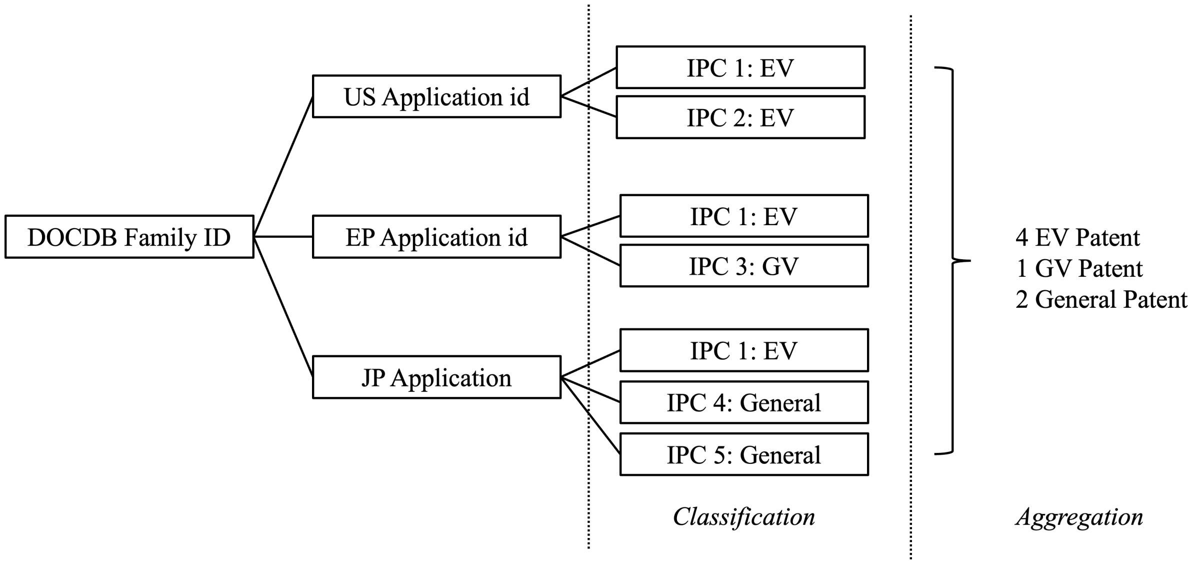
Figure 1: Illustration of Constructing fuel type IPs from the GTA Database



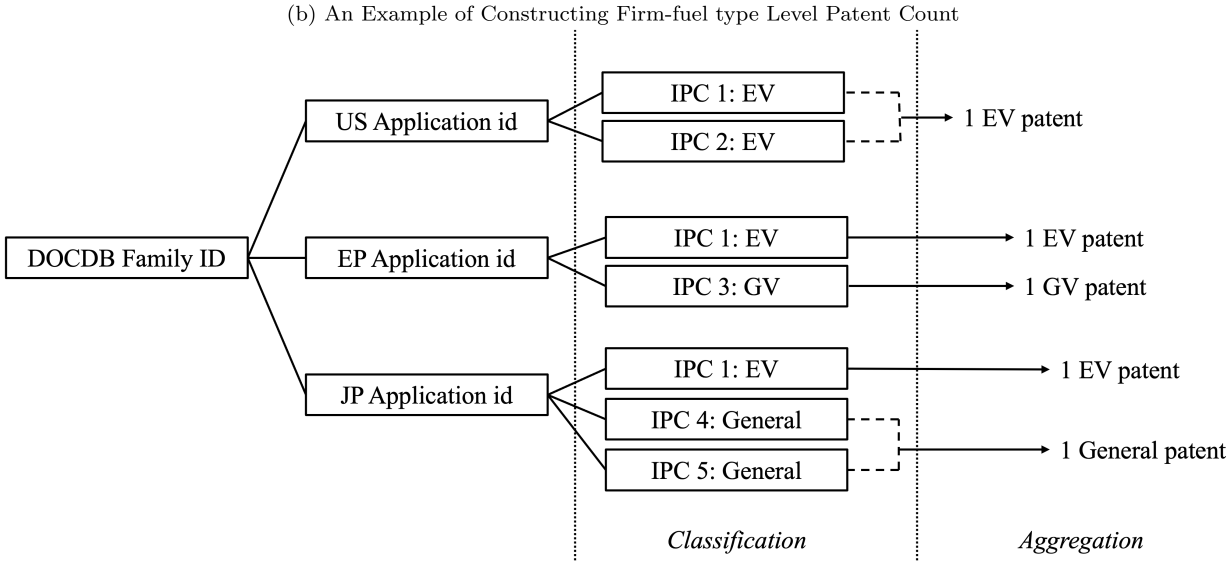
Notes: This figure explains the duplicated data entries in the GTA database and how we address them. One IP could affect multiple countries and products, and the affected products could differ across countries and span different fuel types. In this example, an IP affects two EV-related products in Country 1, one EV product and one GV product in Country 2, and one EV product and two general products in Country 3. We collapse and count each IP only once per fuel type, regardless of the number of affected countries and products within the fuel type. Therefore, when generating the country-year level IP count by fuel type, we obtain three IPs in this example: one for each fuel type.

Figure 2: Illustration of Constructing Patents Data from PATSTAT Database

(a) An Example of Constructing Country-IPC Level Patent Count

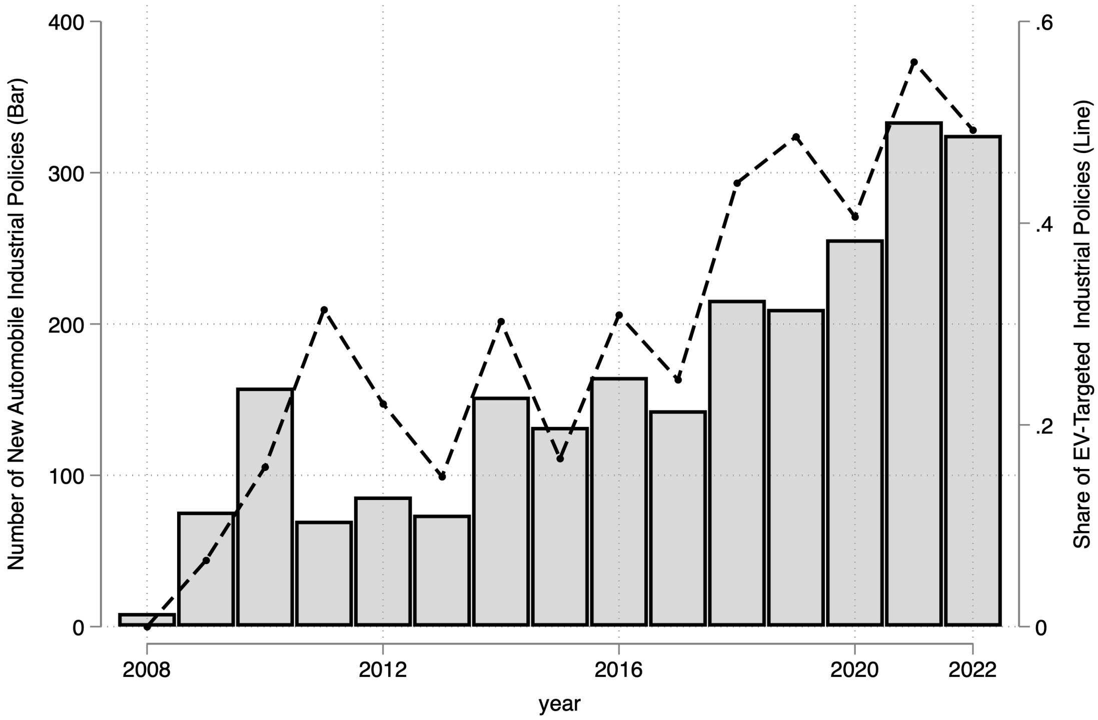


(b) An Example of Constructing Firm-fuel type Level Patent Count



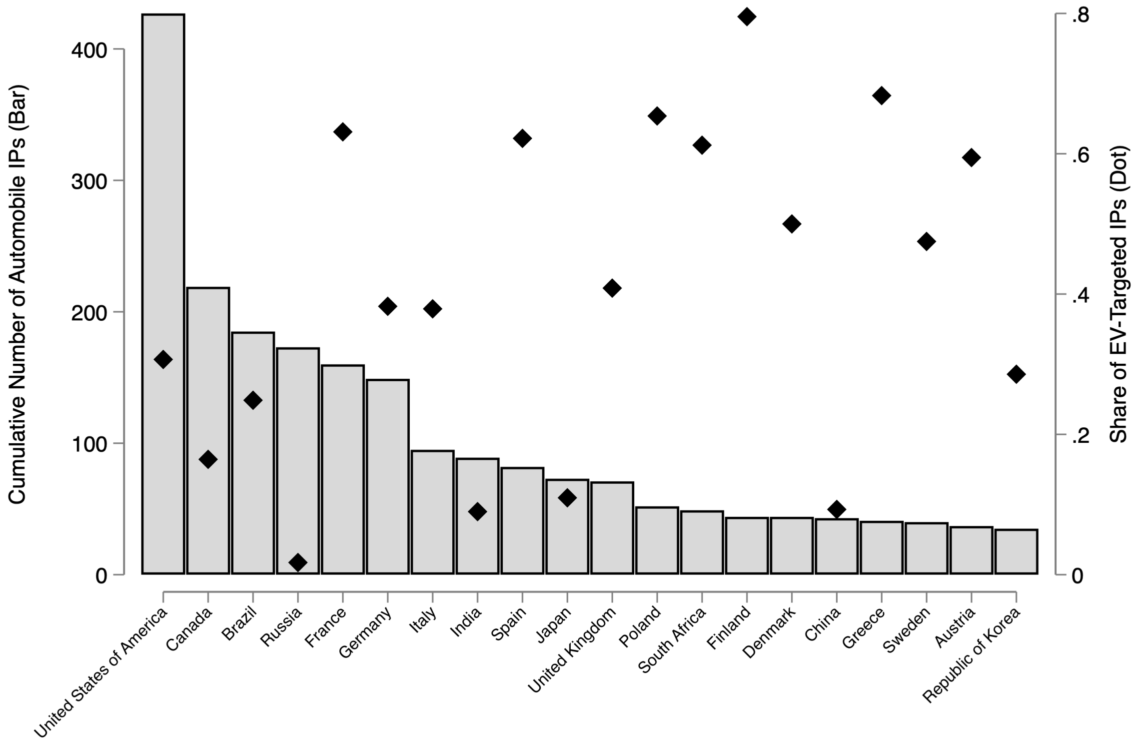
Notes: This figure explains how we address duplicate entries in the PATSTAT database. Panel (a) and (b) illustrate how we generate country-level and firm-level data, respectively. In both examples, a single invention is filed in three patent offices and across 5 IPC codes, with IPC 1 appearing in all offices. For the country-IPC-year level data (which is the number of patents owned by the inventor's country of residence by IPC and year), the seven entries appear as seven patents owned by the residence country of the inventor for this single invention. For the firm-fuel type level data, we consolidate two EV IPC filing records in the first application authority and two general IPC filing records in the third application authority. Thus, we collapse the seven data entries as five patents for the firm associated with this invention: three EV patents (one for each office), one GV patent, and one general patent.

