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DRIVING INNOVATION:
THE POLICY TOOLS POWERING ELECTRIC VEHICLE TECHNOLOGICAL INVENTIONS

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ABSTRACT

Electric vehicles (EVs) are crucial for cutting transportation emissions, yet the policy drivers of EV innovation remain underexplored. This study analyzes firm-level panel data on EV and battery patents, covering more than 4,000 firms across 19 countries from 2010 to 2021, to assess how these policy tools and their interactions in different time horizons influence innovative activity. We test the effects of individual policy instruments that either raise demand for EVs or support the development of EV technologies. Stringent fuel-economy standards, financial incentives, adoption targets, and public R&D investments each significantly increase patenting in EV and battery technologies. Moreover, long-term EV targets amplify the innovative impact of public R&D and standards while diminishing the marginal effect of short-term price signals. The results suggest that governments can accelerate clean automotive innovation by combining long-term adoption commitments with sustained R&D investment or strong performance standards, and by managing these instruments as a coordinated policy portfolio rather than as separate tools. The study contributes cross-country, firm-level evidence that links policy design to the direction of clean technology innovation.

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1. Introduction

The global effort to decarbonize transportation has positioned electric vehicles (EVs) as a central focus of climate policy. Public policy remains critical for accelerating innovation in EV technologies. A growing body of evidence shows that environmental regulations and targeted incentives can redirect inventive activity toward cleaner technologies, with particularly strong effects observed in the conventional automotive sector (Popp, 2019; Aghion et al., 2016). Governments now employ a mix of instruments to accelerate vehicle electrification. This mix includes both demand-pull policies designed to increase consumer demand for EVs, such as performance standards, EV sales targets, consumer purchase incentives, fuel and carbon taxes, as well as technology-push policies that promote innovation through public investments in research and development (R&D). These tools aim to address two persistent market failures: unpriced environmental externalities that depress demand for low-carbon innovations, and knowledge spillovers that weaken private R&D incentives (Aldieri et al., 2019; Bushnell et al., 2022). If they wish to tackle both market failures, policymakers need to coordinate both types of policies rather than rely on any single instrument (Jaffe et al., 2005; Popp, 2019).

EVs now sit at the intersection of several policy and technology domains. They depend on advances in batteries, power electronics, vehicle platforms, and charging networks, and they respond to policies that target both energy use and industrial development. Policymakers in many countries have built increasingly elaborate portfolios that combine both demand-pull and technology-push types. Yet the effectiveness of policy still rests on a patchwork of evidence. Much of what we know about induced innovation comes from stationary renewables or efficiency improvements in internal combustion engine (ICE) vehicles. These early studies show that higher fuel prices increased patenting in fuel-efficient and hybrid powertrains, suggesting that both price signals (Aghion et al., 2016; Crabb and Johnson, 2010) and fuel-economy standards vehicles (Knittel, 2011; Klier and Linn, 2016) can shift R&D toward lower-emission technologies in traditional Internal-Combustion-Engine (ICE) vehicles. More recently, Rozendaal and Vollebergh (2025) find that more stringent emission standards and regulatory mandates strongly induce innovation in zero-emission and fuel-efficient technologies, whereas increases in fuel taxes exert a comparatively modest effect. Luetkehaus (2025) shows that the quality of policies included in demand-pull policy mixes matters but does not test the effect of any specific policy.

Despite this recent work, the unique characteristics of the electric vehicle industry leave several questions unexplored. First, many governments combine short-term policy instruments such as subsidies or standards with long-term policy goals. For example, in 2017, Norway set a target for 100 percent of new vehicle sales to be zero-emission by 2025. These long-term goals may provide firms with predictability and certainty about future EV markets. Our paper contributes to the literature by showing how long-term EV adoption commitments change the way firms react to short term instruments and how policymakers can use the combination of short-term and long-term policies when designing portfolios that support large scale electrification.

Second, we provide EV specific evidence on how policies affect firm level innovation for both electric vehicles themselves and battery/charging technologies. This enables us to see how policy affects innovation across the EV supply chain. It also enables us to include many new entrants into the EV innovation space, unlike existing work focusing on legacy automotive manufacturers (e.g., Rozendaal and Vollebergh, 2025; Luetkehaus, 2025). Third, the paper links policy effects to firm capabilities and knowledge bases. By tracking internal knowledge stocks and external knowledge spillovers in EV, battery, and broader adjacent technologies, we identify which types of knowledge are beneficial and where path dependence in conventional technologies may slow the redirection of inventive effort. Together, these contributions inform the design of coherent EV policy packages that accelerate low carbon innovation while recognizing differences across firms and countries.

2. Background

EVs sit at the intersection of a fast-improving battery industry and a mature, globally integrated car industry. From a small base in the early 2010s, sales grew quickly. In 2021, EV sales worldwide reached 6.6 million, equal to nine percent of new-car sales, and the on-road stock reached about 16.5 million (IEA, 2022). Patent data show that EV-related inventions make up a growing share of low-carbon end-use technologies, and automakers and battery suppliers lead these filings (EPO-IEA, 2021). EVs differ from modular energy-supply technologies such as solar photovoltaics (PV) and wind. PV and wind concentrate learning in manufacturing lines and standardized components. EV progress relies on co-development across the vehicle, the battery, and the charging system. Engineers integrate batteries, power electronics, software, thermal management, and safety systems into a single product and connect it to charging networks and the grid (National Academies of Sciences, 2021). Global firms coordinate EV production through platforms and supplier networks. They design vehicle architectures, battery packs, and software stacks for multiple regions, then localize to meet each market's rules. Rules in one large market can redirect product plans worldwide because firms share platforms and plan for compliance across regions (Sturgeon and Van Biesebroeck, 2011; Dechezleprêtre et al., 2015).

While EV innovation couples fast learning from real-world use with long product cycles, governments need a policy mix that combines near-term policies with a clear long-term direction. In the near term, governments can shift buyers' preferences towards EVs and accelerate production. Many examples illustrate how these short-term policies play a role in stimulating EV adoption[3]. Norway exempted EVs from value-added and registration taxes and added toll relief and other benefits, which lifted early adoption of EVs. France implemented a

[3] These examples are in IEA's Global EV Outlook 2021.

bonus-malus system that rewards low-emission cars and penalizes high-emission models. The United States offered a federal income tax credit of up to $7,500, and several states adopted zero-emission vehicle (ZEV) mandates that created a more predictable market for manufacturers. China combined national purchase subsidies with license-plate access in large cities and then established a New Energy Vehicle credit scheme that ties compliance to EV and plug-in hybrid sales. The Netherlands and Sweden linked registration and company-car taxes to vehicle CO_2 ratings, which stimulated fleet uptake. Public procurement and fleet targets in the United Kingdom and Germany, along with programs in Japan and South Korea, seeded early volumes and built a pipeline of used EVs (IEA, 2021). Fuel-economy and CO_2 standards push firms to improve powertrains and shift portfolios toward electric options, and higher fuel prices raise the private value of efficiency and support demand for cleaner vehicles (Aghion et al., 2016; Johnstone et al., 2010; Sierzchula et al., 2014).

For durable EV development, governments also need to set clear multi-year goals that reduce uncertainty and guide capital planning. In 2017, Norway set a target for 100 percent of new vehicle sales to be zero-emission by 2025. In 2019, Canada set targets for zero-emission light-duty vehicle sales: 10 percent by 2025, 30 percent by 2030, and 100 percent by 2040. China's New Energy Automobile Industry Plan calls for 20 percent ZEV sales by 2025, and the China Society of Automotive Engineers points to more than 50 percent by 2035. Across Europe, binding CO_2 performance standards for cars and vans in 2025 and 2030, combined with national phase-out dates in countries such as Denmark and the Netherlands, give firms a clear trajectory. Near-term instruments generate demand and incremental cost declines. Long-term commitments set desired future direction and coordinate investment across automakers, suppliers, utilities, and charging providers. Together, they align firm strategy with societal goals and convert early incentives into durable market transformation.

3. Literature Review

Research on climate and energy innovation highlights two broad levers that shape inventive effort. Governments pull demand with pricing, regulation, and deployment programs that enlarge markets for clean solutions, and they push technology with public R&D and demonstration that reduce risk and expand the search frontier (Jaffe et al., 2005; Popp, 2019). Knowledge spillovers connect these levers because ideas flow across firms, regions, and technologies, raising social returns above private returns (Popp, 2016; Myers and Lanahan, 2022). Demand signals such as standards, carbon and fuel prices, and targeted deployment support redirecting invention toward cleaner trajectories and influence entry and diffusion (Mowery and Rosenberg, 1979; Nemet, 2009; Johnstone et al., 2010; Aghion et al., 2016). Public R&D, subsidies, and mission-oriented programs build capabilities and generate sizable spillovers that sustain innovation beyond the initial interventions (Veugelers, 2012; Czarnitzki and Lopes-Bento, 2013; Gross and Sampat, 2023; Myers and Lanahan, 2022). A coherent policy mix that balances these instruments and sets credible long-term targets produces the most durable responses at home and through international knowledge diffusion (Rogge and Reichardt, 2016; Schmidt and Sewerin, 2019; Dechezleprêtre and Glachant, 2014; Gugler et al., 2024).

3.1. Demand-pull policies

Demand-pull policies increase the expected market size for clean technologies (Mowery and Rosenberg, 1979; Nemet, 2009). When governments create credible demand through targets and instruments, inventive activity shifts toward cleaner energy options (Nemet, 2009; Johnstone et al., 2010). Past studies show that policy design matters for technological innovation in renewable energy. In solar photovoltaics, feed-in tariffs and renewable certificate schemes raise patenting (Johnstone et al., 2010; Palage et al., 2019). In wind, quantity obligations and tradable green certificates increase innovation (Dechezleprêtre and Glachant, 2014). As these show that demand-pull policies spur innovation in stationary renewables, our study tests whether analogous signals in the transportation sector similarly shift inventive effort toward electrification.

For automobiles, regulatory instruments such as fuel-economy and tailpipe-CO_2 standards set binding performance thresholds and compel firms to either adopt fuel-saving technologies or change vehicle attributes. In the ICE car market, tighter standards increased the rate of adopting efficiency technologies and shifted choices along the performance frontier as producers seek for more efficient solutions in horsepower, torque, and size (Knittel, 2011; Klier and Linn, 2016). Recent evidence also shows that standards can redirect inventive effort from traditional ICE vehicles toward zero-emission platforms (Rozendaal and Vollebergh, 2025). Existing studies reveal how standards shift inventive effort from ICE components to zero-emission parts but seldom analyze EV innovation as an integrated system. Therefore, we focus on EV innovation and show how regulatory demand shapes invention across the EV supply chain, including drivetrains, battery packs and battery-management systems, and charging technologies.

Prices and financial incentives change what buyers value and expect to use, and firms redirect inventive effort toward technologies that match those preferences. In the auto sector, higher expected oil and gasoline prices raise the share of energy-efficient automotive patents (Crabb and Johnson, 2010). In addition, tax-inclusive fuel prices even shift innovation toward cleaner auto technologies, such as electric and hybrid drivetrains, from traditional auto technologies (Aghion et al., 2016). Existing studies provide little insight into the link between fuel prices and pure EV innovation. Fuel prices hold a direct connection to ICE vehicle design choices but have a weaker conceptual tie to the technological processes that guide EV and battery innovation. Beyond fuel prices, many countries deploy purchase-side incentives that expand the near-term market for EVs, including tax credits, rebates, and preferential financing. The energy-innovation literature classifies these tools as demand-pull instruments that raise consumers' willingness to adopt targeted technologies (Popp, 2019). Drawing on prior research, our study examines the EV-specific demand channel by testing whether higher fuel prices and stronger consumer purchase incentives redirect market demand toward EVs and consequently steer firms' inventive efforts toward EV technologies.

3.2. Technology-push policies

Technology-push policies fund upstream research, development, and demonstration to overcome knowledge-market failures that depress private R&D below the social optimum. Two market failures matter most: unpriced environmental damages and the public-good nature of knowledge that creates spillovers and underinvestment in discovery (Jaffe et al., 2005). Public R&D is fundamental in early, uncertain technological stages and when entrenched installed bases tilt incentives toward incumbent technologies. Clean-energy study exemplifies these conditions, which makes early stage support a central lever for redirecting inventive effort (Veugelers, 2012). In the EV domain, these frictions show up across the whole supply chain, such as battery chemistry and manufacturing, power electronics, electric drive systems, and charging infrastructure.

Large public R&D programs and grants both show that technology-push policy can change the level, direction, and geography of innovation (Gross and Sampat, 2023; Myers and Lanahan, 2022). At the firm level, R&D subsidies increase inventive activity and R&D employment without full crowd-out, generating sizable effects across recipient firms (Czarnitzki and Lopes-Bento, 2013). These results support the core premise of technology-push policy, showing that well-designed public R&D can seed discovery, amplify knowledge spillovers, and strengthen private innovation capacity. Most empirical work documenting the power of technology push focuses on broad clean-energy domains or specific renewables, such as wind and solar, rather than on EV technologies as a coherent innovation system. Therefore, we include public R&D in transport energy efficiency as a technology-push policy variable to capture its influence on EV innovation.

3.3. Policy horizons

Most governments use a broad portfolio of policy instruments to promote electric vehicles. In addition to using both demand-pull or technology-push instruments, policies also differ on the time horizons specified. Governments combine policy tools designed to immediately increase EV sales with long-term policy goals to improve predictability and credibility (Rogge and Reichardt, 2016). Long-term, quantified adoption targets shape firms' expectations about the future market for new technologies. For EVs, these targets typically specify either the share of new-vehicle sales or the size of the on-road stock to be reached by a given year. Within EV research, Luetkehaus (2025) includes long-term deployment targets as part of an index to capture the quality of demand-pull policies in a country. However, no prior work separately tests the effectiveness of both long-term and short-term EV policies, either separately or in combination. In this paper, we construct EV adoption targets using announced sales, realized deployment, and the remaining time to the target year. Treating targets as a distinct policy variable, rather than embedding them in a single demand index, allows us to show both how long-run commitments influence on EV and battery patenting across a broad set of firms and to test whether long term commitments also improve the effectiveness of short-term demand-push and technology-pull policies.

3.4. Knowledge spillovers

In addition to policy, the innovation eco-system in which a firm operates influences innovation. Spillovers across different actors along the production chain raise the social return to clean inventions as ideas travel across firms, technologies, and borders. EV innovation draws on multiple fields including battery materials, cells, power electronics, and software to downstream vehicle integration and charging networks. These links shape both the direction and intensity of invention at each stage, so tracking knowledge spillovers along the value chain helps explain who innovates, and what knowledge influences innovation. In the traditional auto industry, firm-level evidence shows that exposure to nearby clean knowledge and a firm's own clean innovation experience both increase clean patenting, while exposure to dirty knowledge reduces it. These trends suggest path dependency shaped by external and internal spillovers affects the direction of research (Aghion et al., 2016). For the EV industry, battery innovation grows outside the auto sector but flows into carmakers through new supplier relationships. For example, Dugoua and Dumas (2024) find that BEV invention accelerated when electronics-based battery firms joined automakers' networks. As such, in this paper we distinguish between potential spillovers from multiple types of knowledge potentially relevant to EV innovation, including technologies related to vehicles, batteries, and charging systems.

4. Hypotheses

4.1. The effects of the policy horizons

H1. Demand-pull policy interactions and EV-domain innovation. Evidence shows that near-term instruments steer automotive invention: higher fuel prices raise clean-tech patenting (Crabb and Johnson, 2010; Aghion et al., 2016), tighter fuel-economy and CO_2 standards increase adoption and shift choices toward efficiency (Klier and Linn, 2016), binding standards redirect effort toward zero-emission platforms (Rozendaal and Vollebergh, 2025), and many jurisdictions use purchase incentives that expand EV demand (Luetkehaus, 2025). This leaves two gaps we address for EVs specifically: most prior work centers on the broader auto sector or efficiency within ICEs, and EV adoption targets often appear inside composite indices based on registrations rather than as numeric policy variables, so we ask whether fuel prices, performance standards, financial incentives, and explicit sales or stock targets direct EV patenting.

H1a. Higher fuel prices, tighter performance standards, more generous financial incentives, and more stringent EV adoption targets increase firm-level patenting in EV relevant technologies.

In addition, EV and battery R&D involve long development cycles and sunk costs, so firms react most when they believe that current signals will persist. Numeric EV adoption targets reduce policy uncertainty and commit governments to future market creation, which changes the expected payoff from investing in EV-oriented innovation in response to fuel prices, standards, and purchase incentives. Therefore, we further test whether long-run targets amplify or substitute for short-run instruments like standards and fuel prices.

H1b. Long-run EV adoption targets act as complementarity for near-term signals. The marginal effect of tighter standards on EV and battery patenting rises where targets are more stringent, and the marginal effect of higher fuel prices also falls where targets are more stringent.

<u>H2. Technology-push policy interactions and EV-domain innovation.</u> Public R&D addresses environmental and knowledge-market failures and lowers the cost and risk of discovery (Jaffe et al., 2005). Cross-country evidence links R&D support to higher patenting, and work in renewables shows that R&D often interacts with deployment support, with stronger innovation effects when feed-in tariffs operate than under certificate schemes (Costantini et al., 2017; Palage et al., 2019). EV-specific research has not established whether EV-focused public R&D changes firms' near-term responses to prices, standards, and purchase incentives, which motivates the interaction tests below.

H2a. Greater public R&D in energy and transport increases patenting in EV-relevant battery technologies.

H2b. Long-run EV adoption targets strengthen the impact of public R&D. The marginal effect of EV-relevant public R&D on EV and battery patenting increases when long-term targets are more stringent.

4.2. The role of knowledge spillovers

We distinguish between internal knowledge stocks and external knowledge spillovers. Internal stocks reflect a firm's accumulated inventive experience, which shapes path dependence and the cost of redirecting search. External spillovers arise when firms draw on knowledge that originates in other firms, sectors, or countries through markets, supply chains, and imitation. Prior work shows that deeper internal clean capabilities and closer technological proximity to clean fields correlate with more green patenting at the firm and country level, and that domestic demand conditions influence invention more strongly than foreign demand, even though foreign demand still shapes innovation through diffusion across borders (Aghion et al., 2016; Verdolini and Galeotti, 2011; Dechezleprêtre and Glachant, 2014).

For EVs, general battery knowledge plays a central enabling role. Firms that master battery chemistry, cell design, and power electronics can integrate packs more effectively into vehicles, manage performance, and improve efficiency. They also benefit when suppliers or foreign innovators expand external stocks of battery knowledge, since these advances enter vehicles through components and collaboration. At the same time, strong experience in traditional automotive engineering or in general electricity technologies may lock firms into incumbent design trajectories and pull effort away from EV-specific search. Existing research links knowledge accumulation and spillovers to green invention but rarely maps EV-specific channels, so this paper investigates the following hypothesis:

H3. Larger internal stocks of EV and battery knowledge increase firm-level EV patenting, because they provide complementary capabilities for EV design and integration, whereas larger internal stocks in adjacent fields such as traditional automobiles and general electricity decrease EV patenting, as they reinforce path dependence on incumbent technologies.

H4. Larger external knowledge flows from traditional automotive or general electricity sectors decrease firm-level EV patenting, because these types of knowledge reinforce firms' focus on incumbent design trajectories and divert effort away from EV-specific innovation.

5. Data and Methods

5.1. Patents

This study uses firm-level patent counts as the measure of inventive output. Patent counts are a well-established proxy for innovation activity, capturing tangible outputs of R&D and reflecting both the pace and direction of technological change (Popp, 2002; Aghion et al., 2016; Noailly and Smeets, 2015; Rozendaal and Vollebergh, 2025; Dugoua and Gerarden, 2025). The study relies on the European Patent Office's PATSTAT database (Spring 2024 edition). Because firms must file separate applications in each country where they seek intellectual protection, a single invention can generate multiple filings. To avoid counting the same invention more than once, this study groups all applications that trace back to a shared first-filed priority application into a single patent family. To ensure patents represent innovations above a minimum quality threshold, we restrict the sample to patent families that contain at least one granted patent. This procedure preserves the uniqueness of each innovation at the firm level and enables accurate construction of country-and-year weights.

Patent families are assigned to six EV-related technology categories using the Cooperative Patent Classification (CPC) system (detailed definitions and CPC code mappings are provided in Appendix A). This classification helps identify specific technological areas and enables precise patent searches. We divide relevant patents into two categories: vehicle technologies and battery technologies. Vehicle technologies include inventions for pure battery EVs, hybrid vehicles that combine ICE with electric traction, and general alternative fuel vehicles that use hydrogen or biofuels. Battery technologies include EV batteries, innovations in battery manufacturing processes, battery management systems, ancillary components, and charging infrastructure such as connectors and charging stations. A patent may fall into both categories when its CPC code covers both vehicle and battery technologies.

5.2. Policies

This study examines policy instruments across a sample of nineteen advanced economies over the period 2009-2021. The selected countries are Austria, Australia, Belgium, Canada, Switzerland, China, Denmark, Finland, France, Germany, Japan, South Korea, the Netherlands, Norway, Poland, Spain, Sweden, the United Kingdom, and the United States. These 19 countries represent major auto-producing and innovating economies with significant EV policy activity, providing substantial innovation output and diverse policy environments. Focusing on advanced economies with reliable data ensures comparability and captures the policy variation needed to identify effects.

The paper uses national-level policy metrics and firm-year patent outcomes. It constructs firm-specific policy exposure indices to translate country-level policy signals into each firm's innovative environment. Firms in the EV sector operate globally and decide where to invest and protect inventions based on market potential and regulatory conditions, not solely on domestic policies. Firm-specific exposure thus provides a more realistic measure of the policy environment faced by globally active firms. It reduces measurement error compared with assigning all firms the same national policy index. Following Aghion et al. (2016), Grégoire-Zawilski and Popp (2024), and Rozendaal and Vollebergh (2025), the weight assigned to firm i's patent activity in country c is defined as:

$$w_{ci} = \frac{w_{ci}^{P} GDP_{c}^{0.35}}{\sum_{c'} w_{c'i}^{P} GDP_{c'}^{0.35}}$$

where w_{ci}^{P} is the in-sample patent share of firm i in country c; GDP_c denotes the real gross domestic product of country c in 2020 USD to reflect market size. w_{ci} is the resulting policy-exposure weight, capturing firm i's patent applications filed in country c, raised to the power of 0.35. $GDP^{0.35}$ reflects that policy salience scales less than linearly with market size. This follows recent clean-innovation studies that combine firm patent shares with concave market-size weights and specifically use an exponent near one-third[4], consistent with the empirical elasticity of patenting with respect to market size (Dechezleprêtre et al., 2021; Grégoire-Zawilski and Popp, 2024; Rozendaal and Vollebergh, 2025). We apply these weights to each policy series and then sum across countries to obtain the firm-level exposure in year t:

[4] The results stay similar when we do robustness checks using an exponent of 1, in Appendix 9.6 and 9.7.

$$Policy\ Exposure_{it}^{policy} = \sum_{c} w_{ci}\ Policy_{ct}$$

We adopt the in-sample weighting scheme because it captures the most complete and contemporaneous information on where firms actively innovate during the study period. While many previous studies use pre-sample weights that rely solely on historical patenting before study period, in-sample weights reflect each firm's current patenting distribution across countries, aligning policy exposure with the markets where firms actually seek protection and commercialization opportunities. Noailly and Smeets (2015) use in-sample weights, weighting country prices and market sizes by each firm's observed patent-designation shares for renewable energy technologies. This improves the accuracy of measured policy exposure for firms that expand into new policy environments or shift their innovation portfolios during the 2010-2021 period. The tradeoff is that using in-sample data may introduce potential endogeneity if firms choose their patenting locations in response to policy changes. However, the gain in completeness outweighs this concern, since in-sample weights capture dynamic patterns of international patenting that pre-sample schemes cannot observe. This approach allows the model to reflect evolving firm strategies, new entrants, and changing market engagement, providing a more realistic mapping between policy conditions and innovation behavior. Of particular importance for this study is the emergence of new EV firms in China whose first patents appear during our sample period. Robustness checks using alternative pre-sample weighting schemes confirm that the main results are not sensitive to this choice, suggesting that potential endogeneity is limited.

We measure end-use gasoline prices with the International Energy Agency (IEA) End-Use Prices Database. For each country and year, we use the annual average retail price of motor gasoline, tax inclusive, expressed in US dollars per liter and converted to 2020 dollars for comparability.

We compile fuel-economy and greenhouse-gas standards by country and year. For China, Japan, South Korea, the United States, and all European Union member states, we use TransportPolicy.net and the International Council on Clean Transportation (ICCT) database. We use the Canada Motor Vehicle Fuel Consumption Standards Regulations from the Justice Laws website for Canada. Jurisdictions report standards in different units, so we convert every limit to grams of CO_2 per kilometer using the ICCT conversion tool. Lower values represent tighter standards. For country c and year t:

$$Standard\ Stringency_{ct} = \max_{c \epsilon C, t \epsilon T}(Standard) - Standard_{ct}$$

where max ($Standard$) is the least stringent standard (e.g. most emissions allowed) across all countries (C) and years (T). This construction benchmarks the scale to the least stringent global standard and assigns higher values to countries with stricter limits. The transformation provides a more intuitive interpretation of standards: while raw standards fall as policies tighten,

$Standard\ Stringency_{ct}$ rises, so a positive coefficient on stringency reads as greater innovation under stricter standards.

We collect financial incentive information from governmental sources (details in Appendix B). We record purchase incentives that reduce the up-front cost of an EV, such as value-added tax exemptions and direct purchase rebates, and convert their face value to 2020 US dollars. In addition, use-phase benefits capture financial relief during ownership and operation. For each country-year, we compute an index as the sum of four binary indicators: lower emissions or circulation taxes for EVs, lower annual road taxes, toll exemptions or discounts, and reduced registration fees. Set each indicator to 0.25 when the benefit applies at the national level in that year and to 0 otherwise. Together, these measures capture both one-time and recurring financial support for EV adoption.

The above policies provide immediate incentives to increase EV demand. To capture long-term policy goals, we create a measure of long-term EV target stringency using official EV adoption targets and actual EV sales data (more information in Appendix C). Unlike fuel economy standards, which target efficiency improvement and CO_2 emission in general and do not require usage of EVs to be met, this target variable specially focuses on EVs. Given different policy paces and EV market demands in each country, we construct a target stringency index that combines each country's stated cumulative EV target and actual cumulative EV sales. For country c in year t, let $Goal_{ct}$ denote the announced target for a future year T, let $Sales_{ct}$ denote cumulative EV sales through year t, and let $Years\ Left_{ct} = T - t$. Using IEA sales data, compute:

$$Target\ Stringency_{ct} = \frac{Goal_{ct} - Sales_{ct}}{Years\ Left_{ct}}$$

The index expresses the annual increases in EV sales needed to meet the target given the remaining years available to meet the target. Larger values indicate more demanding commitments either because the gap is large or because the time to the target year is short. Values decline as countries accumulate EV sales.

Two coding choices keep the measure comparable across countries and over time. First, in years with no national target, we set $Target\ Stringency_{ct} = 0$ to reflect the absence of commitment. Second, when governments revise targets, we update $Goal_{ct}$ and T in the year of the new announcement so the index demonstrates the policy in force at each date.

We apply firm-specific weights to gasoline prices, standard stringency, the financial-incentive measures, and target stringency to obtain firm-level policy exposures. We then relate these exposures to firm-year patenting outcomes in EV technologies.

5.3. Knowledge stocks

We measure each firm's internal and external knowledge stocks in four mutually exclusive technology fields: EV/Hybrid, Batteries and Charging, General Automobile, and General Electricity. We use granted-patent family data from 1995 to 2021 and assign patent families to fields with a concordance of CPC classes described in Appendix D. Following prior work on dynamic knowledge accumulation (Aghion et al., 2016; Grégoire-Zawilski and Popp, 2024; Rozendaal and Vollebergh, 2025), we construct two stocks.