Figure 3: The Number of New Industrial Policies in the Automobile Sector Over Time



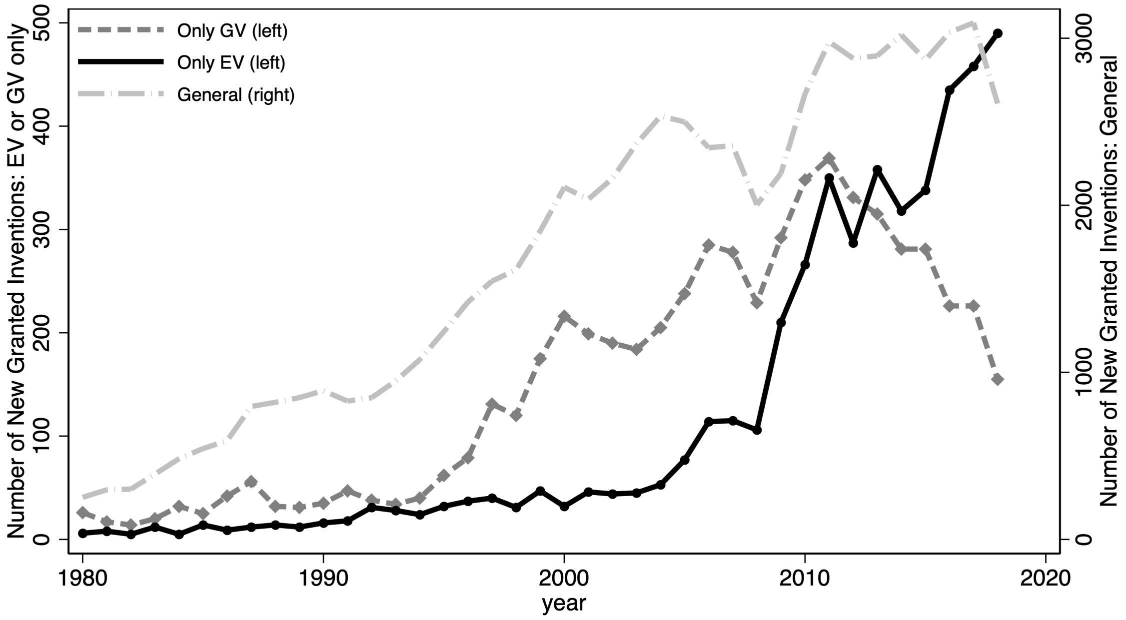
Notes: in this figure, each State Act ID + Intervention ID is counted as one industrial policy (in contrast to fuel type IP counts in regression analyses where an industrial policy can be counted up to three times depending on its policy scope.) The bars (left axis) show the number of new IPs in the automobile sector over time, and the dashed line (right axis) depicts the share of EV-targeted IPs. An IP is defined as an "EV-targeted" IP if 50% of its affected country-products are EV-related. The figure excludes 839 IPs without explicitly affected countries and 387 IPs related to the new waves of electricity projects under the 2009 American Recovery and Reinvestment Tax Act in the US.

Figure 4: Top 20 Countries in Automobile-Related Industrial Policies



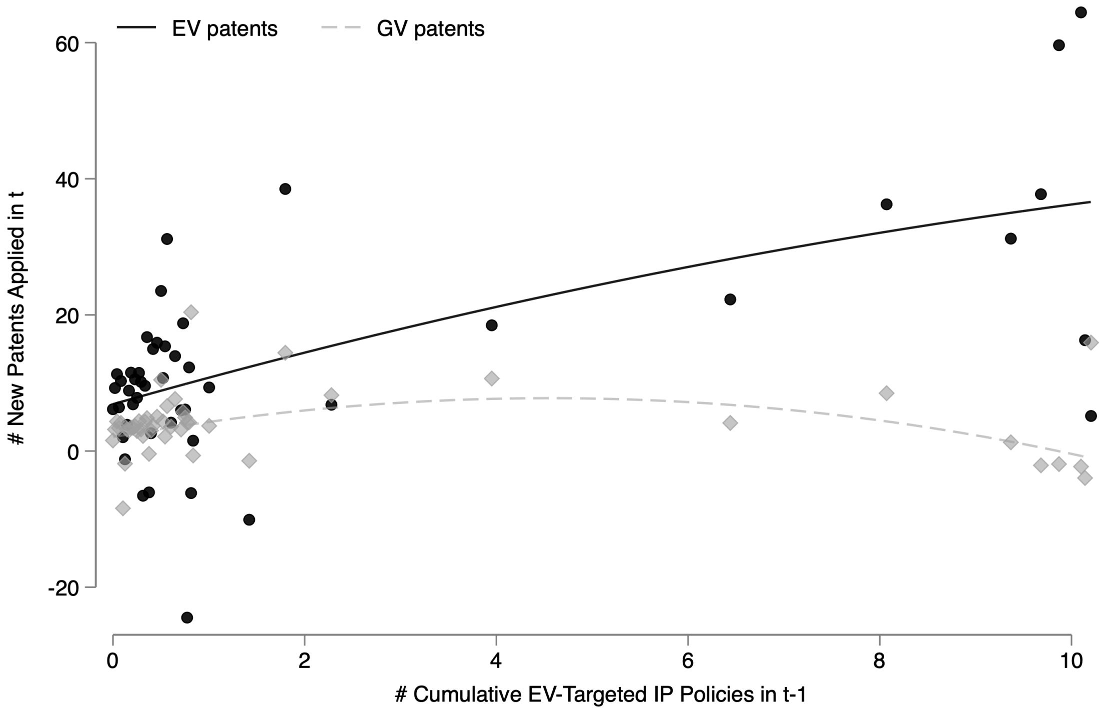
Notes: as in figure 3, each State Act ID + Intervention ID is counted as one industrial policy (in contrast to fuel type IP counts in regression analyses where an industrial policy can be counted up to three times depending on its policy scope.) The figure presents the top 20 counties ranked by their cumulative automobile-related IPs between November 2008 and October 2023. The bars (left axis) show the number of cumulative IPs by country, while the black dots represent the share of EV-related IPs. An IP is defined as an "EV-targeted" IP if 50% of its affected country-products are EV-related.

Figure 5: Global Trend of Newly Granted Inventions: 1980-2018



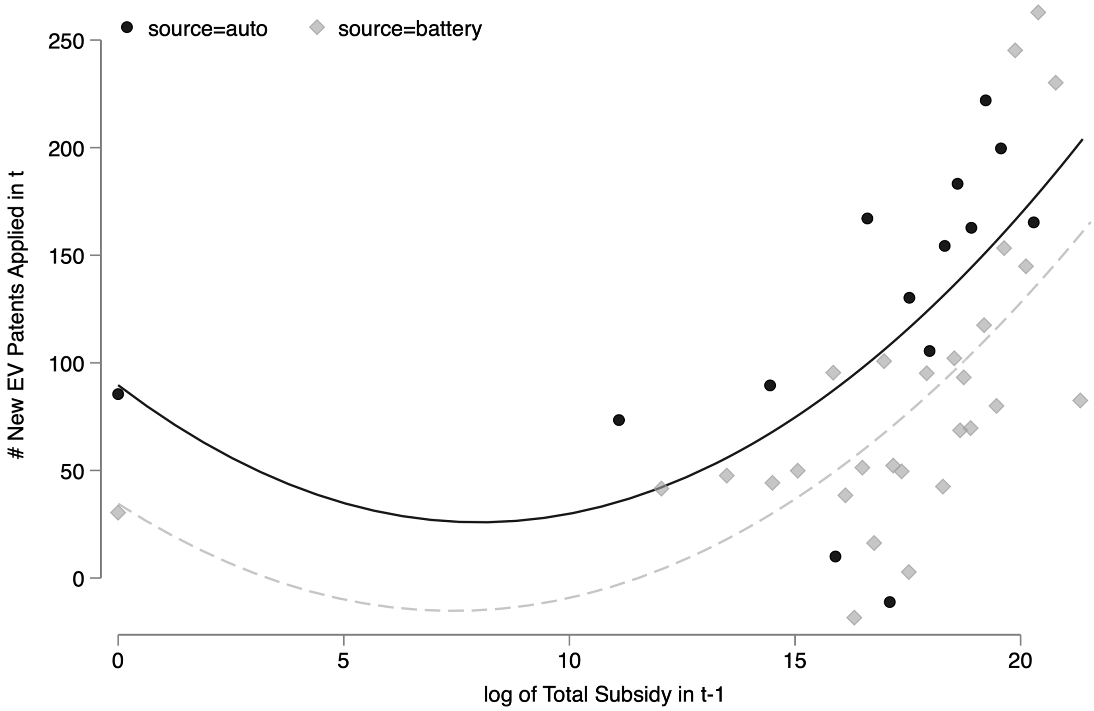
Notes: This figure shows the number of automobile-related triatic inventions that have been granted a patent by one of three major patent offices: USPTO, EPO, and JPO from 1980 to 2018. One invention is identified by a unique DocDB family ID and represents a unique technological innovation. This invention count is different from country-IPC patent count or firm-fuel type patent count used in regression analyses (that treat one invention as multiple patents depending on its IPC codes or fuel type applications). The solid black line (left axis) represents inventions that are exclusively used for EVs. The dark gray dashed line (left axis) represents inventions that are exclusively used for GVs. The light gray dash-dot line (right axis) represents general inventions that can be used for both EVs and GVs.

Figure 6: Patents Applied against Cumulative EV IP: Country-level Analysis



Notes: This figure uses country-IPC-level patent data. It shows the effects of EV industrial policies on patents applied using the binned scatter plot method with covariate proposed by Cattaneo et al. (2024). The control variables and fixed effects are discussed in Section 4.1. The vertical axis is the number of new EV and GV patents applied in year t, and the horizontal axis is the cumulative number of EV-related IP policies in year $t-1$. The black circles and solid fitted line stand for EV patent; the diamond dots and dash fitted line stand for GV patents. The number of bins is 48, which is selected using a data-driven, optimal choice procedure.

Figure 7: EV Patents Applied against Total EV Subsidy Received: Firm-level Analysis



Notes: This figure uses firm-fuel type patent data and shows the effects of EV subsidy incentives on EV patents applied using the binned scatter plot method with covariate proposed by Cattaneo et al. (2024). The control variables and fixed effects are discussed in Section 5.1. The vertical axis is the number of new EV patents applied in year t, and the horizontal axis is the total EV subsidy received in year $t-1$. The black circles and solid fitted line stand for automakers; the diamond dots and dash fitted line stand for batter suppliers. The number of bins is 28, which is selected using a data-driven, optimal choice procedure.

Tables

Table 1: Summary Statistics of Country-Level and Firm-Level Data

Variables	Mean	SD	Min	Max
Panel A: Country-IPC-Year Level				
N new patents applied, EV	7.24	55.00	0.00	1399.00
N cumulative patents granted, EV	75.87	608.46	0.00	11280.00
N new patents applied, GV	2.20	23.58	0.00	673.00
N new patents applied, General	6.78	53.52	0.00	1426.00
N new EV IPs	1.39	6.70	0.00	119.00
N cumulative EV IPs	8.80	47.85	0.00	513.00
N five year cumulative EV IPs	4.23	26.88	0.00	412.00
EPS $\times$ OECD	1.42	1.54	0.00	4.89
Panel B: Firm Level, Automakers				
N new patents applied, EV	93.84	325.96	0.00	3437.00
N new patents applied, GV	75.58	229.47	0.00	2225.00
Knowledge stock, EV	4633.48	7086.59	0.00	28139.75
Knowledge stock, GV	4757.99	7026.71	0.00	26035.73
Incentive per unit ($)	1595.98	2478.45	0.00	10265.60
Incentive per unit ($), IV	1241.98	2281.86	0.00	9385.74
Total incentive (mill. $)	51.98	176.83	0.00	2076.36
Total incentive (mill. $), IV	37.02	132.67	0.00	1453.39
Panel C: Firm Level, Battery Suppliers				
N new patents applied, EV	40.34	116.95	0.00	954.00
N new patents applied, GV	0.30	1.45	0.00	19.00
Knowledge stock, EV	2168.31	1726.46	0.56	5791.71
Knowledge stock, GV	6.15	10.22	0.00	55.55
Incentive per unit ($)	2.65	2.85	0.00	13.78
Incentive per unit ($), IV	2.65	2.99	0.00	20.86
Total incentive (mill. $)	0.12	0.35	0.00	2.77
Total incentive (mill. $), IV	0.09	0.25	0.00	2.61

Notes: This summary statistic table is constructed based on the country-IPC-year level panel data and firm-year level data. Panel A has 67 countries, covering 2008 to 2020. There are 5 EV IPC codes, 9 GV IPC codes, and 15 general IPC codes. EPS $\times$ OECD stands for the environmental policy stringency index compiled by the OECD. For non-OECD countries, we set the value to zero. Panels B and C include 92 automakers and 45 battery suppliers, covering 2013 to 2020. Knowledge stock for EV (GV) is calculated as the cumulative number of EV (GV) patents filed by firms in the same country, with a yearly depreciation rate of 0.2. The IVs (instruments) for average and total incentives are calculated using simulated sales from a structural demand model.