For firm i, technology field j, and year t, let P_{ijt} be the number of granted patent families that firm i filed in field j during year t. We set the annual depreciation rate to δ = 0.15 (15 percent per year). The internal stock accumulates new patents:

$$K_{ijt}^{int} = (1-\delta)K_{ijt-1}^{int} + P_{ijt}$$

External knowledge captures ideas created by others that remain relevant to field j. For each country c, define P_{cjt} as the total number of granted patent families in field j in country c during year t for all assignees, and define P_{icjt} as the number granted to firm i in that country, field, and year. We subtract P_{icjt} to avoid counting the firm's own patents as an outside source. The country-level external stock for firm i as:

$$K_{icjt}^{ext} = (1-\delta)K_{ijt-1}^{int} + P_{cjt} - P_{icjt}$$

Firms operate and learn across several national markets, so we aggregate country-level external stocks with a time-invariant inventor share w_{ic}^{K}. We compute w_{ic}^{K} from the distribution of firm i's inventors across all countries over 1995 to 2021. These shares can include countries outside the 19 economies used in the policy analysis because inventor teams may work and learn there. This weight represents where each firm's inventors do their work. For example, a weight of 0.5 for the U.S signals that half of a firm's inventors have US addresses. The firm-level external stock equals:

$$K_{ijt}^{ext} = \sum w_{ic}^{K} K_{icjt}^{ext}$$

The knowledge weights trace where the firm does research and absorbs ideas. These weights differ from the time-varying policy weights w_{ci} used to form the policy exposure indices, which reflect where the firm seeks patent protection and intends to market their products.

We measure public R&D inputs with national spending on energy efficiency in the transportation sector. EV-specific R&D figures do not exist in a consistent cross-country panel, so the transportation energy-efficiency line in the IEA Technology RD&D Budgets Database provides the best available proxy. Because the IEA database does not report China, we add the transportation R&D budget from China's National Bureau of Statistics. To map R&D to firms, we use the knowledge weights w_{ic}^{K} rather than policy weights w_{ci}, since inventors typically must reside in the country where R&D support is provided.

Table 1 shows descriptive statistics for policy variables, knowledge stocks, and the main outcome, patents. Policy variables and GDP are at the country level, and patents, internal, and external knowledge stocks are at the firm level.

Table 1

Summary statistics.

	Observations	Mean	Std. Dev.	Min	Max
End-Use Gasoline Price	228	1.74	0.48	0.68	2.89
Standard Stringency	228	90.18	25.12	0	118.90
Transport Energy-Efficiency R&D	228	229.96	582.82	0	3,680.24
Financial Incentives	228	22,446.07	81881.52	0	485,426
Use Benefit	228	0.63	0.24	0.25	1
Target Stringency	228	122,125.10	249607.70	0	1,955,000
GDP	228	3,041.21	4721.59	252.49	2,1826.23
Patent	26,361	4.60	28.38	0	1,057
Int. knowledge stocks - EVs	26,361	22.31	178.08	0	6,334.26
Int. knowledge stocks - batteries	26,361	13.41	91.45	0	3,875.07
Int. knowledge stocks - general auto	26,361	27.27	191.38	0	5,463.52
Int. knowledge stocks - general electricity	26,361	11.47	69.07	0	2,519.87
Ext. knowledge stocks - EVs	26,361	10,592.60	8,923.45	0.025	38,815.47
Ext. knowledge stocks - batteries	26,361	8,469.57	8,323.11	0	33,615.63
Ext. knowledge stocks - general auto	26,361	11,822.04	6,254.00	0	22,781.96
Ext. knowledge stocks - general electricity	26,361	9,040.89	7,268.79	0	29,783.45

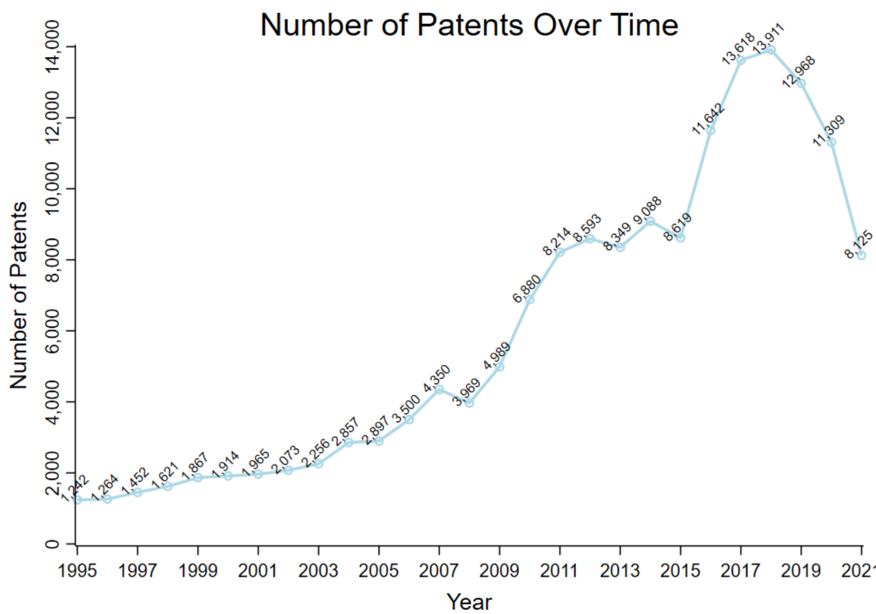
As shown in Figure 1, the volume of EV-related patents rose gradually until about 2009 and then accelerated sharply in the following decade. Inventive output reached a peak of roughly 9,000 patents in 2013, followed by a second peak of around 14,000 patents in 2018. This pattern reflects an incubation phase in the early 2000s, followed by rapid growth coinciding with the introduction of more stringent policies and market incentives supporting EVs. The sample period begins in 2010 to coincide with the onset of rapid acceleration in EV patenting, allowing the analysis to capture the most salient phase of this emerging technology's rise. Toward the end of the sample period, the number of patents appears to drop off, potentially for two reasons. First, there may be truncation bias since patent applications take time to be examined and granted; many late-period filings remain under review and thus are not yet counted in the data. Second, the global COVID-19 pandemic likely dampened inventive activity temporarily, contributing to the recent dip in patent counts. Appendix F provides additional details on patents by technology and lists the top 20 patenting firms.

Figure 2 shows steady tightening of standards across major markets from 2009 to 2020, with clear differences in timing and levels. The EU and Japan start the period with the highest stringency and remain at the front through most years. China raises stringency in a step around the mid-2010s and reaches near-front-runner levels by 2020. The United States and Canada climb gradually from a low base and approach the 90-100 range by the end of the period. South Korea holds flat for much of the decade and then increases late. The pattern points to convergence toward stricter targets, but it also shows that jurisdictions tighten in bursts rather than through smooth annual increments.

Figure 3 highlights two broad messages regarding gasoline prices. First, prices move together across countries over time, with a clear peak around 2012-2013, a sharp drop in 2015, a partial recovery through 2018, and another softening by 2020. Second, large and persistent cross-country gaps remain. High-tax European markets such as Norway, the Netherlands, the United Kingdom, and Germany stay at the top of the price distribution, while the United States sits at the bottom throughout, and China remains relatively low. These patterns suggest that global oil dynamics drive common swings, while national tax and policy regimes create differences in prices that persist over the decade.

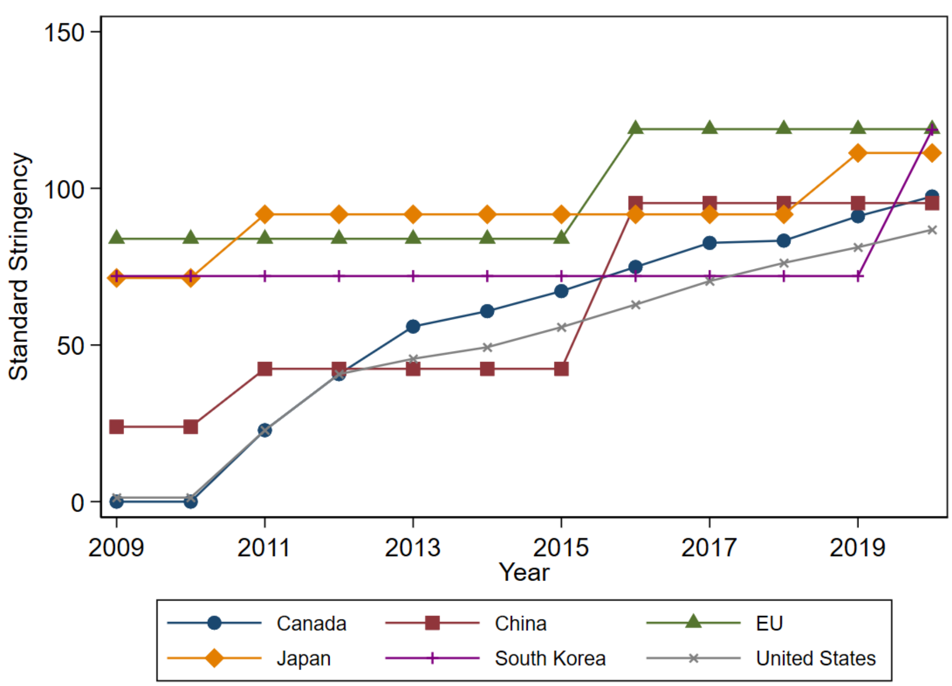
Figure 4 shows target stringency rising slowly through the early 2010s and then jumping towards the end of the sample period. France stands out with the largest surge, peaking around 2019 before a small pullback. Germany and China also post sharp late-period increases. The United States and Canada climb at a steadier pace, while Japan, Norway, the Netherlands, and South Korea change little until a modest uptick near the end. Overall, countries tighten in waves rather than through smooth annual steps. This figure excludes other countries where their target stringency stayed broadly stable over this period.

Fig. 1. Number of EV patents over time.



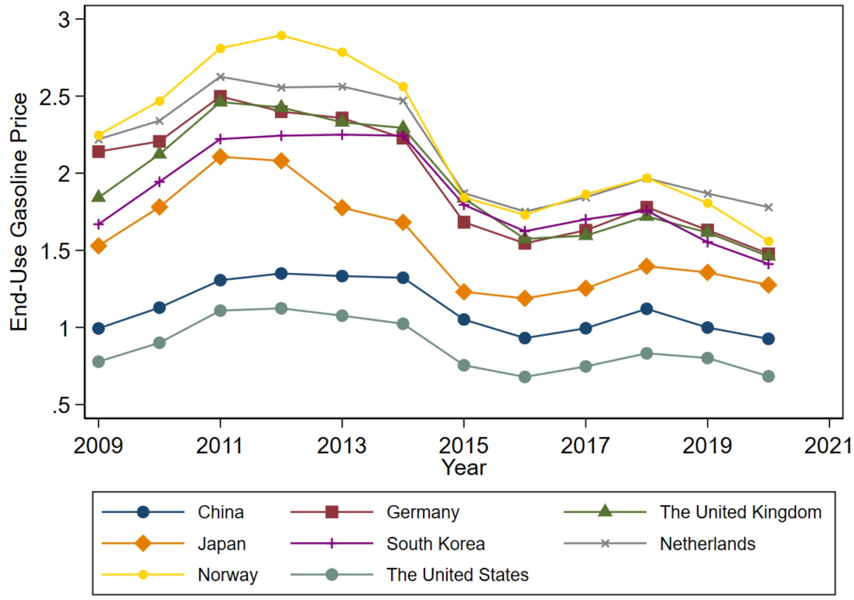
Notes: Based on authors' calculations for patents from selected CPC classes.

Fig. 2. Fuel-economy standard stringency over time by country/region (2009-2020).



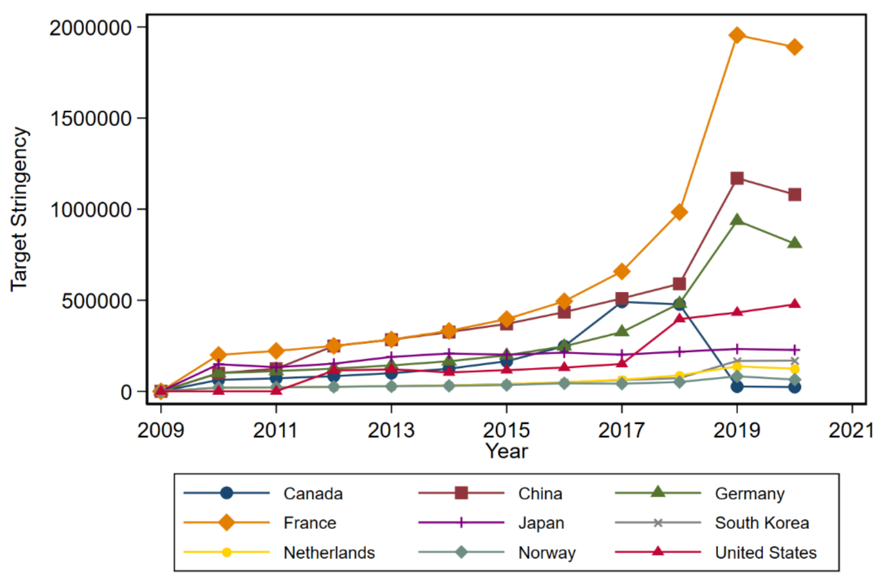
Notes: Authors calculate stringency index using raw fuel-economy standards. See data sources in Method section.

Fig. 3. End-use gasoline price over time in selected countries (2009-2020).



Notes: This figure shows the end-use gasoline price pattern, in 2020 US dollars, by country. This figure only shows the countries with different price patterns, and countries with similar patterns are omitted in this figure for readability. Source: International Energy Agency.

Fig. 4. Target stringency over time in selected countries (2009-2020).



Notes: This figure shows the target stringency pattern by country based on authors' calculations. Countries with relatively small stringency numbers or being less representative are omitted in this figure for readability. Source: see Appendix C.