Table 2: The Effects of Industrial Policies on Innovation: Country-Level Analyses

	(1) Applied	(2) Applied	(3) Applied	(4) Applied	(5) Applied	(6) Granted
Lag 5-year Cum. EV IP	0.045**	0.032***	0.039***	0.040***	0.123***	0.040***
	(0.022)	(0.007)	(0.003)	(0.002)	(0.024)	(0.004)
Lag log(1+Cum. granted P)	0.436***	0.198***	0.371***	0.290***	0.367***	0.355***
	(0.037)	(0.032)	(0.043)	(0.041)	(0.041)	(0.038)
EPS	0.063*	-0.059	-0.047	-0.043	-0.100	-0.033
	(0.033)	(0.156)	(0.211)	(0.200)	(0.191)	(0.271)
Lag 5-year Cum. GV IP					-0.178***	
					(0.053)	
Sample	Full	Intensive	Full	Intensive	Full	Full
Est. Method	OLS	OLS	PPML	PPML	PPML	PPML
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
IPC FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R-squared			0.929	0.899	0.929	0.927
Adjusted R-squared	0.751	0.710				
Obs	4355	738	2990	738	2990	2600

Notes: This table documents the effects of EV-related industrial policies on EV innovation using country-IPC-year level panel data. Columns (1), (3), (5), and (6) use the full sample, while Columns (2) and (4) limit to observations with positive patent counts. Columns (1)-(2) use OLS; Columns (3)-(6) use PPML. The dependent variable in Column (1) is a modified logarithm as suggested in Chen and Roth (2024). The dependent variable in Column (2) is the log of EV patents applied. The dependent variable is EV patents applied in year t in Columns (3)-(5) and EV patents granted in t in Column (6). The number of observations is smaller for the PPML specification as it only includes country-IPC pairs with positive patents in at least one year. "Lag 5-year Cum. EV IP" (Lag "5-year Cum. GV IP") is the cumulative number of EV (GV) IPs from $t-5$ to $t-1$. "Lag ln(Cum. granted P)" is the log of the cumulative number of granted patents at time $t-1$. "EPS" is the OECD environmental policy stringency index. All regressors are normalized and divided by their standard deviation. Standard errors in parentheses are clustered at the country level. Significance levels are denoted by * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 3: Robustness Checks and Heterogeneity for Country-Level Analyses: PPML

	(1)	(2)	(3)	(4)	(5)	(6)
Lag Cum. EV IP	0.114***					
	(0.016)					
Lag 5-year Cum. EV IP, w. # products		0.076***				
		(0.023)				
Lag 5-year Cum. EV IP, Trade			0.043***			
			(0.007)			
Lag 5-year Cum. EV IP, Subsidy				0.038***		
				(0.003)		
Lag 5-year Cum. EV IP, Other					-0.081	
					(0.059)	
Lag ln(1+5-year Cum. EV IP)						0.090*
						(0.053)
Pseudo R-squared	0.934	0.932	0.933	0.933	0.932	0.932
Obs	2990	2990	2990	2990	2990	2990

Notes: This table presents a robustness check of the baseline results shown in Table 2. Except for the key explanatory variable, the empirical specifications are the same as Column (3) of Table 2, which is PPML estimation with the full sample. The dependent variable is new EV patents applied in a country-IPC-year. All columns control for country, IPC code, and year fixed effects. For the explanatory variables, Column (1) uses lagged total cumulative EV IPs (Lag Cum. EV IP); Column (2) augments the lagged 5-year cumulative EV IPs by weighting it using the number of affected products; Columns (3) to (5) use only lagged trade-related, subsidy-related, and other EV IPs, respectively. Column (6) uses the lagged log of five-year cumulative EV IPs. All variables are normalized and divided by their standard deviation. Standard errors in parentheses are clustered at the country level. Significance levels are denoted by * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 4: The Effects of Subsidies on Innovation: Firm-level Analyses

	(1)	(2)	(3)	(4)
Lag ln(1+Total Subsidies)	0.025*	0.041***	0.040***	0.038***
	(0.014)	(0.011)	(0.011)	(0.009)
Lag Knowledge stock, EV	0.199***	0.215***	0.541***	0.541***
	(0.040)	(0.074)	(0.084)	(0.077)
Lag Knowledge stock, GV	-0.028	-0.064	-0.335***	-0.377***
	(0.044)	(0.086)	(0.084)	(0.081)
Sample	Full	Intensive	Full	Intensive
Est. Method	OLS	OLS	PPML	PPML
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Adjusted R-squared	0.894	0.852		
Pseudo R-squared			0.948	0.944
Obs	838	469	616	469

Notes: This table presents results on the effect of EV subsidy incentives on EV innovations using firm-year-level data. Our sample consists of 137 firms (92 automakers and 45 battery suppliers) spanning from 2013 to 2020. The sample is unbalanced due to firm entries. We lose a firm's initial year due to the lagged subsidies. Columns (1) and (2) use OLS, while Columns (3) and (4) use PPML. Columns (1) and (3) use the full sample, while Columns (2) and (4) use firm-years with positive EV patents. The dependent variable is the modified log EV patents applied in year t as suggested in Chen and Roth (2024) in Column (1), log EV patents applied in Column (2), and the number of EV patents applied in Columns (3) and (4). The number of observations is smaller for the PPML specification as it only includes country-IPC pairs with positive patents in at least one year. For the explanatory variables, "Lag ln(Total Subsidies)" is the log of total EV incentives received in year t-1, "Lag Knowledge stock for EV (GV)" is calculated as the cumulative number of EV (GV) patents filed by firms in the same country in year $t-1$, with a yearly depreciation rate of 0.2. Standard errors in parentheses are clustered at the firm level. Significance levels are denoted by * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 5: The Effects of Subsidies on Innovation: Firm-level Analyses, IV Approach

	(1)	(2)	(3)	(4)
Lag ln(1+Total Subsidies)	0.039**	0.040***	0.040***	0.040***
	(0.018)	(0.012)	(0.008)	(0.008)
			[0.014]	[0.011]
$\hat{u}$			0.026*	0.034**
			(0.015)	(0.017)
Lag Knowledge stock, EV	0.192***	0.216***	0.525***	0.540***
	(0.042)	(0.074)	(0.100)	(0.099)
Lag Knowledge stock, GV	-0.022	-0.065	-0.322***	-0.413***
	(0.044)	(0.086)	(0.101)	(0.109)
Sample	Full	Intensive	Full	Intensive
Est. Method	2SLS	2SLS	PPML, CF	PPML, CF
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Adjusted R-squared	0.119	0.137		
Pseudo R-squared			0.948	0.945
Obs	838	469	616	423

Notes: This table uses instrumental variable estimates and a control function approach to estimate the effects of EV subsidies on EV patents applied using firm-year level data. Except for the IVs/control function, the empirical specification and controls for each column are the same as the corresponding columns of Table 4. Columns (1) and (2) report IV estimates, and Columns (3) and (4) report PPML estimates with a control function as suggested by Wooldridge (2015). $\hat{u}$ in Columns (3) and (4) is the control variable, which is the residual from regressing observed lagged subsidies to simulated lagged log subsidies. Standard errors in parentheses are clustered at the firm level, and bootstrap standard errors in square brackets are calculated from 500 sets of bootstrap simulation draws. Significance levels are calculated using standard errors in parentheses and are denoted by * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 6: The Effects of Subsidies on Innovation: Firm-level Analyses, PPML Robustness

	(1) IV	(2) IV	(3) IV	(4) IV	(5) IV
Lag ln(1+Total Subsidies)	0.033***	0.049***			
	(0.009)	(0.012)			
Lag ln(1+Average Subsidy rate)			0.066***		
			(0.016)		
Lag ln(1+Total Subsidies in past 3 years)				0.023***	
				(0.005)	
Lag ln(1+sale weighted cum IPs)					0.083**
					(0.040)
					[0.095]
Sample	Auto	Battery	Full	Full	Full
Firm FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Pseudo R-squared	0.958	0.903	0.947	0.951	0.947
Obs	427	189	616	439	616

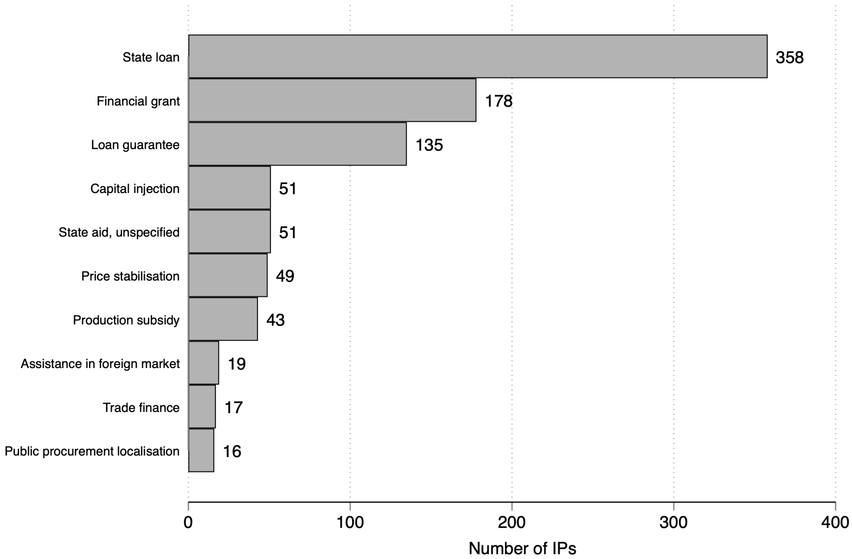
Notes: This table presents robustness results regarding the effect of EV incentives on EV patents applied using the PPML-control-function strategy. The empirical specification is the same as Column (3) of Table 5, which is PPML with a control function. Columns (1) and (2) use separately the automakers and battery suppliers, respectively. Column (3) uses the lagged average subsidy per EV instead of total EV incentives. Column (4) uses lagged total EV incentives over the past three years. Column (5) uses the lagged sales-weighted cumulative IPs. Standard errors in parentheses are clustered at the firm level. Significance levels are calculated using standard errors in parentheses and are denoted by * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Online Appendix

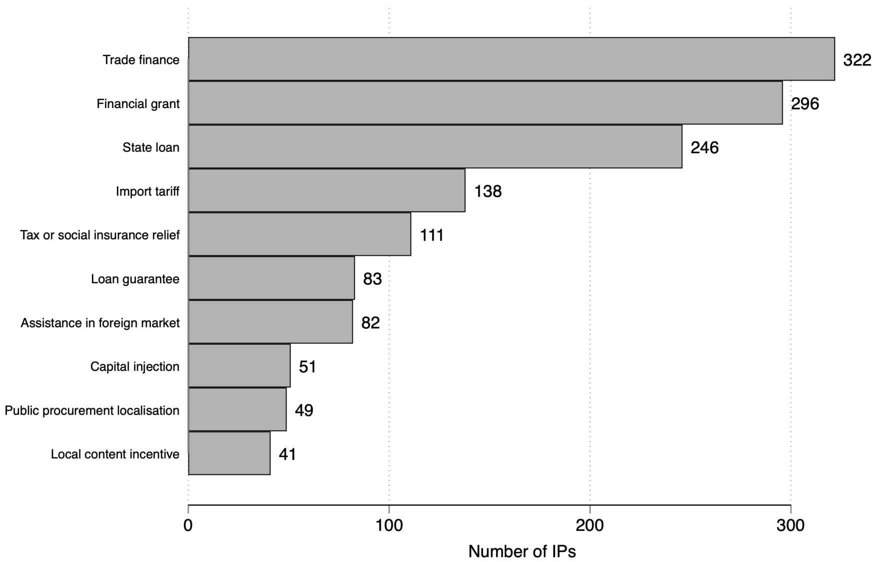
A Additional Figures and Tables

Figure A.1: Number of Industrial Policies by category

(a) EV-Related IPs

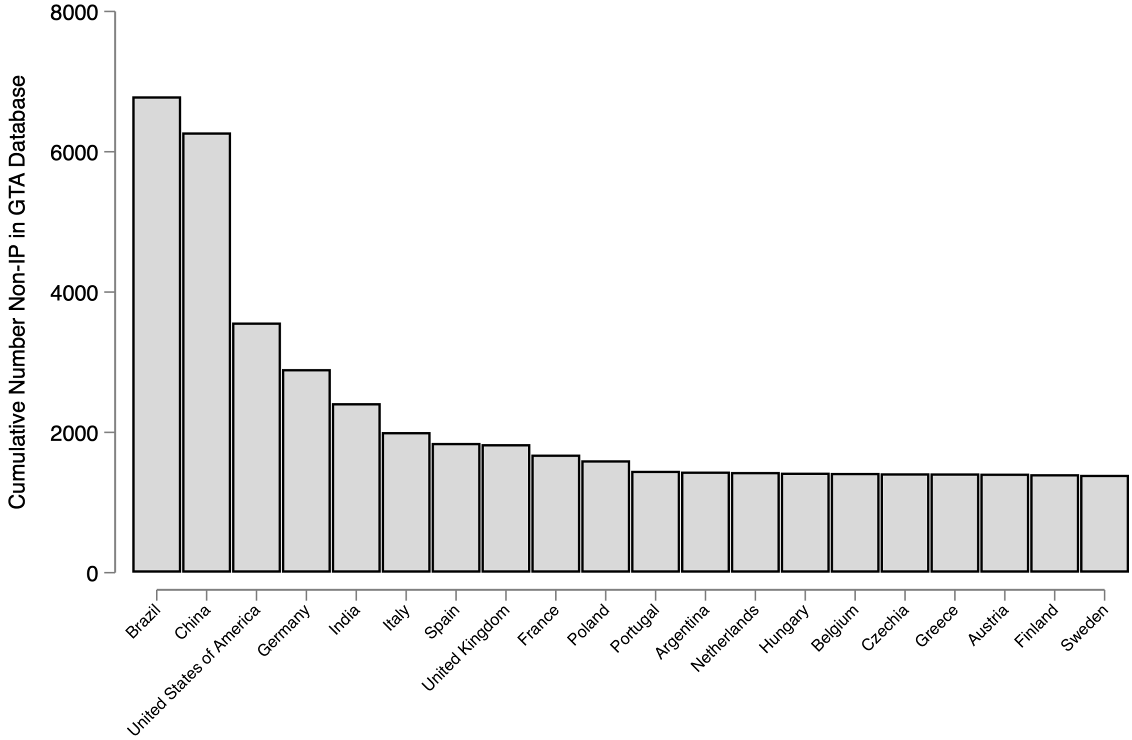


(b) GV-Related IPs



Notes: This figure shows the number of IPs in our data of each sub-category, by EV and GV-related IPs.