6. Empirical Strategy

6.1. Main model

We use a Poisson specification to count patents to assess how policy measures and knowledge stocks influence innovation. The innovative outcome is EV-related patents filed by firm i in year t. Firms' pre-sample mean patent output serves as a control for unobserved, time-invariant heterogeneity in baseline inventive capacity, alongside year fixed effects. We include each firm's average EV patents before 2010 as a covariate for two reasons. The pre-sample mean captures unobserved differences in baseline innovativeness, accounting for the fact that some firms are consistently more innovative than others. More importantly, our specification includes lagged knowledge stocks, meaning that simple firm fixed effects violate strict exogeneity. Using the pre-sample mean absorbs heterogeneity without violating strict exogeneity (Blundell, Griffith, and Van Reenen, 1995; Noailly and Smeets, 2015). We lag policy and knowledge variables by one year to respect timing and limit simultaneity[5], and we include year effects to absorb shocks and global trends such as general advances in battery technology or global economic cycles. The baseline specification can be described as:

$$
\begin{aligned}
Patents_{it} = \exp\,(\beta_0 &+ \beta_1 lnGP_{it-1} + \beta_2 lnSI_{it-1} + \beta_3 lnRD_{it-1} + \beta_4 TS_{it-1} + \beta_5 FI_{it-1} \\
&+ \beta_6 UB_{it-1} + \beta_7 lnIEK_{it-1} + \beta_8 lnIBK_{it-1} + \beta_9 lnIAK_{it-1} + \beta_{10} lnIGEK_{it-1} \\
&+ \beta_{11} lnEEK_{it-1} + \beta_{12} lnEBK_{it-1} + \beta_{13} lnEAK_{it-1} + \beta_{14} lnEGEK_{it-1} \\
&+ \beta_{15} lnX_{it-1} + \beta_{16} avg_{pre} + \beta_{17} zero_{pre} + \gamma_y + \varepsilon_{it})
\end{aligned}
$$

$Patents_{it}$ represents the number of granted patent applications by firm i in year t. The coefficients of interest are the policy variables and knowledge stocks. GP stands for gasoline prices in unit USD/liter in 2020 US dollar; SI is fuel consumption standard stringency; RD captures R&D investment in energy efficient in the transportation sector in 2020 US dollar; TS captures EV target stringency; FI measures purchase-side financial incentives; UB measures use-phase benefits. The model also includes a set of variables to capture both internal and external knowledge stocks. IEK, IBK, IAK, and $IGEK$ are firms' internal knowledge stocks on electric vehicles, batteries/charging, general automobiles, and general electricity respectively. EEK, EBK, EAK, and EGEK are firms' external knowledge stocks in the same technology fields. X is GDP in 2020 US dollars. avg_{pre} is the firm's average annual patenting across all technologies before 2010. $zero_{pre}$ is a binary indicator equal to 1 if the firm recorded no patent fillings before 2010.

To study how instruments work together, the interaction model augments the baseline with pairwise terms that capture complementarity or substitution across demand-pull and technology-push levers. We interact EV target stringency with three policy channels that theory and prior

[5] Two-year lag models reveal similar results; see Appendix 8.

evidence suggest can jointly shape inventive effort: public R&D support, fuel prices, and performance standards.

$$
\begin{aligned}
Patents_{it} = \exp (&\beta_0 + \beta_1 lnGP_{it-1} + \beta_2 lnSI_{it-1} + \beta_3 lnRD_{it-1} + \beta_4 TS_{it-1} + \beta_5 FI_{it-1} \\
&+ \beta_6 UB_{it-1} + \beta_7 lnTS_{it-1} \times lnRD_{it-1} + \beta_8 lnTS_{it-1} \times lnGP_{it-1} \\
&+ \beta_9 lnTS_{it-1} \times lnSI_{it-1} + \beta_{10} lnIEK_{it-1} + \beta_{11} lnIBK_{it-1} + \beta_{12} lnIAK_{it-1} \\
&+ \beta_{13} lnIGEK_{it-1} + \beta_{14} lnEEK_{it-1} + \beta_{15} lnEBK_{it-1} + \beta_{16} lnEAK_{it-1} \\
&+ \beta_{17} lnEGEK_{it-1} + \beta_{18} lnX_{it-1} + \beta_{19} avg_{pre} + \beta_{20} zero_{pre} + \gamma_y + \varepsilon_{it})
\end{aligned}
$$

6.2. By technology models

Policies may act differently on downstream vehicle invention and upstream battery invention. To examine this, two parallel models apply the full specification model with alternative dependent variables. The vehicle model uses the count of EV vehicle patents. The battery model uses the count of battery, energy storage, and charging patents. Both models keep the same covariates, lags, and target interactions as the aggregate specification, including pre-sample means and year fixed effects. This design traces policy effects along the EV value chain and limits bias from changes in the mix of patented technologies.

7. Results

7.1. Main model

Our sample comprises 4,227 firms spanning the period from 2010 to 2021. Table 2 reports how demand-pull and technology-push policies, together with knowledge stocks, relate to firm-level EV patenting. In the baseline specification without policy interactions (column 1), fuel-economy standard stringency, public transport energy-efficiency R&D, and financial incentives are positively associated with innovation: a 10 percent increase in standard stringency correspond to about 4.2 percent more patents. R&D and financial incentives each associate with 0.8 percent more patents. Target stringency is also positive, and results become robust when dropping financial incentives and use-benefits (column 2), suggesting that the effects of target on EV innovation may redirect through incentives.

Knowledge stocks shape who responds. Deeper internal stocks in EVs and in batteries strongly reinforce EV patenting. A 10 percent increase in internal EV knowledge relates to about 5.4 percent more EV patents, and a 10 percent increase in internal battery knowledge relates to about 4.8 percent more. This finding aligns with the concept of innovation path dependence: accumulated expertise and learning-by-doing foster further advances along the same technological trajectory. In contrast, broad internal stocks in general electricity associate with

Table 2

Main models regression results: all firms.

	(1)	(2)	(3)
End-Use Gasoline Price	0.364	0.985	3.995**
	(1.128)	(1.048)	(1.489)
Standard Stringency	0.419***	0.308**	-0.338
	(0.097)	(0.096)	(0.178)
Transport Energy-Efficiency R&D	0.076*	0.084**	-0.171*
	(0.031)	(0.031)	(0.067)
Target Stringency	0.076	0.188*	0.005
	(0.045)	(0.076)	(0.098)
Financial Incentives	0.130***		0.122***
	(0.034)		(0.031)
Use Benefits	0.102		0.225
	(0.528)		(0.536)
Transport Energy-Efficiency R&D × Target Stringency			0.020***
			(0.005)
End-Use Gasoline Price × Target Stringency			-0.277*
			(0.110)
Standard Stringency × Target Stringency			0.052**
			(0.017)
Int. knowledge stocks - EVs	0.543***	0.545***	0.548***
	(0.040)	(0.040)	(0.040)
Int. knowledge stocks - batteries	0.475***	0.486***	0.477***
	(0.036)	(0.036)	(0.035)
Int. knowledge stocks - general auto	-0.053	-0.052	-0.056
	(0.030)	(0.030)	(0.030)
Int. knowledge stocks - general electricity	-0.054*	-0.058*	-0.051*
	(0.024)	(0.025)	(0.023)
Ext. knowledge stocks - EVs	-0.139	-0.103	-0.108
	(0.088)	(0.089)	(0.082)
Ext. knowledge stocks - batteries	0.570**	0.588***	0.488**
	(0.173)	(0.168)	(0.170)
Ext. knowledge stocks - general auto	-0.213*	-0.293***	-0.213*
	(0.094)	(0.083)	(0.094)
Ext. knowledge stocks - general electricity	-0.245	-0.226	-0.196
	(0.209)	(0.207)	(0.197)
Observations	22998	22998	22998
Numbers of firms	4227	4227	4227
Log-likelihood	-68814	-69200	-68337

Notes: Standard errors in parentheses: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$. All models include year fixed effects and pre-sample controls. Standard errors clustered by firm. Every variable in the log form except for use benefits. Column 1 shows all individual policies and knowledge stocks' influences; column 2 excludes the influence of financial incentives and use benefits; column 3 includes the policy interaction terms between target stringency and other three policies.

less EV patenting, which suggests capability lock-in around legacy platforms that diverts attention from transformative EV lines. This outcome may reflect the challenges firms face in absorbing external knowledge or the fact that external innovations are often not immediately applicable across different organizations, especially given differences in firms' technological focus and geographic context.

Table 3 shows clear and differentiated interactions with target stringency. Both R&D by target and standard stringency by target interactions are positive and statistically significant across specifications, indicating complementarity between stringent targets and two short-term policies. In contrast, the gasoline price by target is negative, which means target stringency reduces the marginal influence of fuel prices. After introducing these interactions, the direct effects of standards and R&D shrink or turn negative, so the evidence favors complementarity over large standalone impacts. Model fit improves as the interaction set expands, which indicates that firms respond to the policy mix rather than to isolated instruments.

The marginal-effect calculations in Table 4 reveal how policy interactions shape EV innovation at different levels of EV adoption target stringency. At the 25th percentile, the EV adoption target stringency is zero, representing countries that had yet to implement explicit adoption targets. In such cases, the marginal effect of fuel-economy standard stringency is significantly negative, suggesting that when governments tighten fuel-economy standards without an accompanying adoption target, firms tend to comply by improving ICE vehicles rather than innovating in EV technologies. This substitution effect highlights that standards alone may redirect innovation toward incremental efficiency gains in conventional vehicles instead of inducing technological shifts.

The complementarity between R&D investment and target stringency is particularly pronounced. As target stringency rises, the elasticity of EV patenting with respect to transport energy-efficiency R&D increases monotonically: from a small and statistically weak effect at the 25th percentile to 0.344 at the 75th, 0.479 at the 90th, and 0.808 at the maximum. This pattern implies that a 10 percent increase in public R&D investment corresponds to roughly 3.0-8.0 percent more EV patents in high-target environments. Similarly, the marginal effect of standard stringency shifts from negative to strongly positive as targets tighten, indicating that standards become more effective when aligned with clear adoption goals.

These results highlight the importance of aligning short-term and long-term policy instruments for effective EV innovation. Short-term measures, such as fuel-economy standards and public R&D programs, generate immediate incentives that shape firms' current innovation decisions. However, their impact depends strongly on the presence of credible long-term commitments. When ambitious EV adoption targets signal durable market growth, short-term instruments become more effective in mobilizing firms to invest in high-risk technologies and new product architectures. The results show that stringent, long-term targets amplify the innovation benefits of short-term technology-push and demand-pull policies. Coordinated policy packages that integrate near-term regulatory and fiscal tools with long-term strategic targets appear most successful in accelerating EV-related technological change.

Table 3
Main models regression results with interaction terms.

	(1)	(2)	(3)
End-Use Gasoline Price	0.854	1.989	3.995**
	(1.123)	(1.237)	(1.489)
Standard Stringency	0.231*	0.147	-0.338
	(0.096)	(0.113)	(0.178)
Transport Energy-Efficiency R&D	-0.196**	-0.184*	-0.171*
	(0.073)	(0.073)	(0.067)
Target Stringency	-0.057	0.027	0.005
	(0.056)	(0.107)	(0.098)
Financial Incentives	0.124***	0.124***	0.122***
	(0.032)	(0.032)	(0.031)
Use Benefits	0.164	0.197	0.225
	(0.530)	(0.534)	(0.536)
Transport Energy-Efficiency R&D × Target Stringency	0.023***	0.022***	0.020***
	(0.006)	(0.006)	(0.005)
End-Use Gasoline Price × Target Stringency		-0.088	-0.277*
		(0.091)	(0.110)
Standard Stringency × Target Stringency			0.052**
			(0.017)
Observations	22998	22998	22998
Log-likelihood	-68447	-68429	-68337

Notes: Standard errors in parentheses: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$. All models include year fixed effects and pre-sample controls. Standard errors clustered by firm. Every variable in the log form except for use benefits. Column 1 shows the policy interaction between transport energy-efficiency R&D investment and target stringency; column 2 adds policy interaction between end-use gasoline price and target stringency; column 3 adds the policy interaction between standard stringency and target stringency. Internal and external knowledge stocks are not shown in this table, as their magnitudes and statistical significance are similar to those in the main results (Table 2).

Table 4
Marginal effects at different levels of target stringency.

	(1) End-Use Gasoline Price	(2) Transport Energy-Efficiency R&D	(3) Standard Stringency
At 25th percentile	8.820	-0.415	-0.870*
	(4.828)	(0.278)	(0.443)
At 50th percentile	4.818	0.188	0.900
	(4.605)	(0.129)	(0.488)
At 75th percentile	3.626	0.344*	1.351*
	(5.278)	(0.138)	(0.584)
At 90th percentile	2.572	0.479**	1.737*
	(5.904)	(0.149)	(0.687)
At maximum	-0.111	0.808***	2.677**
	(7.608)	(0.195)	(1.020)
Observations	22998	22998	22998

Notes: Standard errors in parentheses: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$. All variables in the log form. Marginal effects are calculated at different percentiles of EV adoption target stringency to illustrate interaction effects between target stringency and each policy variable.

7.2. Results by technology models

Separate regressions for vehicle and for battery or charging patents assess whether the same policy levers and capabilities matter across technologies. Policy effects look similar in both models; observed differences arise mainly from precision rather than coefficient magnitude. Firm capabilities carry substantial weight in both domains, and the most valuable knowledge is technology-specific rather than generic. Fuel-economy standard stringency enters positively and significantly in both technologies throughout Table 5, mirroring the full specification. Target stringency keeps a positive sign in both technologies but loses precision. The interaction terms follow the full-sample pattern, showing complementarity between target stringency and R&D, as well as between target stringency and standard stringency, while the influence of gasoline prices declines as targets become more stringent.

Within-firm capabilities shape vehicle-technology patenting. A deeper internal EV experience translates into greater output in vehicle technologies. A 10 percent increase in internal EV knowledge translates to roughly a 6.0 percent increase in vehicle-technology patents. Battery expertise spans the firm and supports integration work, with a 10 percent increase in internal battery knowledge resulting in approximately 4.3 percent more vehicle-technology patents. Broad internal knowledge in conventional auto links to lower EV-vehicle patenting, with 0.8 percent fewer patents per 10 percent increase, which signals legacy lock-in. Broad internal electricity knowledge shows little independent effect.

Battery innovation responds to both push and pull policies. In the baseline battery model, a 10 percent rise in fuel-economy standard stringency relates to about 4.3 percent more patents, and a similar increase in transport energy-efficiency R&D relates to about 0.8 percent more. Targets also yield 1.9 percent more patents per 10 percent increase even excluding financial incentives. These results fit an intuitive story: targets create predictable demand for improved storage, while R&D and incentives reduce technical and adoption risk. These findings indicate that demand-pull and technology-push instruments operate through distinct but reinforcing channels, jointly enabling technological progress and expansion across the battery supply chain.

Cross-technology learning is clear. A 10 percent increase in internal EV knowledge relates to roughly 5.5 percent more battery patents, and a similar increase in internal battery knowledge relates to about 4.7 percent more. Internal general electricity knowledge links to fewer battery patents by about 0.5 percent. These findings show that domain-specific capabilities matter most. EV platform learning and battery know-how help teams locate bottlenecks and turn improvements into patentable designs, while generic electrical expertise does not substitute for EV-specific battery expertise. External battery knowledge also supports patenting, which is consistent with the diffusion of ideas among firms at the battery frontier.