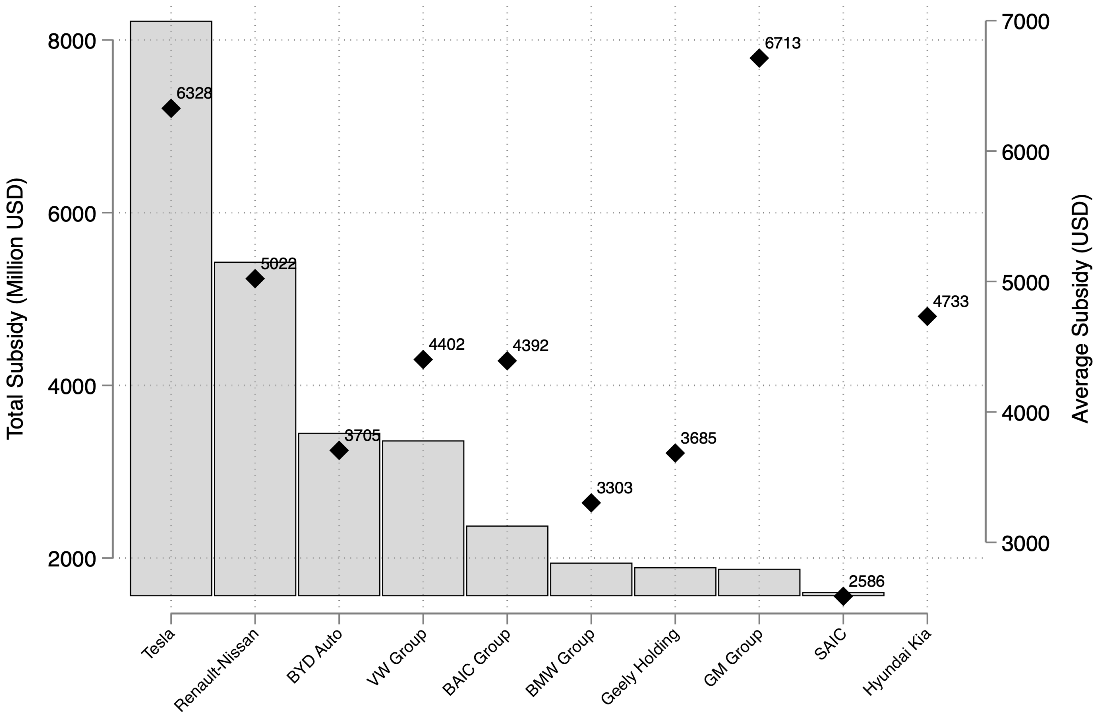
Figure A.2: Top 20 Countries in Launching non-Industrial Policies in GTA Database



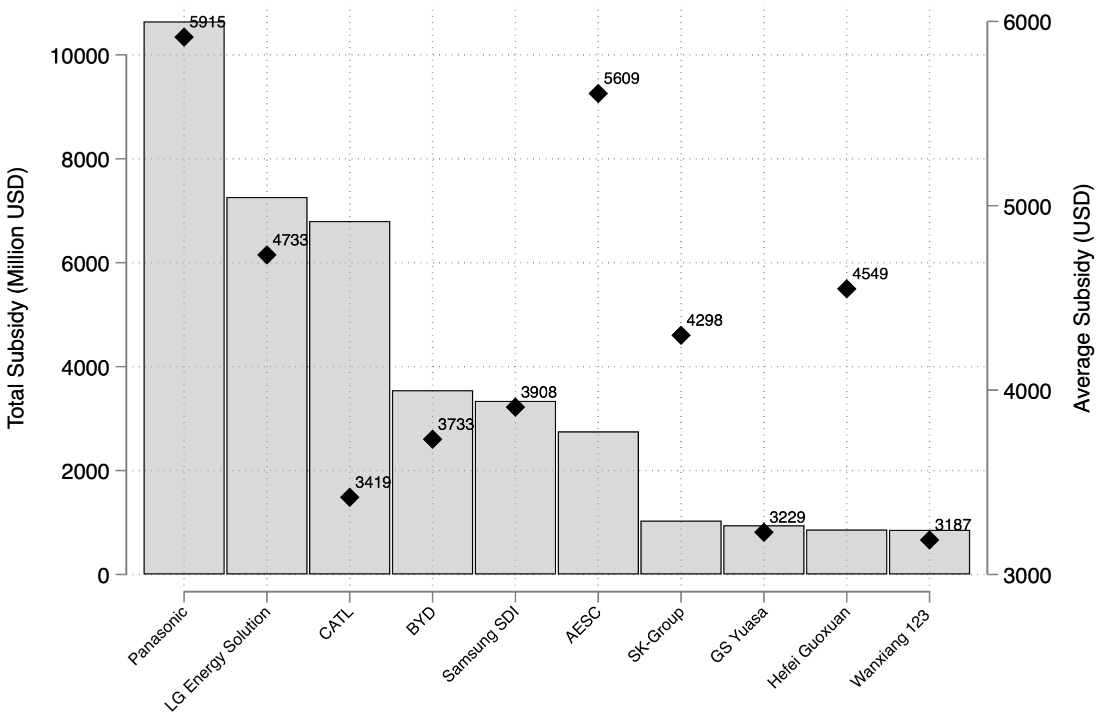
Notes: This figure presents the top 20 counties ranked by their cumulative non-industrial policies as of October 2023. We applied the trained ML model to predict the IPs from the entire GTA database. There, we classified 350,395 IP policies and 840,228 non-IP policies.

Figure A.3: Firm-Level Total Subsidy and Average Subsidy

(a) Automaker Groups

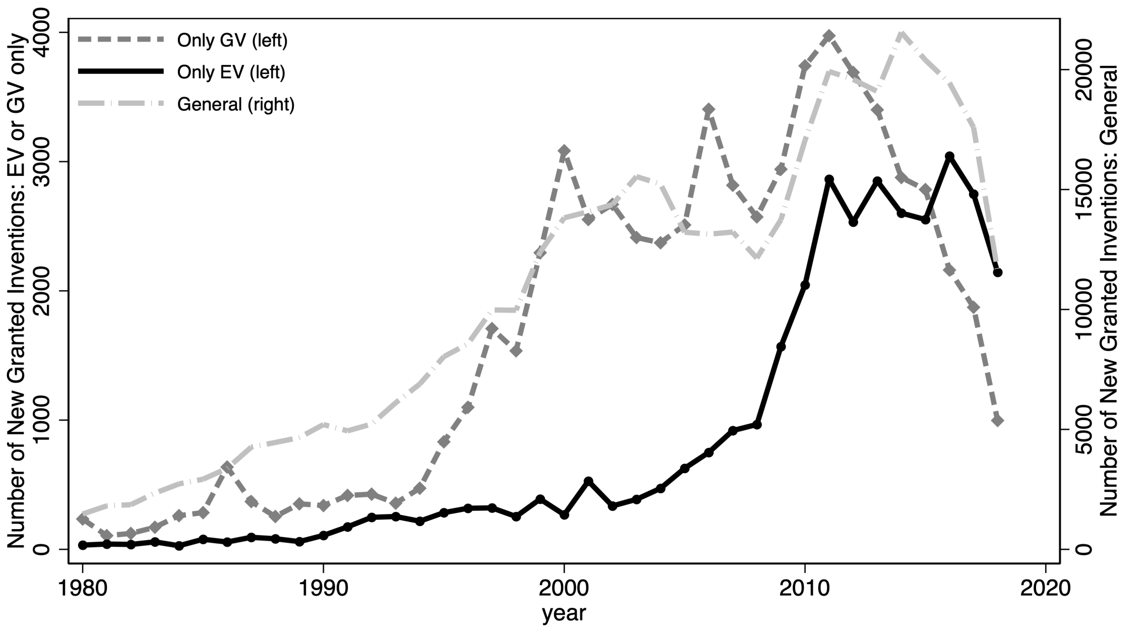


(b) Battery Suppliers



Notes: This figure shows the top 10 automakers and battery suppliers ranked by total subsidies, measured in million dollars. The grey bar refers to the total subsidy, calculated by multiplying the subsidy for each model with the sales of that model, and then aggregating across models and years. The black dots with numbers refer to the sales-weighted average subsidy by year and firm (in dollars).

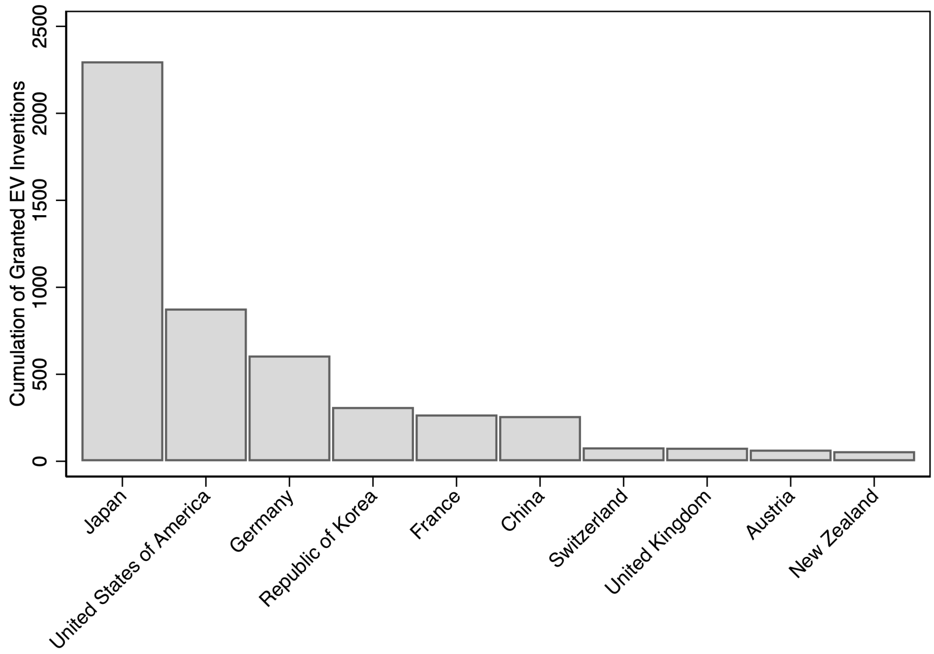
Figure A.4: Global Trend of Newly Granted Patents - Same Patent Definition as Regression



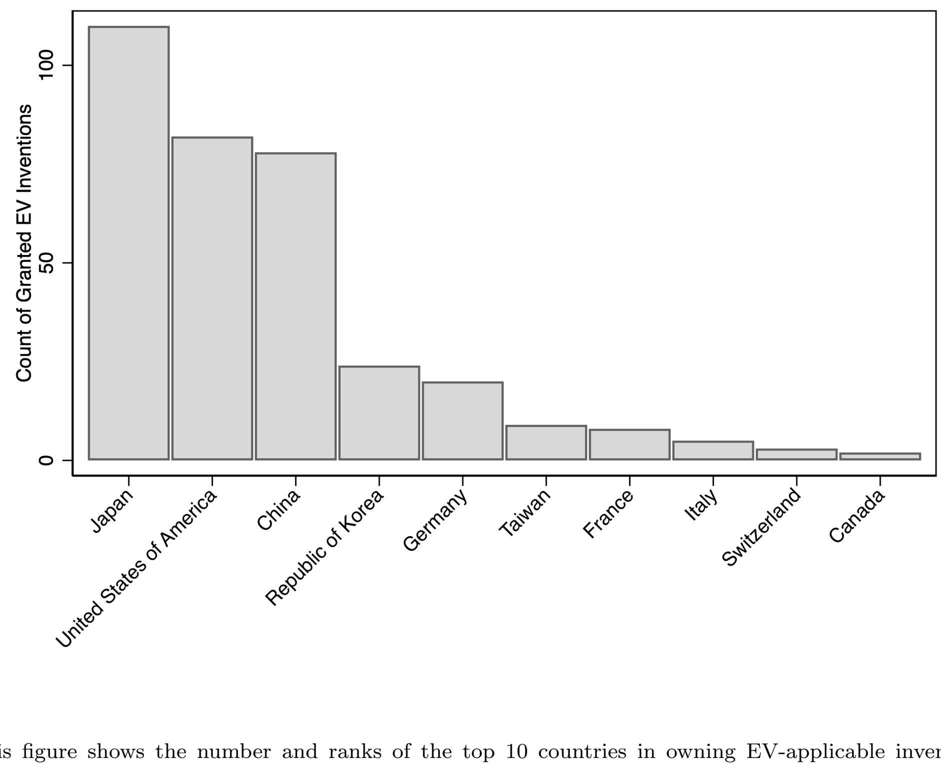
Notes: This figure shows the trend of the number of granted automobile patents over time from 1980 to 2020. Note this figure is for patents instead of inventions, as one invention can be filed multiple times as different patents. One patent is identified by a unique DocDB family ID, application office, and IPC code. This is the same as what we used in regression. For the left axis, the solid black line represents patents that can only be used for GV. The dark gray dashed line represents patents that can only be used for EVs. For the right axis, we also plot in the light gray dash-dot line the general patents that can be used for both GV and EV.