Some policy coefficients for vehicle technologies do not reach conventional significance, and the most likely reason is limited precision. The vehicle sample comprises 13,780 observations from 2,196 firms, while the battery sample comprises 21,671 observations from 3,934 firms. The smaller vehicle sample raises standard errors, so several coefficient estimates align with the battery results yet fall short in statistical tests. The interaction terms follow the full-sample pattern: standards and targets reinforce one another, R&D becomes more effective when targets are stronger, and higher fuel prices weaken the effect of targets. A coordinated policy mix that pairs performance standards with clear targets, R&D, and well-aimed incentives, combined with firm investment in EV- and battery-specific knowledge, encourages innovation in both vehicle systems and batteries.

Table 5

Regression results by technology fields.

	(1) Vehicle	(2) Vehicle	(3) Vehicle	(4) Battery	(5) Battery	(6) Battery
End-Use Gasoline Price	0.382	0.968	4.062*	0.299	0.930	4.030**
	(1.306)	(1.222)	(1.723)	(1.141)	(1.061)	(1.517)
Standard Stringency	0.473***	0.355**	-0.370	0.426***	0.314**	-0.363*
	(0.121)	(0.121)	(0.221)	(0.099)	(0.097)	(0.180)
Transport Energy-Efficiency	0.057	0.069	-0.198*	0.076*	0.084**	-0.174*
R&D	(0.038)	(0.038)	(0.084)	(0.032)	(0.031)	(0.068)
Target Stringency	0.084	0.191	-0.019	0.078	0.193*	0.001
	(0.061)	(0.098)	(0.121)	(0.046)	(0.079)	(0.102)
Financial Incentives	0.121**		0.111**	0.131***		0.123***
	(0.041)		(0.038)	(0.034)		(0.032)
Use Benefits	-0.200		-0.094	0.104		0.233
	(0.625)		(0.635)	(0.552)		(0.559)
Transport Energy-Efficiency			0.021***			0.021***
R&D × Target Stringency			(0.006)			(0.005)
End-Use Gasoline Price ×			-0.276*			-0.286*
Target Stringency			(0.130)			(0.112)
Standard Stringency × Target			0.058**			0.054**
Stringency			(0.020)			(0.017)
Int. knowledge stocks - EVs	0.591***	0.595***	0.597***	0.545***	0.547***	0.549***
	(0.050)	(0.050)	(0.050)	(0.040)	(0.040)	(0.040)
Int. knowledge stocks -	0.428***	0.439***	0.431***	0.469***	0.480***	0.472***
batteries	(0.044)	(0.043)	(0.043)	(0.036)	(0.036)	(0.035)
Int. knowledge stocks - general	-0.081*	-0.083*	-0.085**	-0.054	-0.054	-0.058
auto	(0.033)	(0.033)	(0.032)	(0.031)	(0.031)	(0.030)
Int. knowledge stocks - general	-0.036	-0.038	-0.033	-0.054*	-0.058*	-0.051*
electricity	(0.029)	(0.029)	(0.028)	(0.024)	(0.025)	(0.023)
Ext. knowledge stocks - EVs	-0.146	-0.133	-0.111	-0.143	-0.108	-0.110
	(0.100)	(0.098)	(0.093)	(0.089)	(0.089)	(0.082)
Ext. knowledge stocks -	0.531*	0.520**	0.442*	0.578***	0.597***	0.500**
batteries	(0.209)	(0.201)	(0.204)	(0.176)	(0.170)	(0.172)
Ext. knowledge stocks -	-0.215*	-0.272**	-0.225*	-0.207*	-0.288***	-0.208*
general auto	(0.109)	(0.095)	(0.107)	(0.095)	(0.084)	(0.094)
Ext. knowledge stocks -	-0.199	-0.157	-0.137	-0.262	-0.244	-0.224
general electricity	(0.267)	(0.262)	(0.254)	(0.213)	(0.210)	(0.200)
Observations	13780	13780	13780	21671	21671	21671
Number of firms	2196	2196	2196	3934	3934	3934
Log-likelihood	-50000	-50245	-49603	-67307	-67690	-66827

Notes: Standard errors in parentheses: *** p < 0.001, ** p < 0.01, * p < 0.05. All models include year fixed effects and pre-sample controls. Standard errors clustered by firm. Every variable in the log form except for use benefits.

7.3. Robustness checks

The main specification constructs in-sample weights from each firm's patenting distribution during 2010-2021. Governments may adopt stronger policies in markets where EV activities are already expanding, which can blur whether observed innovation responses stem from the policies themselves or from firms reallocating their patenting portfolios toward more active policy environments. To address this concern, we implement robustness checks that replace in-sample weights with a set of pre-sample assignments.

This alternative scheme anchors each firm's policy exposure to its geographic and technological footprint before 2010, when the main study window begins. The advantage is that pre-sample weights reduce simultaneity bias between policy changes and patenting locations, since the weights are determined before the estimation period. The trade-off is that the approach sacrifices completeness: it cannot reflect new entrants that began patenting after 2010 or firms that expanded into new policy jurisdictions as EV markets globalized. New entrants have no pre-2010 patents, so we identify three options. First, we assign a weight of 1 to the headquarters country and 0 elsewhere to construct the home-country weights. This assigns exposure fully based on home market. Second, we replace the home country indicator with the average pre-2010 country shares of incumbents that share the same headquarters country. Third, we consider technological variation by computing pre-sample shares separately for vehicles and for batteries.

Table 6 reports the results using the third method to derive weights for new entrants: pre-sample by technology average weights. Results for the other two weighting schemes are in Appendix I and tell a similar story. In this model, R&D investment and target stringency remain positive and statistically significant for EV patenting, while financial incentive policy retains its positive signs but loses precision. This pattern suggests that the main relationships are not artifacts of the in-sample construction and that endogeneity in weighting does not drive the core results. The lost precision comes from how the weights map country policies to each firm's exposure. In-sample weights update this presence to reflect current markets, allowing them to track how current policies influence innovation. Pre-sample weights lock exposure to earlier market shares, which can lag the firm's shift into fast-growing EV markets. That lag reduces power for instruments that move quickly, such as targets and incentives. The persistent and significant effect of standard stringency under both schemes shows that the key finding is robust. In-sample weights do not create spurious correlation; they sharpen sensitivity to certain policy effects.

Under pre-sample by technology weights (in Table 7), the by-technology estimates mirror the main results in both sign and relative size. Vehicle-technology coefficients retain the same directions as in Table 5, with interaction terms showing similar prominence. Battery-technology coefficients also match the main patterns, with policy and interaction effects preserving their positive directions and comparable magnitudes. Knowledge-stock coefficients align as well,

TABLE 6

Main regression results using pre-sample by technology average weights.

	(1)	(2)	(3)
End-Use Gasoline Price	1.072	1.078	0.218
	(0.800)	(0.852)	(1.227)
Standard Stringency	0.302*	0.255*	0.065
	(0.129)	(0.124)	(0.168)
Transport Energy-Efficiency R&D	0.083*	0.106***	-0.196**
	(0.033)	(0.029)	(0.062)
Target Stringency	0.030	0.048	-0.287**
	(0.023)	(0.035)	(0.088)
Financial Incentives	0.042		0.037
	(0.030)		(0.029)
Use Benefits	-0.842		-0.698
	(0.506)		(0.493)
Transport Energy-Efficiency R&D × Target Stringency			0.024***
			(0.004)
End-Use Gasoline Price × Target Stringency			0.102
			(0.106)
Standard Stringency × Target Stringency			0.027
			(0.020)
Int. knowledge stocks - EVs	0.542***	0.543***	0.543***
	(0.039)	(0.039)	(0.039)
Int. knowledge stocks - batteries	0.473***	0.485***	0.474***
	(0.037)	(0.036)	(0.036)
Int. knowledge stocks - general auto	-0.043	-0.050	-0.046
	(0.027)	(0.029)	(0.027)
Int. knowledge stocks - general electricity	-0.049	-0.050*	-0.046
	(0.025)	(0.025)	(0.024)
Ext. knowledge stocks - EVs	-0.069	-0.069	-0.060
	(0.087)	(0.091)	(0.082)
Ext. knowledge stocks - batteries	0.670***	0.593***	0.595***
	(0.168)	(0.169)	(0.160)
Ext. knowledge stocks - general auto	-0.361***	-0.341***	-0.356***
	(0.081)	(0.073)	(0.080)
Ext. knowledge stocks - general electricity	-0.232	-0.198	-0.169
	(0.202)	(0.210)	(0.184)
Observations	22998	22998	22998
Number of firms	4227	4227	4227
Log-likelihood	-69462	-69653	-69006

Notes: Standard errors in parentheses: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$. All models include year fixed effects and pre-sample controls. Standard errors clustered by firm. Every variable in the log form except for use benefits. Column 1 shows all individual policies and knowledge stocks' influences; column 2 excludes the influence of financial incentives and use benefits; column 3 includes the policy interaction terms between target stringency and other three policies.

Table 7

By technology regression results using pre-sample by technology average weights.

	(1) Vehicle	(2) Vehicle	(3) Vehicle	(4) Battery	(5) Battery	(6) Battery
End-Use Gasoline Price	0.161	-0.061	2.575	0.099	-0.093	2.462
	(0.690)	(0.694)	(1.540)	(0.564)	(0.529)	(1.280)
Standard Stringency	0.614**	0.509**	-0.064	0.484**	0.410**	-0.137
	(0.212)	(0.188)	(0.229)	(0.148)	(0.134)	(0.182)
Transport Energy-Efficiency R&D	0.074	0.099**	-0.180*	0.093**	0.112***	-0.152*
	(0.038)	(0.035)	(0.078)	(0.032)	(0.029)	(0.064)
Target Stringency	0.010	0.036	-0.214	0.008	0.032	-0.191*
	(0.026)	(0.040)	(0.113)	(0.019)	(0.029)	(0.090)
Financial Incentives	0.069*		0.064*	0.067*		0.062*
	(0.034)		(0.032)	(0.029)		(0.027)
Use Benefits	-0.944		-0.840	-0.667		-0.573
	(0.528)		(0.518)	(0.462)		(0.454)
Transport Energy-Efficiency			0.021***			0.020***
R&D × Target Stringency			(0.005)			(0.005)
End-Use Gasoline Price ×			-0.178			-0.184
Target Stringency			(0.154)			(0.127)
Standard Stringency × Target			0.070**			0.066**
Stringency			(0.027)			(0.021)
Int. knowledge stocks - EVs	0.592***	0.596***	0.593***	0.543***	0.548***	0.545***
	(0.048)	(0.049)	(0.049)	(0.039)	(0.039)	(0.039)
Int. knowledge stocks -	0.424***	0.437***	0.427***	0.470***	0.481***	0.473***
batteries	(0.043)	(0.042)	(0.043)	(0.037)	(0.036)	(0.036)
Int. knowledge stocks - general	-0.079*	-0.080*	-0.080**	-0.049	-0.051	-0.051
auto	(0.030)	(0.032)	(0.030)	(0.029)	(0.030)	(0.028)
Int. knowledge stocks - general	-0.031	-0.032	-0.030	-0.052*	-0.054*	-0.051*
electricity	(0.029)	(0.029)	(0.028)	(0.025)	(0.025)	(0.024)
Ext. knowledge stocks - EVs	-0.103	-0.074	-0.096	-0.071	-0.043	-0.061
	(0.093)	(0.093)	(0.089)	(0.086)	(0.086)	(0.081)
Ext. knowledge stocks -	0.597**	0.570**	0.516*	0.647***	0.633***	0.582**
batteries	(0.217)	(0.210)	(0.210)	(0.190)	(0.180)	(0.182)
Ext. knowledge stocks -	-0.316***	-0.326***	-0.332***	-0.328***	-0.345***	-0.339***
general auto	(0.088)	(0.079)	(0.087)	(0.079)	(0.070)	(0.079)
Ext. knowledge stocks -	-0.186	-0.210	-0.097	-0.263	-0.285	-0.206
general electricity	(0.262)	(0.268)	(0.252)	(0.222)	(0.224)	(0.208)
Observations	13780	13780	13780	21671	21671	21671
Number of firms	2196	2196	2196	3934	3934	3934
Log-likelihood	-50427	-50687	-50005	-68020	-68259	-67519

Notes: Standard errors in parentheses: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$. All models include year fixed effects and pre-sample controls. Standard errors clustered by firm. Every variable in the log form except for use benefits.

including positive intra-firm spillovers from EV and battery know-how and weaker or negative links for broad general-auto and general-electricity stocks.

To further test the sensitivity, we also estimate an in-sample specification that excludes Chinese firms to test whether results rely on China's large patent volume and intense policies (in Appendix I.1). China accounts for the largest share of firms in the dataset, and many are new entrants that patent almost exclusively in the domestic market, where policies are unusually strong. This could amplify estimates of policy effects by overrepresenting one national context. Dropping Chinese firms verifies that the estimated coefficients capture broad cross-country regularities rather than China's distinct policy regime or industrial structure. Across all robustness checks, the direction and relative magnitudes of policy effects remain consistent with the main estimates, reinforcing the conclusion that the results are stable to alternative weighting constructions and sample definitions.

8. Discussion

Our findings, focused on EV innovation, confirm some general patterns from past innovation studies while revealing distinct dynamics unique to the EV sector. In line with induced innovation theory, performance standards emerge as a strong driver of EV-related patenting, steering inventors toward zero-emission vehicle technologies much as prior work found in conventional automotive innovation (Klier and Linn, 2016; Rozendaal and Vollebergh, 2025). In contrast, we do not find a robust effect of gasoline prices on EV patenting, which marks a notable divergence from earlier studies in other contexts that showed higher energy prices spur energy-efficient innovation (Popp, 2002; Aghion et al., 2016). One explanation is that by the 2010s, EV-specific policy mandates (such as adoption targets) combined with rapid declines in battery costs had reduced the marginal importance of fuel prices for firms' innovation decisions. In other words, clear regulatory signals and technological progress in EVs may have diminished the role of gasoline prices as an incentive for inventors, whereas in previous technology domains lacking such focused policies, price signals played a larger role. This underscores that the EV sector responds differently: targeted electrification policies and improvements can overshadow general market price effects that were more influential in other energy technology innovations.