Figure A.5: Top 10 Countries in Holding Granted EV-Related Inventions

(a) Cumulative Number of Granted EV-only Inventions

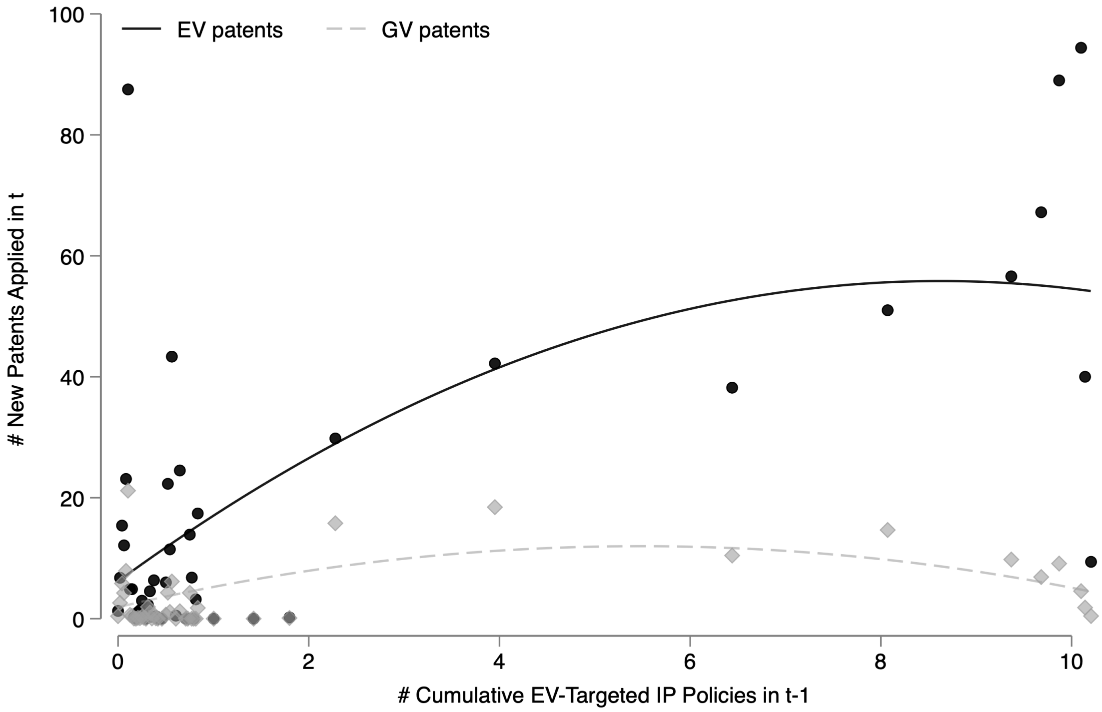


(b) Count of EV-only Inventions in 2019



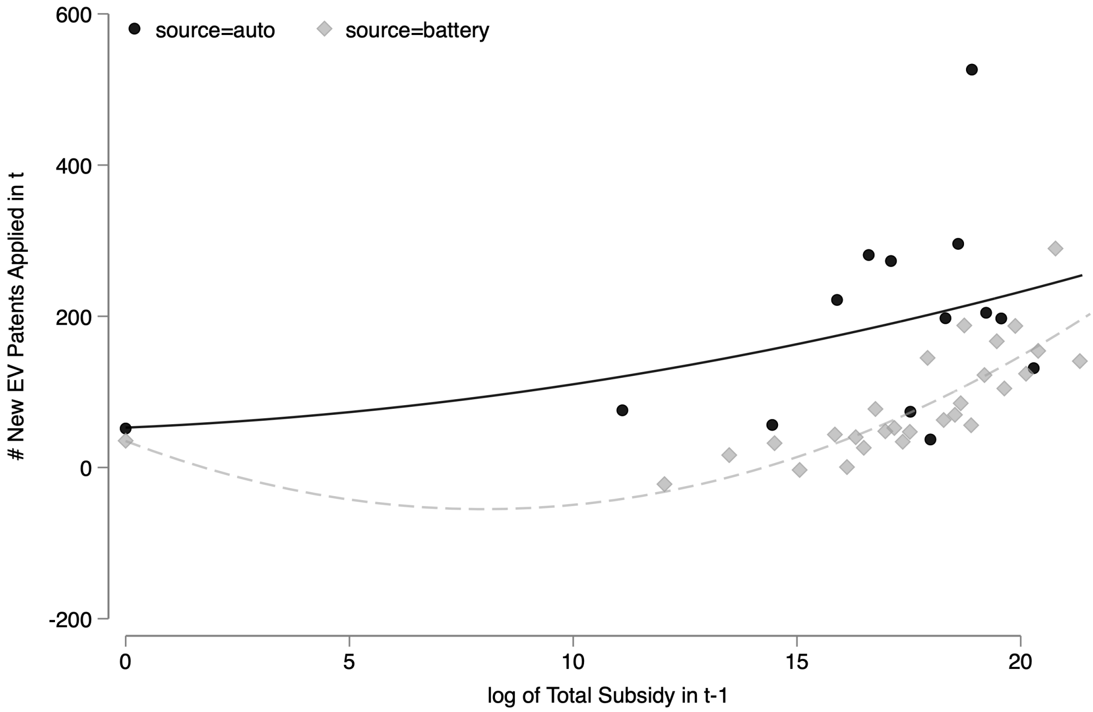
Notes: This figure shows the number and ranks of the top 10 countries in owning EV-applicable inventions. EV-applicable inventions include those inventions that can only be used for EVs and GVs, but can also be applied to EVs. Panel (a) uses the cumulative number of granted inventions until 2019, while panel (b) uses the number of newly granted inventions in the year 2019.

Figure A.6: Binned Scatter Relation Between Number of Patents Applied and Cumulative Number of EV-Related IP, No Covariate



Notes: This figure shows the graphical results of the effects of EV industrial policies on patents applied using the binned scatter plot method suggested by Cattaneo et al. (2024). The figure does not include any controls and fixed effects. The number of bins is 48, which is selected using the data-driven, optimal choice procedure. The data is country-IPC-level panel data. The black circle and solid fitted line stand for the EV patent; the diamond dots and dash fitted line stand for the GV patent.

Figure A.7: Binned Scatter Relation Between Number of EV Patents Applied and Total EV Subsidy Received, No Covariate



Notes: This figure shows the graphical results of the effects of EV subsidy incentives on EV patents applied using the binned scatter plot method suggested by Cattaneo et al. (2024). The figure does not include any controls and fixed effects. The number of bins is 22, which is selected using the data-driven, optimal choice procedure. The data is firm-level panel data. The black circle and solid fitted line stand for the automaker firm data; the diamond dots and dash fitted line stand for the batter firm data.

Table A.1: Classification of 6-Digit HS Codes into Fuel Types

Type	**6-Dight HS Code**
EV	850110, 850120, 850140, 271600, 850760, 850153, 850650, 282520, 850161, 850162, 850163, 850164, 850152, 850131, 850151, 850132, 850133, 850134, 870911
GV	840790, 840991, 850231, 850300, 870323, 271112, 271119, 271121, 870321, 870423, 850239, 850710, 870324, 870332, 870210, 870431, 870322, 870422, 870333, 870421, 851140, 870331, 870432, 271113, 851190, 851150, 851110, 851180, 271114, 271129, 830120, 840729, 840731, 840732, 840733, 840734, 840820, 840890, 840999, 841330, 842123, 842131, 850211, 850212, 850213, 850220, 851120, 851130
General	870870, 870600, 870899, 870410, 870892, 870590, 841520, 870810, 870829, 870830, 870840, 870850, 870880, 870891, 870893, 870894, 870895, 870390, 870490, 870821, 870530, 870540, 870510, 870520, 851220, 851230, 851240, 851290, 870710, 870790

Notes: IPs are categorized as EV, GV, and general based on the Harmonized System (HS) 6-digit code of its targeted products. We used multiple keywords as the main identification method, such as "electrical", "lithium," and "batteries," which are only for EVs, and "combustion engine" and "diesel," which are only for GVs. Many non-power-related mechanical products are classified into the general category, like brakes, safety airbags, and wheels. The number of HS codes for EV, GV, and general is 19, 48, and 30, respectively.

Table A.2: Examples of Industrial Policy Classes

Implementing Country	Description	HS Code	Type	Classification	Year
United States	As part of the Electric Drive Vehicle Battery and Component Manufacturing Initiative, the Department of Energy (DOE) made an award to Dow Kokam of $161 million for the production manganese oxide cathode/graphite lithium-ion batteries for hybrid and electric vehicles. The precise date for this award is not available from the data that the DOE has made public. The January 1, 2010 date shown here is an estimate. The funding for this project came from the stimulus package that Congress approved in the financial crisis...	850650	EV	Subsidy	2010
United States	The U.S. Government has provided billions of dollars in loans and other forms of support to two of the Big Three automotive producers (i.e., Chrysler and General Motors). Ford has thus far declined government aid. There is no single instrument through which this aid has been extended; see the chronology below for details on the evolving measures. The relationship between the government and General Motors (GM) has grown especially tight. The Obama administration and GM reached an arrangement on March 30, 2009 by which, in exchange for funds already committed by the U.S. Treasury and a new injection of $30.1 billion, the U.S. government will receive approximately $8.8 billion in debt and preferred stock in 'New GM' and approximately 60% of the equity. The governments of Canada and Ontario also lent $9.5 billion to GM and New GM, in exchange for which they received approximately $1.7 billion in debt and preferred stock and approximately 12% of the equity...	870324	GV	Subsidy	2009
Canada	Effective January 1, 2017, the Registrar of Imported Vehicles (RIV) vehicle import fee for registering a vehicle imported from the United States into Canada will be $295. This represents a substantial increase from the existing level of $195. On that same date, the existing fee of $60 for parts-only vehicles rises to $90. The RIV was created to establish and maintain a system of registration, inspection and certification to Canadian standards of vehicles originally manufactured for distribution in the U.S. market that are being permanently imported into Canada. The announcement of the increase gave no reason for the change in the fee structure...	870410	General	Trade	2017