Our results also show that long-term EV adoption targets and financial purchase incentives are each positively associated with increased EV patenting. Long-term deployment targets shape expectations about future market size and encourage firms to invest in EV technology. At the same time, consumer incentives such as subsidies and tax credits expand early markets and reduce adoption risk, thereby increasing the expected returns to EV-oriented R&D and patents, consistent with demand-pull theory (Ziegler et al., 2021).

On the technology-push side, we find that public R&D investment in energy-efficient transportation significantly boosts EV patenting, consistent with prior evidence across various energy technologies that public research support increases innovative output (Popp, 2016). In our EV-focused setting, public R&D funding appears to finance foundational work and generate knowledge spillovers that firms can build on, thereby accelerating upstream invention in areas like advanced batteries. This result reinforces the view that technology-push and demand-pull policies work together: R&D support is especially impactful when there is a clear market signal for EVs, a pattern consistent with classic accounts of innovation policy (Nemet, 2009). We also observe that firms' internal knowledge stocks strongly condition innovative outcomes. Companies with deeper prior expertise in EV and battery technologies produce significantly more new EV patents, reflecting an absorptive capacity effect (Cohen and Levinthal, 1990), in which accumulated know-how makes firms more productive innovators. By contrast, firms heavily invested in conventional ICE knowledge tend to generate fewer EV patents, suggesting a degree of technological lock-in and incumbent inertia (Penna and Geels, 2015). These findings echo prior studies on path-dependent innovation trajectories. Still, our firm-level evidence in the EV context highlights how strong in-house capabilities in clean technologies can amplify responses to external policy signals. In contrast, legacy knowledge can impede redirection toward electrification.

A central contribution of this paper is to demonstrate that aligning long-horizon market-shaping goals with short-term policies strengthens their overall effectiveness. We find a significant positive interaction between EV adoption target stringency and public R&D investment: in environments with ambitious EV targets, the elasticity of EV patenting with respect to public R&D more than doubles compared to cases with weak or no targets. In practical terms, as countries set more stringent long-term EV targets, each dollar of public R&D yields a greater increase in EV innovation than it would under low-target scenarios. This complementarity suggests that well-defined long-term targets enhance the payoff of R&D support by lowering market uncertainty and strengthening expected demand for new EV technologies. Firms are more willing to pursue high-risk, high-reward innovations when they know that future markets are secured by policy commitments, which is exactly when public R&D funding can have an outsized impact. Notably, this interaction reflects the specific needs of the EV sector. For example, much of the dramatic improvement in battery technology has resulted from advances in research (Ziegler et al., 2021), and the presence of long-term EV deployment goals makes those research investments even more valuable.

A similar interplay emerges between long-run targets and near-term regulatory standards. Fuel economy standards on their own push firms toward more EV inventive activities. We find that stricter EV targets amplify the marginal impact of these standards. When policymakers set ambitious EV adoption targets, tightening performance standards produces a larger increase in EV patenting than the same tightening under weak targets. Strong targets clarify the destination, and standards create immediate pressure to invest and comply. Working together, they expand

and accelerate inventive activity in electrification. When policymakers do not announce an EV target, stronger fuel economy standards can channel effort into more efficient ICE technologies rather than EV technologies, which weakens the link between standards and electrification. Our results show that coordinating long-term targets with short-term standards delivers the highest inventive output when both are ambitious, because targets shape expectations while standards convert those expectations into near-term deployment. This evidence provides empirical support for the arguments of Rogge and Riechardt (2016), who posit that coherent, long-horizon policy packages provide greater impetus for innovation than isolated measures. In practical terms for the EV sector, EV sales targets set the horizon for change, and performance standards apply immediate pressure. When policymakers design them in concert, they steer technological search toward electrification more effectively than either tool alone.

Overall, these results highlight how the EV sector differs from earlier contexts by demonstrating the importance of an integrated policy strategy. Past innovation literature often emphasized single instruments, but our study shows that for EV technology, the interplay of multiple policies and firm capabilities is crucial. In summary, EV targets are potent drivers of invention, and their impact is amplified by complementary technology-push support. At the same time, firms with the right knowledge base are best positioned to capitalize on these policy signals, whereas those locked into older technologies are less responsive. These insights show that accelerating clean innovation in the auto industry is most likely when policies include a long-term commitment, supportive short-term incentives, and attention to firms' starting capabilities, a combination not empirically demonstrated in previous studies on other technologies to the extent shown here for EVs.

9. Conclusions and Policy Implications

Our evidence shifts the policy debate from "which instrument works" to "which instruments work together in different time frames." Therefore, for policy makers wishing to promote further EV innovation, a practical policy package can build on three key pillars. First, set quantified, time-bound EV targets with credible compliance pathways and regular interim checkpoints, since targets shape expectations and convert upstream R&D into marketable inventions. Second, fund targeted public R&D that prioritizes upstream battery invention, power electronics, and charging that stimulate EV innovation. Third, use performance standards as near-term bridges. Standards exert the strongest inventive pressure when targets are moderate, but this instrument should gradually adjust as targets become binding and technology costs decline. Sequencing these three pillars on a transparent regulatory calendar, with clear milestones and periodic review, turns predictable commitments into sustained EV innovation and adoption.

The lessons learned from the rapid development of electric vehicles over the past decade provide lessons applicable to other complex emerging technologies. Clear long-term EV targets improve the effectiveness of public R&D and performance standards. Similar targets could be applied to encourage innovation on grid management and energy storage to both fortify and reduce emissions from electricity systems needed to support large EV fleets. The same logic applies to other complex, capital intensive technologies such as heavy duty zero emission vehicles and building decarbonization, where credible long term deployment goals can encourage private investment and increase the payoff from short horizon subsidies and standards.

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Online Appendix

Appendix A. CPC Classification for Patent Choices (Main Dependent Variable)

We use the Cooperative Patent Classification (CPC) to identify EV-related inventions. The European Patent Office and the United States Patent and Trademark Office developed the CPC, which organizes technologies hierarchically. Section symbols indicate broad fields. For example, B denotes Performing Operations; Transporting, and Y denotes Emerging Cross-Sectional Technologies. Class numbers and subclass letters then locate specific technology groups, such as B60 for Vehicles in General and B60L for Propulsion of Electrically Propelled Vehicles. Within these groups, finer subgroups allow us to isolate EV-relevant technologies. We assign these inventions to six specific domains and then aggregate them into two broad domains related to upstream and downstream EV technologies: vehicle and battery. The vehicle domain covers pure battery-electric drivetrains, hybrid drivetrains, and other alternative-fuel vehicle architectures. The battery domain covers electrochemical cells and materials, battery packs and management systems, and charging and power-conversion technologies. If a patent lists codes from both domains, we assign one vehicle label and one battery label, since many EV inventions link a vehicle platform with a battery or a charger.

We considered estimating the by-technology model at the level of six technological fields to sharpen the mapping between policies and the specific part of the EV system a firm advances. That approach reduces statistical power for two reasons. First, enforcing mutual exclusivity across technology fields splits a firm's portfolio into smaller bins. For example, if we assign a patent in the hybrid-vehicle field, we do not re-assign it in the pure EV field, even the technology may belong to both fields. This increases zero counts at the firm-year level and produces sparse firm-country panels. Second, the policy series correlate across countries, and the same firm-level weights enter multiple categories, which raises multicollinearity and inflates standard errors. As a result, coefficient signs often align with the broader two-domain results but the precision deteriorates. We therefore choose to only include vehicle versus battery technology in the results.

Table A.1

CPC classification and definitions by categories.

CPC Code	Definitions
	Pure EV
B60L 15	Methods, circuits, or devices for controlling the traction-motor speed of electrically-propelled vehicles
B60L 50/60	Electric propulsion with power supplied within the vehicle using power supplied by batteries

B60L 50/64; B60L 50/66	Electric propulsion with power supplied within the vehicle using propulsion power supplied by batteries or fuel cells: Constructional details of batteries specially adapted for electric vehicles; Arrangements of batteries
Y02T 10/64; Y02T 10/70	Road transport of goods or passengers Other road transportation technologies with climate change mitigation effect: Electric machine technologies in electromobility, e.g. batteries
Y02T 10/72	Road transport of goods or passengers Other road transportation technologies with climate change mitigation effect: Electric energy management in electromobility
B60Y 2200/91	Indexing scheme relating to aspects cross-cutting vehicle technology: Electric vehicles
	Hybrid Vehicles
B60L 50/15	Electric propulsion with power supplied within the vehicle using propulsion power supplied by engine-driven generators, e.g. generators driven by combustion engines with additional electric power supply
B60L 50/61; B60L 50/62	Electric propulsion with power supplied within the vehicle using power supplied by batteries by batteries charged by engine-driven generators, e.g. series hybrid electric vehicles charged by low-power generators primarily intended to support the batteries, e.g. range extenders
Y02T 10/62	Road transport of goods or passengers Other road transportation technologies with climate change mitigation effect: Hybrid vehicles
Y10S 903	Technical subjects covered by former USPC cross-reference art collections [XRACs] and digests: Hybrid electric vehicles, HEVS
B60W 20	Control systems specially adapted for hybrid vehicles
B60K 6	Arrangement or mounting of plural diverse prime-movers for mutual or common propulsion, e.g. hybrid propulsion systems comprising electric motors and internal combustion engines
B60Y 2200/92	Indexing scheme relating to aspects cross-cutting vehicle technology: Hybrid vehicles
	General Alternative Fuel Vehicles
B60L 3/0046	Electric devices on electrically-propelled vehicles for safety purposes; Monitoring operating variables, e.g. speed, deceleration or energy consumption relating to electric energy storage systems, e.g. batteries or capacitors
B60L 50/50	Electric propulsion with power supplied within the vehicle using propulsion power supplied by batteries or fuel cells

B60L 50/72; B60L 50/75	Electric propulsion with power supplied within the vehicle: Constructional details of fuel cells specially adapted for electric vehicles using propulsion power supplied by both fuel cells and batteries
B60L 58/40	Methods or circuit arrangements for monitoring or controlling batteries or fuel cells, specially adapted for electric vehicles for controlling a combination of batteries and fuel cells
B60K 1	Arrangement or mounting of electrical propulsion units in vehicles
Y02T 90/16	Information or communication technologies improving the operation of electric vehicles
	Battery Invention
B60L 58/16	Methods or circuit arrangements for monitoring or controlling batteries or fuel cells, specially adapted for electric vehicles responding to battery ageing, e.g. to the number of charging cycles or the state of health [SoH]
B60L 58/10	Methods or circuit arrangements for monitoring or controlling batteries or fuel cells, specially adapted for electric vehicles for monitoring or controlling batteries
B60W 10/24; B60W 10/26	Conjoint control of vehicle sub-units of different type or different function including control of energy storage means for electrical energy, e.g. batteries or capacitors
B60Y 2400/11; B60Y 2400/112	Indexing scheme relating to aspects cross-cutting vehicle technology: Electric energy storages; Batteries
Y02T 10/70	Road transport of goods or passengers Other road transportation technologies with climate change mitigation effect: Energy storage systems for electromobility, e.g. batteries
	General Battery Innovation
H01M 6	Processes or means, e.g. batteries, for the direct conversion of chemical energy into electrical energy: Primary cells
H01M 10	Processes or means, e.g. batteries, for the direct conversion of chemical energy into electrical energy: Secondary cells
	Charging Infrastructure
B60L 53	Methods of charging batteries, specially adapted for electric vehicles; Charging stations or on-board charging equipment therefor; Exchange of energy storage elements in electric vehicles
B60L 58/12; B60L 58/13; B60L 58/14; B60L 58/15	Methods or circuit arrangements for monitoring or controlling batteries or fuel cells, specially adapted for electric vehicles for monitoring or controlling batteries responding to state of charge [SoC]: Maintaining the

	SoC within a determined range; Preventing excessive discharging; Preventing overcharging
B60L 58/16	Methods or circuit arrangements for monitoring or controlling batteries or fuel cells, specially adapted for electric vehicles for monitoring or controlling batteries responding to battery ageing, e.g. to the number of charging cycles or the state of health [SoH]
B60L 58/18; B60L 58/19; B60L 58/20; B60L 58/21; B60L 58/22	Methods or circuit arrangements for monitoring or controlling batteries or fuel cells, specially adapted for electric vehicles for monitoring or controlling batteries of two or more battery modules: Switching between serial connection and parallel connection of battery modules; having different nominal voltages; having the same nominal voltage; Balancing the charge of battery modules
H02J 2310/40; H02J 2310/48	The network for supplying or distributing electric power characterised by its spatial reach or by the load: The network being an on-board power network for electric vehicles or hybrid vehicles
Y02T 90/10; Y02T 90/12	Enabling technologies or technologies with a potential or indirect contribution to GHG emissions mitigation: Technologies relating to charging of electric vehicles; Electric charging stations
Y02T 10/7072; Y02T 10/92	Road transport of goods or passengers Other road transportation technologies with climate change mitigation effect: Electromobility specific charging systems or methods for batteries, ultracapacitors, supercapacitors or double-layer capacitors
Y04S 10/126	Systems supporting electrical power generation, transmission or distribution: the energy generation units being or involving electric vehicles [EV] or hybrid vehicles [HEV], i.e. power aggregation of EV or HEV, vehicle to grid arrangements [V2G]

Appendix B. Financial Incentives Sources and Operationalization

Table B.1

Financial incentive sources by country/region.

Country or Region	Data Source
European Union	European Automobile Manufacturers' Association - Electric Cars: Tax Benefits and Incentives Report
The United States	Department of Energy, Alternative Fuels Data Center
Canada	Transports Canada
China	Finance Ministry's Announcements
South Korea	Ministry of Environment Transportation and Environment Division - EV Distribution and Charging Infrastructure Construction Project Subsidy Processing Guidelines
Japan	Ministry of Economy, Trade and Industry's Announcements

Table B.1 lists the primary sources we used to code national financial incentives for electric vehicles in the European Union, the United States, Canada, China, South Korea, and Japan. We extract the level and timing of each instrument directly from these official compilations and announcements to build consistent country-year series.

Many acquisition subsidies vary by vehicle characteristics such as driving range or battery capacity. To standardize the series across countries, we evaluate each incentive for a representative EV with a driving range up to 300 miles. This establishes a uniform reference point consistent with most incentive structures and reduces potential cross-country discrepancies. We express all monetary amounts in 2020 U.S. dollars for comparability over time.