Table A.3: IPC Patent Classes

IPC Codes for EV Patents	
B60K 1	Arrangement of electrical propulsion units
B60K 7	Disposition of motor in, or adjacent to, traction wheel
B60L 1	Supplying electric power to auxiliary equipment of vehicles
B60L 3	Electric devices on electric vehicles for safety purposes
B60L 5	Current collectors for power supply lines of electric vehicles
B60L 15	Methods, circuits, or devices for controlling the traction-motor speed of electricvehicles
B60L 50	Electric propulsion with power supplied within the vehicle
B60L 53	Methods of charging batteries, specially adapted for electric vehicles; Exchange of energy storage elements in electric vehicles
B60L 55	Arrangements for supplying energy stored within a vehicle to a power network
B60L 58	Methods or circuit arrangements for monitoring or controlling batteries or fuel cells, specially adapted for electric vehicles
B60M 1, 5, 7	Power supply lines and devices along rails for electric vehicles
B60W 10/08, 10/24, 10/26, 10/28	Conjoint control of vehicle sub-units such as electric populstion units, energy storage means, batteries, and fuel cells
B60W 60	Drive control systems adapted for autonomous road vehicles
H01M 8	Fuel cells
H01M 10/02, 10/04, 10/052, 10/0525	Secondary cells including lithium-ion batteries
H01M 50/00	Constructional details or processes of manufacture of the non-active parts of electrochemical cells other than fuel cells
Consolidated EV IPC codes in regression: B60K, B60L, B60M, B60W, and H01M	
IPC Codes for GV Patents	
B60K 5	Arrangement of internal-combustion or jet-propulsion units
B60K 6	Arrangement or mounting of plural diverse prime-movers for mutual or common propulsion
B60K 13	Arrangement in connection with combustion air intake or gas exhaust of propulsion units
B60K 15	Arrangement in connection with fuel supply of combustion engines; Mounting or construction of fuel tanks
B60S 5/02	Supplying fuel to vehicles
B60W 10/06	Conjoint control of combustion engines
B60W 20	Control systems specially adapted for hybrid vehicles
F02 B, D, F, M, N, P	Combustion engine technologies
Consolidated GV IPC codes in regression: B60K, B60S, B60W, F2B, F02D, F02F, F02M, F02N, and F02P	

IPC Codes for General Patents	
B60B	Vehicle wheels, castors, and axles
B60C	Vehicle types
B60D	Vehicle connections
B60G	Vehicle suspension arrangement
B60H	Arrangements of heating, cooling, ventilating, or other air-treating devices
B60J	Windows, whindscreens, non-fixed roofs, doors, or similar devices
B60K 8	Arrangement or mounting of propulsion units not provided for connection with cooling, air intake, gas exhaust, fuel supply, or power supply of propulsion units
B60K 11	Arrangement in connection with cooling of propulsion units
B60K 17-37	Arrangement or mounting of transmissions, change-speed gearing control devices, auxiliary drives, propulsion unit control devices, safety devices, speed operators, dashboards, etc
B60L 7	Electrodynamic brake systems for vehicles in general
B60N	Vehicle seats
B60Q	Signalling or lighting devices
B60R	Vehicle fittings and parts
B60S 5/02	Supplying fuel to vehicles
B60T	Vehicle brake control systems in general
B60W 10 except for 10/06, 10/08, 10/24, 10/26, 10/28	Conjoint control of vehicle sub-units of different type or different function
B60W 30	Purposes of road vehicle drive control systems
B60W 40	Estimation or calculation of driving parameters for road vehicle drive control systems
B60W 50	Details of control systems for road vehicle drive control
H01Q 1/32	Antennas for use in or on road or rail vehicles
Consolidated General IPC codes in regression: B60B, B60C, B60D, B60G, B60H, B60J, B60K, B60L, B60N, B60Q, B60R, B60S, B60T, B60W, and H01Q	

Notes: This table lists all original IPC codes in PATSTAT and classifies them into three mutually exclusive fuel type categories: EV, GV, and general. The list (in bold) at the bottom of each panel shows the list of consolidated IPC used in our regression that only considers the first three fields of IPC: section, class, and subclass. Note that we treat hybrid (non-plug-in) technologies as GV technologies.

Table A.4: The Effects of EV IPs, Country-Level Results, Alternative Specifications

	(1)	(2)	(3)	(4)	(5)
	Family ID-Application Office-IPC Aggregation				Family ID-IPC Aggregation
	Applied	Applied	Applied	Cum. Cite	Applied
Lag 5-year Cum. EV IP	0.028***	0.047***	0.036***	0.005**	0.038***
	(0.005)	(0.002)	(0.003)	(0.002)	(0.003)
Lag ln(1+Cum. granted P)		0.853***	0.259***	0.492***	0.374***
		(0.056)	(0.076)	(0.088)	(0.048)
EPS		-0.137	0.023	-0.119	-0.016
		(0.198)	(0.210)	(0.121)	(0.208)
Est. Method	PPML	PPML	PPML	PPML	PPML
Country FE	Yes	Yes	Yes	Yes	Yes
IPC FE	No	No	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Country-by-IPC FE	No	No	Yes	No	No
Pseudo R-squared	0.926	0.922	0.925	0.975	0.933
Obs	3220	2990	1833	2535	2990

Notes: This table examines the robustness of the baseline results of the effects of EV-related Industrial Policies by using alternative controls and fixed effects, outcomes, and patent data aggregation methods. The estimation method is PPML. Compared with the preferred specification, Column (1) removes lagged patent cumulation, EPS index, and IPC FEs. Column (2) adds back the lagged patent cumulation and EPS index as controls. Column (3) additionally includes country-by-IPC FEs. Column (4) uses the preferred specification but changes the outcome variable as the patent's cumulative citations by time t. The last column changes the data aggregated method. As we explained, one invention (family ID) may show as multiple entries in the raw data. Our preferred specification aggregated patent as Family ID-Application Office-IPC code. In column (5), we instead aggregated one patent as one Family ID-IPC code. We present standard errors clustered at the country level in parentheses. Significance levels are denoted by * p < 0.1, ** p < 0.05, *** p < 0.01.

Table A.5: The Effects of EV IPs, Country-Level Results, Alternative Outcomes, OLS

	(1) ln(N)	(2) ln(N + 1)	(3) IHS(N)	(4) CR
Lag 5-year Cum. EV IP	0.032***	0.042**	0.044**	0.054*
	(0.007)	(0.016)	(0.020)	(0.030)
Lag 5-year Cum. GV IP				-0.016
				(0.032)
Sample	Intensive	Full	Full	Full
Country FE	Yes	Yes	Yes	Yes
IPC FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Adjusted R-squared	0.710	0.763	0.757	0.773
Obs	738	4355	4355	3055

Notes: This table examines the robustness of the baseline results of the effects of EV-related Industrial Policies by using alternative outcome variables. The empirical specifications and controls are the same as Column (5) of Table 2, which is OLS estimation with a full sample. For dependent variables, Column (1) uses the log number of EV patents; Column (2) uses the log of 1 plus the number of EV patents; Column (3) uses the inverse hyperbolic sine of the number; Column (4) use the log terms with explicit transformation of the intensive/extensive margins as suggested in Chen and Roth (2024). "Lag 5-year Cum. EV IP" is the cumulative number of EV-related industrial policies from $t-5$ to $t-1$, while "5-year Cum. GV IP" stands for GV-related industrial policies. "Intensive" if only positive dependent variables are used. We present standard errors clustered at the country level in parentheses. Significance levels are denoted by * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A.6: The Effects of EV IPs on non-EV Patents, Country-Level Results

	(1) GV	(2) GV	(3) GV	(4) GV	(5) General	(6) General	(7) General	(8) General
Lag 5-year Cum. EV IP	-0.003	-0.006*			0.036***	0.036***		
	(0.004)	(0.003)			(0.003)	(0.003)		
Lag Cum. EV IP			-0.009	-0.004			0.074***	0.071***
			(0.009)	(0.008)			(0.009)	(0.008)
Lag ln(1+Cum. granted P)	0.296***	0.224***	0.295***	0.224***	0.621***	0.547***	0.626***	0.552***
	(0.061)	(0.065)	(0.061)	(0.065)	(0.074)	(0.089)	(0.074)	(0.089)
EPS	-0.260	-0.169	-0.256	-0.169	-0.067	0.006	-0.145	-0.072
	(0.232)	(0.195)	(0.235)	(0.198)	(0.118)	(0.102)	(0.103)	(0.090)
Sample	Full	Intensive	Full	Intensive	Full	Intensive	Full	Intensive
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
IPC FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R-squared	0.929	0.901	0.929	0.901	0.9321	0.899	0.932	0.899
Obs	4212	655	4212	655	10140	2269	10140	2269

Notes: This table presents the effects of EV-related industrial policies on non-EV innovation using country-level panel data. For Columns (1) to (4), the dependent variable is the number of GV patents applied. For Columns (5) to (8), the dependent variable is the number of general patents applied to both EVs and GVs. The empirical specifications and controls are the same as Table 2, which is PPML estimation. For the explanatory variables, "5-year Cum. EV IP" is the cumulative number of industrial policies from $t-5$ to $t-1$. "Lag Cum. IP" is the lagged total cumulative IPs. The sample used is labeled as "Intensive" if only positive dependent variables are used. We present standard errors clustered at the country level in parentheses. Significance levels are denoted by * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A.7: The Effects of EV IPs without Major Countries, Country-Level Results

	(1) No JP	(2) No CN	(3) Positive IPs	(4) Positive Patents
Lag 5-year Cum. EV IP	0.040***	0.028***	0.040***	0.045**
	(0.002)	(0.008)	(0.003)	(0.021)
Est. Method	PPML	PPML	PPML	OLS
Country FE	Yes	Yes	Yes	Yes
IPC FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Pseudo R-squared	0.935	0.825	0.932	
Adjusted R-squared				0.746
Obs	2925	2925	2080	3575

Notes: This table examines the robustness of the baseline results of the effects of EV-related Industrial Policies by removing countries from the analysis. The dependent variable is the number of EV patents applied. The empirical specifications and controls are the same as Column (1) of Table 2, which is PPML estimation. Columns (1) and (2) remove Japan and China samples, respectively. Column (3) keeps countries that have used EV-related industrial policy at least once. Column (4) keeps countries that have at least one patent. We are using OLS in this column because the PPML drops the all-zero patent countries naturally. We present standard errors clustered at the country level in parentheses. Significance levels are denoted by * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A.8: The Effects of EV Subsidy: Firm-level Analysis, Alternative Outcomes, OLS

	(1) IHS	(2) ln(1+N)	(3) CR	(4) ln(N)
Lag ln(1+Total Subsidies)	0.039**	0.037**	0.039**	0.040***
	(0.017)	(0.015)	(0.018)	(0.012)
Lag Knowledge stock, EV	0.180***	0.153***	0.192***	0.216***
	(0.040)	(0.035)	(0.042)	(0.074)
Lag Knowledge stock, GV	-0.024	-0.024	-0.022	-0.065
	(0.042)	(0.036)	(0.044)	(0.086)
Mean of Dep	2	1.7	1.2	3.4
Sample	Full	Full	Full	Intensive
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Adjusted R-squared	0.117	0.113	0.119	0.137
Obs	838	838	838	469

Notes: This table examines the robustness of the baseline results of the effects of EV-related subsidies by using alternative outcome variables. The empirical specifications and controls are the same as Column (3) of Table 4, which is OLS estimation with a full sample. For depend variables, Column (1) uses the inverse hyperbolic sine of the number; Column (2) uses the log of 1 plus the number of EV patents; Column (3) uses the log terms with explicit transformation of the intensive/extensive margins as suggested in Chen and Roth (2024); Column (4) uses the log number of EV patents. "Intensive" if only positive dependent variables are used. We present standard errors clustered at the firm level in parentheses. Significance levels are denoted by * p < 0.1, ** p < 0.05, *** p < 0.01.

Table A.9: The Effects of EV Subsidy on EV Patents: Firm-level Analysis, Only Triadic Patents

	(1) EV	(2) EV	(3) EV	(4) EV
Lag ln(1+Total Subsidies)	0.019**	0.026**	0.048***	0.049***
	(0.009)	(0.011)	(0.013)	(0.012)
Lag Knowledge stock, EV	0.109***	0.105**	0.651***	0.661***
	(0.041)	(0.041)	(0.072)	(0.102)
Lag Knowledge stock, GV	-0.080**	-0.077**	-0.411***	-0.420***
	(0.036)	(0.036)	(0.109)	(0.118)
Sample	Full	Full	Full	Full
Est. Method	OLS	2SLS	PPML	PPML, CF
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Pseudo R-squared			0.89	0.89
Adjusted R-squared	0.846	0.020		
Obs	838	838	315	315

Notes: This table presents the effects of EV subsidies on EV patents. Different from the baseline results, we only use the "Triadic" patent, which refers to patents filed at all three major patent offices in the world: USPTO, EPO, and JPO. Column (1) uses the PPML approach; Column (2) uses the IV PPML with control function approach; Column (3) uses OLS estimation; and Column (4) uses 2SLS estimation. standard errors clustered at the firm level in parentheses. Significance levels are calculated using standard errors in parentheses and are denoted by * p < 0.1, ** p < 0.05, *** p < 0.01.