For use-phase benefits, we track four national policy instruments: emission-based taxes, annual road taxes, tolls or congestion charges, and registration taxes We set an indicator to 1 if EVs receive a nationally applicable discount, reduced rate, or full exemption on that instrument in that year; otherwise, we set it to 0. Then, we develop a usage-benefit index, and the presence of each instrument adds 0.25 to the index. We do not scale the index by the size of the relief, which improves cross-country comparability.

Table 2.2.

Operationalization of financial incentives

Incentive Type	Measurement	Unit
Acquisition Incentives	VAT reduction Purchase discount/credit	2020 dollars
Use Benefits	Emission tax benefit Road tax benefit	0.25 each and add up to 1

Toll benefit
Registration tax benefit

Appendix C. Target Resources with Actual Target Announcement

The following table summarizes national-level EV adoption targets announced by each country during the study period. These targets typically specify a quantitative goal to be achieved by a specific year. Because the United States did not establish a federal EV adoption target within the examined period, California's state-level target is used as a representative proxy, given the state's leadership in EV policy and its significant influence on national market trends and regulatory standards. From each policy document, we extract two key elements: (1) the year in which the target was first announced, and (2) the actual EV adoption number of the target.

Country	Year	Target	Source
Austria	2010	250,000 EVs by 2020	Energie-Strategie Österreich (Energy Strategy Austria)
	2012	250,000 EVs by 2020	Implementation Plan - Electromobility in and from Austria
	2019	250,000 EVs by 2020; all new cars zero-emission by 2030	National Energy & Climate Plan (NECP)
Australia		No target at governmental/national level	
Belgium	2016	Around 76,000 EVs by 2020	The consolidated Belgian NPF submitted to the European Commission
Canada	2009	500,000 EVs by 2018	Electric Vehicle Technology Roadmap for Canada
	2019	10 % of new LDV sales ZEV by 2025; 30 % by 2030; 100 % by 2040	Government of Canada invests in zero-emission vehicles
Switzerland	2018	⩾ 15 % plug-in share in new-car registrations by 2022	Gemeinsame Roadmap zur Förderung der Elektromobilität
China	2009	Reach production capacity of 500,000 battery, plug-in hybrid, and hybrid electric vehicles (new energy vehicle)	Auto Industry Adjustment and revitalization Plan
	2012	Annual production and sale of 500,000 plug-in electric vehicles by 2015 and 2 million by 2020	Energy-Saving and New Energy Vehicles Industry Development Plan
Denmark	2013	200,000 electric cars by 2020	The European Union Climate Commission
	2018	Around 1 million electric cars on the road by 2030	The Danish Government Anncounment

Finland	2016	⩾ 250 000 electric cars	National Energy and Climate Strategy of Finland for 2030
	2017	Around 20,000 electric vehicles in 2020	National Alternative-Fuels Infrastructure (AFI) Plan
France	2009	2 million EVs by 2020	Plan national pour le d´eveloppement des v´ehicules ´electriques et hybrides rechargeables
Germany	2009	One million electric vehicles on road by 2020	National Development Plan for Electric Mobility (2009)
	2013	One million electric vehicles on road by 2020 and six million by 2030	Sixth National Communication under the United Nations Framework Convention on Climate Change
Japan (The targets are set for all "new" vehicles: majority of this type are FCEV and hydrogen, but EVs and hybrid vehicles are also affected)	2010	set goals for popularization of such vehicles in 2020 and 2030, and defined five types of "next-generation vehicles": hybrid electric vehicles that combine a gasoline or other fuel engine with an electric motor; plug-in hybrid electric vehicles that can be charged externally; battery electric vehicles; fuel-cell electric vehicles that generate power from hydrogen and oxygen in the air; and clean diesel vehicles • aim to increase the share of new automobiles accounted for by next-generation automobiles to between 50 % and 70 % by 2030	Next-Generation Vehicle Strategy 2010
	2014	aim to increase the share of new automobiles accounted for by next-generation automobiles to between 50 % and 70 % by 2030	2014 Automobile Industry Strategy
	2018	aim to increase the share of new automobiles accounted for by next-generation automobiles to between 50 % and 70 % by 2030	METI's Long-term Strategy as Growth Strategy

South Korea	2010	Plan to produce 1.2 million green cars by 2015 (reach 21% share of domestic vehicle market) • aims to start mass producing plugged-in hybrid vehicles in 2012	Green Car Promotion Strategy 2010 (also called Green Car Roadmap)
	2010	200,000 EVs in 2020	Green Car Industry Stimulation Plan (2010)
Netherlands	2009	200,000 EVs in 2020	National Action Plan
	2013	200,000 EVs in 2020; 1 million by 2025	Energy Agreement for Sustainable Growth
	2017	100 % of new passenger cars sold must be zero-emission by 2030	Confidence in the Future 2017-2021 Coalition Agreement
Norway	2009	200,000 EVs in 2020 Battery-electric + plug-in-hybrid cars to reach 10 % of the passenger-car fleet	Action Plan for the Electrification of Road Transport
	2013	50,000 ZEVs on the road by 2018	Storting (Parliament) resolution
	2017	All new private cars, city buses and light vans sold to be zero-emission by 2025	National Transport Plan 2018-2029
Poland	2016	1 million EVs on the road by 2025	Ministry of Energy announcement
	2018	⩾ 10 % EV share by 2022	Act on Electromobility & Alternative Fuels
	2019	50,000 EVs by end-2020; 600,000 EV/HEV by 2030; 1 million by 2025	Strategy for Sustainable Transport Development 2030
Spain	2008	1 million EVs on the road by 2014	Energy-saving plan presented to Parliament
	2010	70,000 EVs registered by 2012; 250,000 EVs circulating by 2014	Estrategia Integral para el Impulso del Vehículo Eléctrico 2010-2014
	2014	Around 150,000 EVs in circulation by 2020	Estrategia de Impulso del Vehículo con Energías Alternativas (VEA) 2014-2020
Sweden	2009	fossil-fuel-independent vehicle fleet by 2030	Government communication on climate & energy policy
	2018	142,211 battery-electric & plug-in hybrid cars in use by 2020	Supplement to Sweden's National Policy Framework (NPF) for the EU

	2019	no new petrol- or diesel-driven cars will be sold after 2030	Statement of Government Policy to the Riksdag
The United Kingdom	2011	Government expects: hundreds of thousands of plug-in vehicles on the road by 2020	Making the Connection The Plug-In Vehicle Infrastructure Strategy
	2018	50%-70% new car sales as ultra low emission by 2030 All new cars and vans to be effectively zero emission by 2040	The Road to Zero Next steps towards cleaner road transport and delivering our Industrial Strategy
The United States	2009	Manufacturers had to earn ZEV credits equal to 11 % of their California light-duty sales for model-year 2009	Zero-Emission-Vehicle (ZEV) regulation
	2012	1.5 million ZEVs on California roads by 2025	Executive Order B-16-12
	2014	⩾ 1 million ZEVs & near-ZEVs by 2023	Charge Ahead California" Act
	2018	5 million ZEVs on the road by 2030	Executive Order B-48-18
	2020	100 % of new passenger-car and light-truck sales to be zero-emission by 2035	Executive Order N-79-20

Appendix D. Broad CPC Classification for Knowledge Stocks Construction

We construct a broader firm-level knowledge stock than the patents used in the main regressions because EV invention builds on capabilities that span adjacent technological fields. We track four categories that capture the main sources of spillovers into EV innovation: general alternative-fuel vehicles, batteries and charging, general automobile, and general electricity. The alternative-fuel category covers technologies such as fuel-cell, hybrid, and other non-petroleum drivetrains that share power-management architectures with EVs. The batteries and charging category includes cell chemistry, pack design, battery-management systems, thermal management, power electronics for charging, and communication protocols that govern fast and bidirectional charging. The general automobile category captures system-integration know-how, including vehicle bodies, chassis, braking and steering systems, safety, manufacturing processes, and platform engineering. The general electricity category covers electrical machines, control systems, and power-conversion technologies that underpin traction motors, inverters, converters, and grid interfaces. These four groups mirror the way firms generate EV patents: teams integrate a vehicle platform, an electrified powertrain, and a battery system while drawing on prior experience with other alternative-fuel designs and with generic electrical engineering.

CPC Code	Categories & Definitions
	EV or Hybrid Vehicles (General Alternative Fuel Vehicles)
B60L 15	Methods, circuits, or devices for controlling the traction-motor speed of electrically-propelled vehicles
B60L 50	Electric propulsion with power supplied within the vehicle
B60K 1	Arrangement or mounting of electrical propulsion units in vehicles
B60K 6	Arrangement or mounting of plural diverse prime-movers for mutual or common propulsion, e.g. hybrid propulsion systems comprising electric motors and internal combustion engines
B60W 20	Control systems specially adapted for hybrid vehicles
B60Y 2200/91	Indexing scheme relating to aspects cross-cutting vehicle technology: Electric vehicles
B60Y 2200/92	Indexing scheme relating to aspects cross-cutting vehicle technology: Hybrid vehicles
Y02T 10	Road transport of goods or passengers
Y02T 90	Climate Change Mitigation Technologies related to Transportation: Enabling technologies or technologies with a potential or indirect contribution to GHG emissions mitigation
Y10S 903	Technical subjects covered by former USPC cross-reference art collections [XRACs] and digests: Hybrid electric vehicles, HEVS
	Batteries / Charging
B60L 3/0046	Electric devices on electrically-propelled vehicles for safety purposes; Monitoring operating variables, e.g. speed, deceleration

	or energy consumption relating to electric energy storage systems, e.g. batteries or capacitors
B60L 53	Methods of charging batteries, specially adapted for electric vehicles; Charging stations or on-board charging equipment therefor; Exchange of energy storage elements in electric vehicles
B60L 55	Arrangements for supplying energy stored within a vehicle to a power network, i.e. vehicle-to-grid [V2G] arrangements
B60L 58	Methods or circuit arrangements for monitoring or controlling batteries or fuel cells, specially adapted for electric vehicles
B60W 10/24; B60W 10/26	Conjoint control of vehicle sub-units of different type or different function including control of energy storage means for electrical energy, e.g. batteries or capacitors
B60S 5/06	Supplying batteries to, or removing batteries from, vehicles (exchanging batteries for electric propulsion of vehicles
B60Y 2400/10; B60Y 2400/11; B60Y 2400/14; B60Y 2400/16	Special features of vehicle units: energy storage (e.g. hydrogen fuel; electric energy; batteries)
H01M	Processes or Means, e.g. Batteries, for the Direct Conversion of Chemical Energy into Electrical Energy
H02J 2310	The network for supplying or distributing electric power characterised by its spatial reach or by the load
Y02T 90	Enabling technologies or technologies with a potential or indirect contribution to GHG emissions mitigation
Y04S 10/126	Systems supporting electrical power generation, transmission or distribution: the energy generation units being or involving electric vehicles [EV] or hybrid vehicles [HEV], i.e. power aggregation of EV or HEV, vehicle to grid arrangements [V2G]
Y04S 30	Systems supporting specific end-user applications in the sector of transportation
	General Automobiles
B60B	Vehicle Wheels; Castors; and Axles
B60L 7	Electrodynamic brake systems for vehicles in general
B60K 5	Arrangement or mounting of internal-combustion or jet-propulsion units
B60K 7	Disposition of motor in, or adjacent to, traction wheel
B60K 8	Arrangement or mounting of propulsion units not provided for in one of the preceding main groups
B60K 11	Arrangement in connection with cooling of propulsion units
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
B60K 17	Arrangement or mounting of transmissions in vehicles
B60K 20	Arrangement or mounting of change-speed gearing control devices in vehicles

B60K 23	Arrangement or mounting of control devices for vehicle transmissions, or parts thereof, not otherwise provided for
B60K 26	Arrangements or mounting of propulsion unit control devices in vehicles
B60R	Vehicle Fitting or Parts
B60W 10	Conjoint control of vehicle sub-units of different type or different function (for propulsion of purely electrically-propelled vehicles with power supplied within the vehicle)
B60W 60	Drive control systems specially adapted for autonomous road vehicles
F01	Machines or Engines in General; Engine Plants in Gneral; Steam Engines
F02B	Internal-combustion Piston Engines; Combustion Engines in General
F02D	Controlling Combustion Engines
F02F	Cylinders, Pistons or Casings, for Combustion Engines; Arrangements of Sealings in Combustion Engines
F02M	Supplying Combustion Engines in General with Combustible Mixtures or Constituents Thereof
F02N	Starting of Combustion Engines; Starting Aids for Such Engines
F02P	Ignition, Other than Compression Ignition, for Interal-Combustion Engines; Testing of Ignition Timing in Compression-ignition Engines
	General Electricity
H01B 9	Power Cables
H01B 12	Superconductive or hyperconductive conductors, cables, or transmission lines
H01G	Capacitors
H01R	Electrically-Conductive Connections; Structural Associations of a Plurality of Mutually-Insulated Electrical Connecting Elements; Coupling Devices; Current Collectors
H02J 7	Circuit Arrangements of Systems for Supplying or Distributing Electric Power; Systems for Storing Electric Energy: Circuit arrangements for charging or depolarising batteries or for supplying loads from batteries
Y02E 40	Technologies for an efficient electrical power generation, transmission or distribution
Y04S 20	Management or operation of end-user stationary applications or the last stages of power distribution; Controlling, monitoring or operating thereof
Y10S 310	Electrical generator or motor structure
Y10S 320	Electricity: battery or capacitor charging or discharging
Y10S 323	Electricity: power supply or regulation systems
Y10S 439	Electrical connectors

Appendix E. List of Merging Firms

Patent assignee names in the European Patent Office database exhibit considerable variation in spelling, translation, and corporate structure. To ensure consistency, we reviewed each raw assignee string and standardized alternative translations, typographical variants, and regional name formats into a single English-language identifier. Where assignees represent business groups with multiple subsidiaries, we mapped each subsidiary name back to its ultimate corporate parent as of the filing date. In cases where independent firms were acquired or merged before or during the 2010-2021 window, we assigned all related patents to the post-acquisition parent name. This is based on the information on firms' official websites and annual reports. The mapping table below lists the canonical firm names in the left column alongside their raw variants in the right column.