Table A.10: The Effects of Subsidy on Innovation: Firm-level Analysis, More Robustness Results

	(1)	(2)	(3)
Lag ln(1+Total Subsidies)	0.031***	0.032***	0.037***
	(0.008)	(0.011)	(0.008)
Lag Knowledge stock, EV		0.542***	0.515***
		(0.102)	(0.092)
Lag Knowledge stock, GV		-0.258**	-0.307***
		(0.103)	(0.085)
EV spillover	0.404***		
	(0.093)		
GV spillover	-0.243***		
	(0.087)		
Own EV stock	0.191**		
	(0.080)		
Own GV stock	-0.067		
	(0.119)		
Sample	Full	No big Auto firms	No big Battery firms
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Pseudo R-squared	0.95	0.905	0.954
Obs	616	595	595

Notes: This table presents additional robustness check results of the effect of EV incentives on innovation using the PPML IV strategy. The dependent variables are new EV patents applied for all columns. The empirical specifications are the same as Column (1) of Table 5, which is PPML IV with a control function approach. Columns (1) separate the knowledge stock measurement by own known stock and spillover from other firms' knowledge in the same country. Columns (2) drop Toyota, Honda, and Renault-Nissan Alliance; Columns (3) drop Samsung SDI, LG Energy Solution, and CATL. Columns (4) and (5) use total incentives received from home and foreign markets, respectively. standard errors clustered at the firm level in parentheses. Significance levels are calculated using standard errors in parentheses and are denoted by * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

B Details in Processing the Global Trade Analysis (GTA) Database

This section describes how we process the GTA data. Three key steps involved are Refinement, Classification, and Aggregation. The structure of the GTA database is shown in Figure 1. A unique policy is identified by Intervention & State Act ID, and for each Policy, the database records multiple affected countries and affected products. Therefore, each row in the raw GTA database is a unique combination of Intervention & State Act, Affected country, and Affected product. The first step of our work is to identify the set of policies that satisfy the criteria of "Industrial Policy". Then, the second step classified and labeled the type of IP based on the fuel types of vehicles that were affected by it. Finally, the third step aggregated the data to calculate the number of IPs of each type.

B.1 Identify Industrial Policy

Following Juhász et al. (2022), we define Industrial Policies as those with specific or implicit goals aimed at shaping the composition of economic activities. These policies typically focus on targeted activities such as exporting or research and development (R&D), or aim to alter the long-term composition of economic activities. Specifically, a policy must meet two criteria to be classified as an Industrial Policy:

- Stated goal - Industrial policy is goal-oriented state action. The purpose is to shape the composition of economic activity. Specifically, industrial policy seeks to change the relative prices across sectors or direct resources towards certain selectively targeted activities (e.g., exporting, R&D), with (ii) the purpose of shifting the long-run composition of economic activity.
- National state implementation - Industrial policy is aimed at the stated goals at the level of the national economy. Specifically: industrial policy action is taken by a national, or extranational, state. These actions are sanctioned and financed by national governments, supranational bodies, or amalgamations of these units.

B.1.1 Methodology

In our study, we use Machine Learning, specifically Natural Language Processing (NLP), to classify industrial policies within the GTA database. Each policy in the GTA database is accompanied by a concise English description, with an average length of 82 words and the first and third quartiles being 30 and 99 words, respectively. We employ these descriptions to conduct supervised learning, aiming to train a model that can accurately predict classifications across the entire dataset. Our methodology involves several steps:

Data Selection and Labeling: Initially, we randomly selected 1,023 policies, representing 1.6% of the total policies in the GTA database, to form our training and test sets. For supervised learning, this subset is manually labeled according to our predefined criteria for industrial policies. Each policy is independently annotated by three individuals, categorizing the policies as 0 (Non-Industrial Policy), 1 (Industrial Policy), or 2 (Insufficient Information). Majority voting determines the final label in cases of inconsistency among 3 annotators. Of the 1,023 policies, 384 (37.5%) are labeled as Industrial Policies, 447 (43.7%) as Non-Industrial Policies, with the remainder classified as Insufficient Information. Conservatively, we treat all policies labeled as '2' as '0' (Non-Industrial Policy).

Data Preprocessing and Vectorization: The textual data is first tokenized and converted to lowercase. Subsequently, all stop words, punctuations, and numerical values are removed. Rows containing only null values, typically arising from descriptions with only stop words like "The," are excluded, reducing our training set to 1,000 policies. We then employ n-gram and TF-IDF (Term Frequency-Inverse Document Frequency) methods for text vectorization. The n-gram approach, using combinations of 1-gram and 2-gram, is found to be most effective for our dataset. Although we experimented with the Word2Vec model, TF-IDF provided superior performance, reflecting the unique characteristics of policy texts. Each description is ultimately transformed into a numerical vector of 35,077 dimensions. The dataset is split into a training set (80%, 800 policies) and a testing set (20%, 200 policies).

Addressing Data Imbalance: We apply data oversampling techniques to mitigate the imbalance caused by the low proportion of Industrial Policies in the training set. Two methods are tested: simple redrawing of data points labeled as '1' to equalize the number of Industrial and Non-Industrial Policies and the Synthetic Minority Oversampling Technique (SMOTE), which generates new instances through interpolation in feature space. The simple redrawing approach yielded better results in our dataset.

Model Testing and Evaluation: Various models are employed and assessed by using K-fold cross-validation. These include the Logistic Regression model with L2 regularization, Random Forest, XGBoost, Recurrent Neural Network (RNN), and a pre-trained Large Language Model (BERT). To better capture the optimal hyperparameters of different models, we use the Grid Search method, which iterates different sets of hyperparameters into the model and preserves the parameters that have the best performance.

B.1.2 Example of Labeling and Explanation

Below, we provide several examples commonly found in our dataset to illustrate this concept.

Firm Specific Policies: In manual labeling, the most frequent scenario involves policies pertaining to a specific firm, like subsidies or regulatory support. In these cases, we classify the policy as Industrial Policy if it explicitly mentions a specific policy objective; otherwise, it is categorized as Non-Industrial Policy or marked as having insufficient information. For example, policies that explicitly support firm activities, such as R&D or export activities, are identified as Industrial Policies. Furthermore, support or funding for firms often originates from programs designed with specific objectives in mind, such as enhancing a particular activity or industry. These programs, identifiable by their names that suggest a targeted aim, are also classified under Industrial Policies.

- *(No.21) On May 10, 2013, the Department of Agriculture approved funding to support an export operation conducted by Cfsit, Inc. The total grant amounted to USD 18 million, with the operation located in the United States of America. This support was provided through the Export Guarantee Program.*

We classify this as an Industrial Policy for two main reasons. First, the objective is clearly to support the export operations of this firm. Second, the funding support is provided by the Export Guarantee Program, which is highly likely designed to stimulate export activities across the country.

- *(No.992) On 30 July 2019, the Department of Agriculture approved a loan guarantee worth USD 25 million to Westport, L.l.c. The support was granted through the Business and Industry Loans program.*

In this case, although the company has received a loan guarantee, the objective of this loan has not been specified. In other words, the policy does not articulate the activities targeted by this specific loan. Additionally, the program, known as Business and Industry Loans, does not differentiate among industries and sectors or specify particular activities. Therefore, we classify this as *Non-Industrial Policy*.

Tariffs: Traditionally, policies related to tariffs are often considered Industrial Policies. However, Juhász et al. (2022) argue that not all tariff-related policies should be classified as Industrial Policies because "they may be implemented to raise government revenue or for other objectives, such as influencing terms of trade." In practice, applying these criteria is challenging, as most tariff-related policies do not specify their purpose; instead, they typically list the specific goods for which tariffs are increased or decreased. Our approach is to assess these policies on a case-by-case basis. If we can deduce that the purpose of the tariffs is to protect nascent industries, we label them as *Industrial Policies*. Otherwise, we categorize them as *Non-Industrial Policies*. However, we acknowledge that this process might be difficult for a machine learning algorithm to replicate due to the nuanced and inferential nature of determining policy objectives.

- *(No.118) On 18 December 2017, the Trade Commission of MERCOSUR adopted Directive 77/17, revoking Directive 63/17 and allowing Argentina to increase the tariff rate quota set on certain artificial and prepared waxes. The new legislation affects products classified under tariffs subheading NCM 3404.90.19. Directive 77/17 allows Argentina to increase from 600 tonnes to 1,200 tonnes the quota of artificial and prepared waxes that can be imported with a 2% import duty. According to the WTO tariff download facility, the applicable import tariff outside the quota is 10.6%. In addition, the application of the decision has been extended from 6 to 12 months. The new legislation only affects countries outside the MERCOSUR. MERCOSUR's Directives Since 2014, all Directives adopted by the MERCOSUR concerning import tariff quotas adopted under the policy framework established by Resolution GMC 08/08 are adopted by a simplified procedure not requiring its publication on the Official Gazette.*

- *(No.16) On July 31, 2017, the Argentine Government adopted Decree 1207/2016, modifying the list of products affected by the export. This change led to increasing the applicable export rebates on certain products enclosed in 9 eight-digit tariff lines. The new export rebate levels have increased between 0.5% and 4.5%, depending on the product. In two particular cases (NCM 0207.13.00 and 0207.14.00), the increase in the export rebate has a temporary character, valid for twelve months. After this period, rebates go back to their previous value.*

The examples provided are typical of the tariff-related policies found in the dataset. In both cases, despite detailing the specific goods affected by tariff adjustments, there is a lack of explicit objectives in these policies. Consequently, we label both of these policies as having 'not enough information' due to the absence of clearly stated goals. This classification stems from the inability to discern the underlying intent or purpose of the tariff adjustments from the information provided.

- *(No.65) On 18 November 2013, the Russian Government (according to Decree Nr. 1029) eliminated export tariffs (previously at 5%) on liquefied natural gas (code 2709 00 100 1 0) and gas condensate (code 2711 11 000 0 0), extracted on the territory of the Yamal peninsula. Previously, these products could only be exported without tariffs within the customs territory of Russia, Belarus and Kazakhstan. This policy forms part of the previously approved state policy (Decree Nr. 1713/11.10.2010) to stimulate the production of liquefied natural gas in Russia.*

In the given example, where the specific goal of eliminating export tariffs is to stimulate the production of liquefied natural gas in Russia, the intent is clearly stated. Therefore, in cases like this, we label the policy as an Industrial Policy. This classification is based on the direct and explicit link between the policy action (eliminating export tariffs) and its industrial objective (stimulating production in a specific sector, in this case, liquefied natural gas in Russia).

Antidumping and Investigation: In the GTA database, a significant portion of the policies relate to anti-dumping measures. Some are solely anti-dumping investigations, while others result in the increase or decrease of taxes on certain products. We classify all these actions as Non-Industrial Policies.

- *(No. 38) On 21 April 2016, the Eurasian Economic Commission initiated an anti-circumvention investigation on imports of cold-worked seamless pipes and tubes of stainless steel from Malaysia. This investigation follows suspicion that the definitive antidumping duty imposed on imports of the same products from China might be circumvented. The products subject to investigation are classified under the following HS code subheading: 7304.41. On 15 December 2017, the Eurasian Economic Commission issued Decision No. 169 extending the definitive duty imposed on imports of the subject good from*

China to imports of the same good from Malaysia following the conclusion of the above anti-circumvention investigation. The rate of duty is 19.4%. The duty enters into force on 14 January 2018. On 19 January 2018, the Eurasian Economic Commission initiated a sunset review of the antidumping duty imposed on cold-worked seamless pipes and tubes of stainless steel from China, see related intervention. This follows the request lodged by OOO TMK-INOX, PJSC (Chelyabinsk Tube Rolling Plant), and PJSC (Pervouralsky Novotrubny Plant). Since the anti-dumping duty imposed on imports of the subject good from China was extended to imports of the same good from Malaysia following an anti-circumvention investigation, the sunset review and its conclusion will hold for this country as well...

In this example, the policy not only states the initiation of an anti-dumping investigation but also implements related actions, such as the extension of anti-dumping duties. We label it as *Non-Industrial Policy*.

B.1.3 Model Performance

We use several criteria to evaluate the performances of different models. This includes the accuracy of the testing set, the precision, recall, and F1-score. Table B.1 shows how the different machine learning models perform on each of these metrics.

The precision metric indicates the accuracy of the positive predictions. In other words, it shows what proportion of predicted positives are actually positive. Mathematically, it can be expressed as $\frac{TruePositive}{TruePositive+FalsePositive}$. For the Logistic Model Non-Industrial Policy category, the precision is 95%, meaning that when the model predicts an instance as Non-industrial policies, it is correct 95% of the time. For those classified as industrial policies, 84% of them are true industrial policies.

The recall percentage measures the ability of the classifier to find all the positive instances. Mathematically, the recall score can be calculated by using $\frac{TruePositive}{TruePositive+FalseNegative}$. For class Non-Industrial Policies, the recall is 89%, indicating that the model correctly identifies 89% actual Non-Industrial Policies instances. For class Industrial Policies, the recall is 92%, meaning it identifies 92% of all actual class Industrial Policies instances, while a small proportion of the policies are identified as Non-Industrial Policies even though they are actually Industrial policies.

The F1-Score is the harmonic mean of precision and recall and is a single metric that combines both precision and recall. It is particularly useful when the class distribution is imbalanced. The F1-score for class Non-Industrial Policies is 92% (and for industrial policies is 88%), suggesting a good balance between precision and recall.

The support shows the actual number of occurrences of each class in the testing dataset. The accuracy shows how many samples are accurately predicted in the testing set.

Table B.1: Classification Report for Different Machine Learning Models

Model	**Non Industrial Policies**				**Industrial Policies**				
	Precision	**Recall**	**F1-Score**	**Support**	**Precision**	**Recall**	**F1-Score**	**Support**	**Accuracy**
Logistic Regression	95%	89%	92%	123	84%	92%	88%	77	90%
XGBoost	94%	87%	90%	123	81%	91%	86%	77	89%
Random Forest	92%	89%	91%	123	84%	87%	85%	77	89%
RNN	88%	93%	90%	123	87%	81%	84%	77	88%

In this classification task, our goal is to identify Industrial Policies with the highest possible accuracy. While Logistic Regression does not yield the highest precision for Industrial Policies, it is chosen as our baseline model due to its superior F1-Score in the Industrial Policies category. This indicates a better balance between accurately identifying Industrial Policies and maximizing the identification of relevant instances. Furthermore, the model's highest accuracy rate, which stands at 90%, further demonstrates its superior performance in this classification task. However, given the similar performances across various models, the overall statistical outcomes are expected to be comparable post-classification, regardless of the method employed.

B.2 Classification and Aggregation

We applied the trained ML model to predict the IPs from the entire GTA database. There, we classified 20,495 IP policies and 42,228 non-IP policies. Among these, we identified 3,385 unique IPs related to the automobile market in this analysis. We describe this process further below.

To identify the IPs related to electric vehicles (EVs) and gasoline vehicles (GVs), we classify the relevant IPs using the 6-digit HS product code.[31] Specifically, each IP has one or more affected products that are indexed by their corresponding HS code. We first manually selected the products that could potentially be used in EVs, GVs, or both. For example, products such as lithium oxide and hydroxide (282520), and cells and batteries: primary, lithium (850650) are classified under the EV category. Similarly, products such as internal combustion engines (840731) and petroleum gases and other gaseous hydrocarbons (271112) are categorized as relevant to GVs. There are also products, such as steering wheels (870894) and brakes (870830), that can be used in both EVs and GVs. In total, we have 19 products categorized as EV-related products; 53 are GV-related, and 34 are general.

Once the product categorization was complete, we examined the affected products of each policy. If a policy's affected product list included one or more products classified under EVs, we labeled the policy as EV-related. Similarly, if a policy included products classified as GV-related, we labeled it as GV-related. If a policy included products that could be used in both sectors, we labeled it as a policy relevant to both EVs and GVs. Once the product categorization was complete, we examined the affected products of each policy. If a policy's affected product list included one or more products classified under EVs, we labeled the policy as EV-related. Similarly, if a policy included products classified as GV-related, we labeled it as GV-related. If a policy included products that could be used in both sectors, we labeled it as a policy relevant to both EVs and GVs.

If one unique IP can affect products of multiple fuel types, we count them multiple times. But for multiple affected HS codes for the same fuel type and same IP, it is counted only as one. Using this approach, the original 3,385 unique IPs become 5,090 IP-fuel type combinations. Among all IP-fuel type combos, we have 2,580 IPs classified as EV-related IPs, 1,548 are GV IPs, and 962 are general IPs (applicable to both EVs and GVs).

Additionally, we define a direction variable to indicate whether the corresponding IP has a positive or negative impact on the affected countries. Specifically, we manually labeled all IPs related to EVs, GVs, and general sectors. For instance, certain policies are anti-dumping measures, which typically impose tariffs or restrictions on imported goods to protect local industries. These types of policies can lead to reduced access to foreign markets or increased costs for the affected countries, which we define as a negative impact, and thus assign a value of 0. On the other hand, policies such as subsidies or government procurement of certain locally manufactured products tend to provide competitive advantages or incentives for production and market access. These are considered to have a positive impact on the affected countries and are assigned a value of 1. In our dataset, most of the IPs can be labeled by their policy type, such as subsidies and anti-dumping. We manually labeled the rest of them.

[31] For example, products such as lithium oxide and hydroxide (282520), and cells and batteries: primary, lithium (850650) are classified under the EV category.

C Details in Processing the PATSTAT Global Database

This section describes how we process the PATSTAT Global data. We accessed the PATSTAT Global database on Oct. 2023. The database is maintained by the European Patent Office (EPO). Our analysis covers patent applications filed up to 2023, focusing on electric vehicle (EV) and gasoline vehicle (GV) technologies across various industries. The raw data encompasses over 3.9 million unique patent applications, under approximately 2.5 million unique patent families.

Key data fields used in our analysis include:

- Application data (TLS201): *applna_id*, *appln_auth*, *appln_kind*, *appln_filing_date*, *docdb_family_id*
- IPC code data (TLS209): *appln_id*, *ipc_class_symbol*
- Person data (TLS206, TLS207, TLS226): *person_id*, *person_name*, *person_ctry_code*, *psn_sector*

Figure 2 shows an example of the structure of the raw PATSTAT database. Each row in the raw PATSTAT database is a unique combination of DOCDB families, application authorities, IPC codes, and applicants. The first step of our data processing is to classify and label the type of Patent based on the fuel types of products that were affected by it. Then, the next step aggregates the data to calculate the count of Patent number of each type. We also generate several patent quality indicators: (1) number of IPC codes per application and family, (2) Forward citations (directly from *nb_citing_docdb_fam*), and (3) Family size (directly from *docdb_family_size*).

We classify patents as EV, GV, or general at the IPC-code level using the *ipc_class_symbol* variable from the TLS209 table. The classification is based on a predefined list of IPC codes associated with EV and GV technologies. The basis of this list comes from Aghion et al. (2016). We have significantly enriched it to incorporate technologies developed in the past years, especially in the battery sector. The classification process involves: a) Extracting the *ipc_class_symbol* for each patent application; b) Comparing the extracted IPC codes against the predefined EV/GV classification list; c) Assigning the appropriate category (EV, GV, General) based on the match.

When constructing country-level data, we reclassified and refined the IPC code by collapsing the original PATSTAT IPC section (e.g., B), IPC class (e.g., 60), IPC subclass (e.g., L), and fuel type (EV, GV, and General). We did this to reduce the number of observations with zero value when estimating.

D Details in Processing Other Data

D.1 Matching Firm-Level Patent Data

The firms considered in our analysis include 92 major automobile groups and 45 battery suppliers worldwide. The lists are selected based on several factors, such as annual sales, reputation, regional distribution, and data accessibility. The list of automobile firms includes the major EV automakers, which contains 57 Chinese groups, 16 European groups, 8 US groups, and 8 Japanese groups. Among these firms, 25 were founded in the last decade. 72 firms have manufacturing lines of both EV and GV. It should be noted that there may be multiple brands within one group, such as Lexus in the Toyota Group and Volvo in the Geely Group. The list of battery suppliers contains 34 Chinese firms, 4 Japanese firms, 3 Korean firms, and 1 US firm. 16 firms were founded in the last decade. Among all firm applicants (in contrast to individual applicants), our list accounts for 38% of unique auto groups and 67% of unique battery suppliers.

We combine fuzzy matching with a manual matching approach to link patent applicant information to each auto and battery firm. We download all unique firms in the quadratic (patents filed in US/EU/JP/CN) EV patents dataset cleaned from PATSTAT Global and use keywords to match the firm names. The fuzzy matching procedure is as follows. We first calculate the distance between firm names using three methods: Levenshtein distance, cosine distance and Euclidean distance. Then we generate a score based on the average distance from the three methods: the higher the score, the closer the distance is between the the firm name in PATSTAT and our list. We keep and label as "matched" those pairs whose score is above 80 (with the full score equals 100).

Generative AI assists us with the first step as a rough match. For example, we use "Nissan" and "Renault" to search automakers under "Nissan-Renault Alliance", and use "BYD" and "FinDreams" to search battery suppliers under "BYD".[32] We then manually filter the data by dropping inventors that contain similar keywords, such as "Stanford" for "Ford", "Lockheed Martin" for "Aston Martin" and all individual inventors. In total, we have retrieved 945 observations for auto groups and 360 for battery suppliers. Around 92% of firms in the lists are matched with at least one inventor in the patent dataset. Given that patent application and attribution are different among brands, there could be multiple inventors associated with each automaker and battery supplier, especially for transnational groups. For example, "LG Chem" and "LG Chemical LTD." refer to the same firm, but are classified as separate inventors in the patent dataset; we treat patents from both these entities as patents from the parent battery supplier company "LG Energy Solution".

The matched data is then combined with subsidy and sales data at the model-country-year sales (where each firm may sell multiple models). According to current data, 22 auto groups and 17 battery suppliers received subsidy yet applied for 0 EV-related patents, and 41 auto groups and 22 battery suppliers received no subsidy yet applied for at least 1 EV patent. The calculation of the average and total subsidy are elaborated in the next section.

D.2 Constructing Country-Model-Specific EV Subsidy

We compiled subsidy data on financial incentives at the country, year, and model levels from various reputable sources, including the European Automobile Manufacturers' Association (ACEA) tax guides, the International Energy Agency (IEA) policies, and official government websites.[33] These sources provided comprehensive information on the types and amounts of financial incentives available in each country.

For consistency, we focus solely on central or federal policies (with the exception of a couple of countries where policies are largely regional, as we describe below). The forms of financial incentives considered included direct consumer subsidies, acquisition tax credits, and ownership tax credits. These financial incentives vary not just by country and year but also by specific EV model attributes such as driving range, battery capacity, curb weight, and CO_2 emissions. After collecting these incentive policies of 13 countries, we combine them with vehicle characteristics data to calculate the total amount of each type of financial incentives (in dollars) assigned to each model at each year in each country. Then we summed up all financial incentives for each

[32] FinDreams is the battery supply division of BYD.

[33] Sources to major references: EU commission ,ACEA 2013 report, ACEA 2014 report, ACEA 2015 report, ACEA 2016 report, ACEA 2017 report, ACEA 2018 report, ACEA 2019 report, ACEA 2020 report , IEA, OECD report, Norwegian Electirc Car Association, IMF, Netherlands Enterprise Agency, Energieschweiz,UK government ,Sweden, Tesla .

model at each year in each country and refer to that as the "subsidy" for that model (i.e., the total dollar amount of the financial incentive that the consumer is eligible for if they purchase that EV). In our empirical analysis, we then aggregate the subsidy at the model-country-year to a measure of subsidy exposure at the firm-year level.

Since data structures and policy characteristics vary across countries, there are some adjustments that we make when dealing with data from different countries.

European countries' financial incentives were primarily derived from the ACEA's annual tax guides on purchase and tax incentives for electric vehicles. These reports provide a thorough view of European countries' financial incentive policies including tax acquisitions and ownership and some subsidies. We refer to the ACEA tax guide to calculate the vehicle taxes and deductions for each country in each year. We also check some other official websites, such as the Norwegian Electric Car Association and the Netherlands Enterprise Agency. It is worth noting that, to the best of our knowledge, Switzerland has no central subsidies, so we used a population-weighted average of metropolitan area tax credits offered by cities like Zurich, Lausanne, Basel, Bern, and Geneva. Each canton had its own tax credit system determined by factors such as cylinder capacity or vehicle weight, which we incorporated to reflect the subsidy accurately.

We deal with the lack of central/federal policies in Canada in a similar manner. In the absence of a central subsidy, we estimate national-level incentives by calculating the population-weighted average of provincial direct subsidies provided by British Columbia, Quebec, and Ontario. This approach reflects regional differences in domestic financial incentives in Canada.

Japan and the United States both provide direct financial incentives at the central level. The government of Japan provided direct consumer subsidies at the model-year level, which were incorporated into our dataset to reflect the incentives available for each specific model and year. Consumers in the United States received federal income tax credits calculated based on the battery capacity of each EV model. This provided a direct financial incentive tied to the technological attributes of the vehicle.

China's EV subsidies are primarily attribute-based (Barwick et al., 2024a). Therefore, following Table 2 of Li et al. (2021), we apply the range-based calculation method to calculate the incentives for buying EVs in China. The range-based subsidy is year-specific from 2013 to 2018. In 2019, the government began offering a central subsidy that depends on both driving range and battery capacity. In 2020, the government stopped offering this central subsidy for models with prices above 300,000 RMB.