Parent Firm	**Merged Firm**
AAM (American Axle & Manufacturing)	AAM Driveline Systems
	Metaldyne Company
AESC Group	Envision AESC Energy
	Envision AESC Japan Ltd.
Albermarle Corporation	Chemetall
	Rockwood Lithium
AGC	Asahi Glass Company
Aichi Electric Group	Aichi Automotive Company
	Aichi Emerson Electric Company
	Aichi Kikai Kogyo
Aisin Co., Ltd.	Aisin AW company
	Aisin Fukui Corporation
	Aisin Keikinzoku Company
	Aisin Seiki Company
Arkema	Atofina (Chemicals; Research)
	Elf Atochem (renamed to Arkema in 2000)
	Polytec Pt
Asahi Kasei	Asahi Chemical Company
AUO Corporation	Behr-Hella Thermocontrol
BAIC Group	Beiqi Foton Motor Company
	Blue Park Smart Energy (Beijing) Technology Company
	Blue Valley Smart Energy Technology Company
Baoneng Group	Qoros Automotive Company
BMW	Rolls-Royce
Bombardier	BRP (-Rotax&Company; Powertrain&Company)
Borg Warner	Akasol (AG, Engineering)
	Borgvarner Torktransfer Systems
	Drivetek
	Haldex Traction
	Remy International/Technologies

	Sevcon
Bridgestone	Asahi Carbon
Brrokfield	Graftech
Burelle	Cie Plastic Omnium SE
	Compagnie Plastic Omnium
	Inergy Automotive Systems Research
	Faurecia Bloc Avant
	Faurecia Industries
	HBPO
	Ingergy Automative Systems Research
	Plastic Omnium Advanced Innovation
Caterpillar Inc	Caterpillar (Commercial; Global Mining Equipment; Paving Products; Underground Mining)
CNH Industrial	Steyr-Daimler-Puch
Continental AG	Continental Automotive Technologies GMBH
	Continental Powertrain
	Continental Teves
	Contitech
Corning Inc.	Samsung Corning Precision Materials Company
Daihen Corporation	Kyuhen Company
Delta Electronics	Cyntec
	Eltek
Denka	Denki Kagaku Kogyo (Former name, changed in 2015)
Denso Corporation	Asmo Company
	Blue Nexus Corporation
	Denso Automotive; Electronics; Thermal Systems
	Fujitsu Ten
	Hamanako Denso Company
	Kyosan Denki Company
	Mirise Technologies Corporation
Dow Inc	Dow Chemical
	Dow Corning Corporation
	Dow Global Technologies
Dowa Holdings	Dowa Eco-system Co., Ltd.
	Dowa Electronics Materials Company
	Dowa Mining Company
Eaton Corporation	Eaton Cummins Automated Transmission Technologies
	Eaton Intelligent Power
	Eaton Power Quality Corporation
ENEOS Holdings	JX Metals Company
	JX Nippon Mining & Metals Corporation
	JX Nippon Oil & Energy Corporation
Envision Energy	Envision Dynamic Technology Company
	Envision Intelligent Innovation Dynamics Technology Ltd.

	Envision Power Technology Company
Enovix Corporation	Routejade
Evonik	Degussa
	Evonik (Industries; Litraion; Operations)
Geely	Shanghai Volvo Car R&D Company
	Volvo
	Lotus Cars
	Smart Automobile
Hanon Systems	Halla Climate Control Corporation (changed name in 2015)
	Halla Cisteon Climate Control Corporation (changed name in 2015)
Hanwha Corporation	Hanwha Aerospace Company
	Hanwha Global Asset Corporation
	Hanwha L&C Corporation
	Hanwha Polydreamer Company
Hanwha Solutions Corporation	Hanwha Advanced Materials Company
	Hanwha Energy Company
	Hanwha Q Cells & Advanced Materials Corporation
	Hanwha TechM Company
	Hanwha Techwin Company
Hanwha Systems Company	Hanwha Defense Company
	Hanwha Land Systems Company
Haohua Chemical Science&Technology	Sinochem Lantian Company
Honda	Asian Honda Motor Company
Ingersoll Rand	Thermo King
	Trane
Integer Holdings	Greatbatch
JMV Se&Co. Kg	Voith Turbo
Johnson & Johnson	Biosense Webster
	Cilag International
	Depuy Synthes Products
	Ethicon
JTEKT Corporation	Koyo Bearing North America
Kawasaki Heavy Ind	Kawasaki Iron Mining
	Kawasaki Jukogyo Kabushiki Kaisha
	Kawasaki Plant Systems
	Kawasaki Steel Corporation
	Kawasaki Trading Company
	Kawasaki Shipbuilding Corporation
	Kawasaki Robotics
LG Corporation	LG Cable
	LG Chern Ltd.
	LG CNS Company

	LG Hitachi
	LG Household &Health Care
	LG Information & Communications
	LG Magna E-Powertrain Co., Ltd.
	LG Metals Corporation
	LG N-Sys
	LG Precision Company
	LG Siltron
	LG Telecom
	LG Twin Towers
	LG Uplus Corporation
	LG-Caltex Gas Company
	LG-Nortel Company
LG Chem	LG New Energy Co., Ltd.
	LG Energy Solutions Ltd.
Linde	Praxair Technology
Lotte Energy Materials Corporation	Iljin Materials Company
	Iljin Steel Corporation
	Iljin LED Company
LX Semicon	Silicon Works Company
Lyondellbasell	Basell Polyolefine
Mahle Group	Behr & Company
Marelli Holdings	Calsonic Kansei Coporation
Mercedes-Benz Group	Daimler (Truck; Benz; Chrysler)
Meritor	Arvinmeritor Emissions Tech
	Arvinmeritor Light Vehicles Systems
	Arvinmeritor Technology
Microchip Tech	Atmel Automotive
	Atmel Corporation
Mitsuba Corporation	Tatsumi
Montana Tech Components	Varta Microbattery
Murata Manufacturing Company	Primatec
Nikola Corporation	Romeo Power
	Romeo Systems Technology
Nippon Denko Co., Ltd.	Chuo Denki Kogyo
Niterra Co., Ltd.	NGK Spark Plug Company
Nissan	Autech (Company; Japan)
Occidental Petroleum	Kerr-Mcgee Chemical Corporation (2006)
Onsemi	Fairchild Semiconductor Corporation (in 2016)
Panasonic	Sanyo Component
	Sanyo Electric Company
Raytheon Technologies Corporation	Goodrich Actuation Systems
	Goodrich Aerospace Services Private Limited
	Goodrich Corporation
	Goodrich Lighting Systems

	Hamilton Sundstrand
	Otis Elevator Company
	Rockwell Collins (Control Technologies)
	ROHR
	Rosemount
	Simmonds Precision Products
RESONAC	Showa Denko (Materials; Packaging Company)
Sany Group	Putzmeister Engineering/Moertelmaschinen
Schaffler AG	Vitesco Technologies
SERES Group	SF Motors
Solvay	CYTEC Industires
Stanley Black&Decker	Black&Decker
	MTD Products
Stellantis	Automobiles Citroen
	Automobiles Peugeot
	Chrysler (Corporation; Group)
	FCA (Fiat Chrysler Automobiles)
	FIAT Auto
	FPT Industrial
	Opel Elsenach
	Peugeot Citroen Automobiles
	PSA Automobiles
STIHL International	Andreas Stihl & Company
	FA. Andreas Stihl
Sumitomo Electric	Nissin Electric Company
TATA Group	Jaguar
	Jaguar Land Rover
	Land Rover
	Marcopolo
TE Connectivity	Tyco Electronics
Teijin	Nanogram Corporation
TDK Corporation	Densei Lambda
	EPCOS
	Hutchinson
Tenneco	Federal Mogul Corporation (in 2018)
Textron	BB Buggies
	Bell (Communications research; Helicopter)
Thales	Diehl Aerospace
	Gemalto
Thannhuber AG	Einhell
Toyota	Daihatsu Motor Company
Tuthill Corporation	Eagle-Picher (Industries; Technologies; Energy Products Coporation)
UACJ Corporation	Furukawa-Sky Aluminum Corporation
Volkswagen	Audi

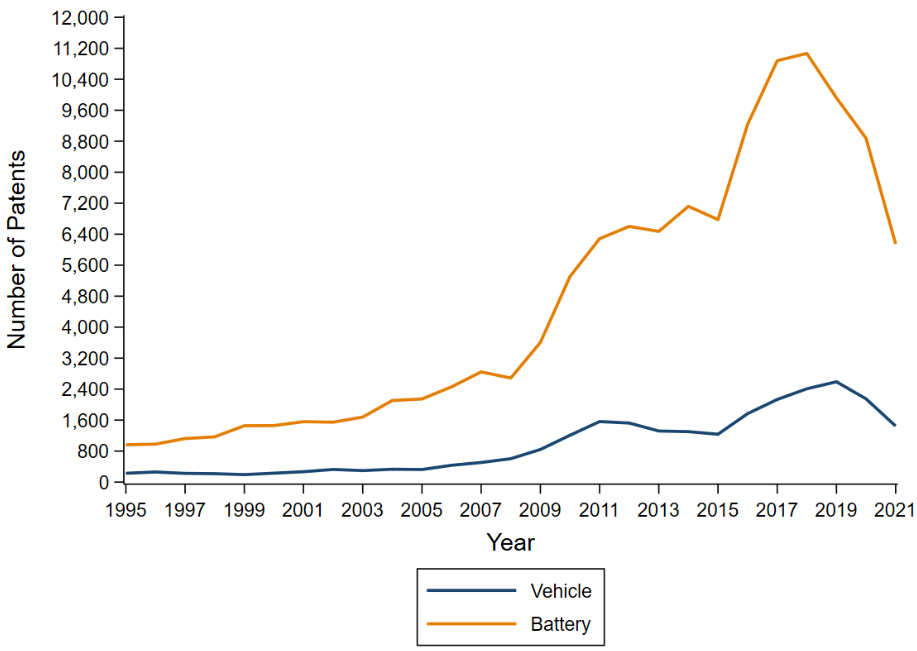
	Automobili Lamborghini
	Bentley Motors
	Porsche
Yuasa Corporation	Blue Energy
ZF Friedrichshafen AG	Fichtel & Sachs

Appendix F. Descriptive Results on Patents and Policies

This section documents descriptive evidence on EV innovation and policy. We plot the evolution of patenting by technology and identify the firms that contribute most to innovation during 2010-2021.

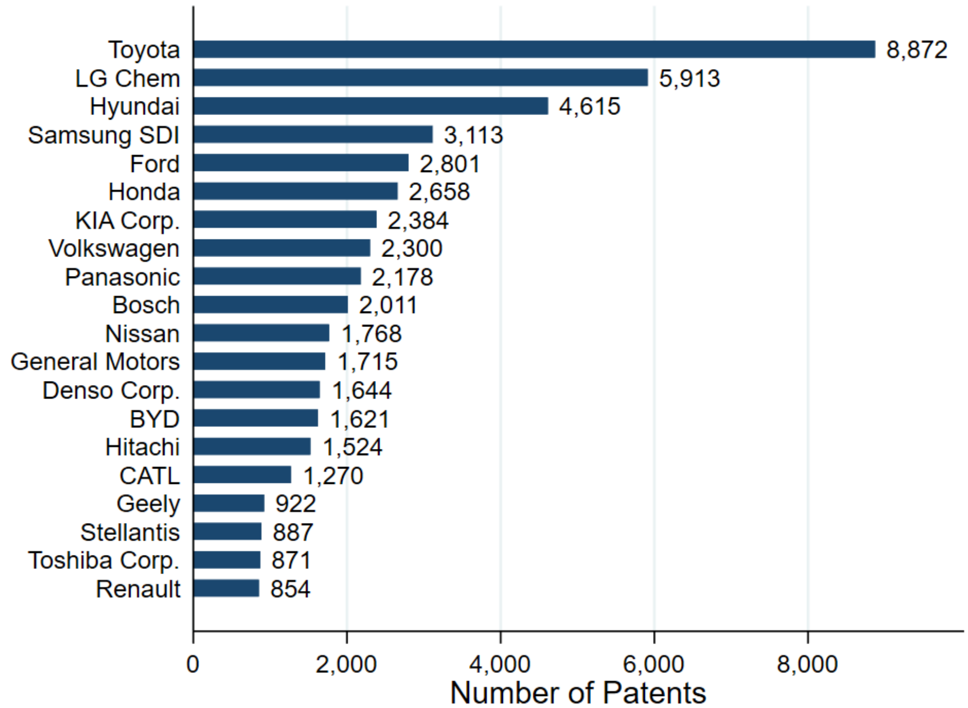
In addition to the overall patenting growth figure, we also plot the number of patents by technology. Battery inventions dominate throughout 1995-2021. Battery counts rise from roughly 1,000 per year in the late 1990s to more than 6,000 by 2011 and exceed 10,000 in 2016-2018. Vehicle patents start from a few hundred per year, accelerate after 2009, reach around 1,600 in 2011-2012, and peak near 2,400-2,500 in 2019. The ratio of battery to vehicle patents stays above three to one for most of the period and reaches about five to one at the 2017 peak. We start our analytical sample in 2010 to coincide with the sharp upswing in activity.

Fig. F.1. Number of Patents by Technology over Time



The top 20 firms mix two kinds of actors: global car manufacturers and specialized component suppliers. Toyota leads the global ranking. These top firms show strong representation from Japan and Korea, with notable contributions from the United States, Germany, and China. The prominence of dedicated battery firms indicates that upstream policy instruments that affect materials, cell manufacturing, and battery management may influence a large share of EV innovation.

Fig. F.2. Top 20 Firms' Patents from 2010 to 2021



Appendix G. Four Schemes on Weighting Construction

Below we formalize the four weighting schemes that translate national policy series into firm-level exposure. We define the study window as 2010-2021 and treat all earlier years as the pre-sample. We compile firm-country patenting from patent families and publication authorities, map publication authorities into the set of policy countries, and drop jurisdictions outside the policy sample. We classify firms as incumbents when they file at least one pre-sample patent in a sample country and as new entrants otherwise. We then compute country weights and apply GDP scaling that reflects market size. For firm i and country c, the exposure weight takes the form:

$$w_{ci} = \frac{w_{ci}^{P} GDP_{c}^{0.35}}{\sum_{c'} w_{c'i}^{P} GDP_{c'}^{0.35}}$$

Pre-sample weights with a home-country indicator: We anchor exposure at the firm's headquarters country. For incumbents who have patents during the pre-sample period, we calculate w_{ci}^{P} based on

$$w_{ci}^{P} = \frac{\#(pre-sample\ patents\ of\ firm\ i\ in\ country\ c)}{\#(pre-sample\ patents\ of\ firm\ i\ across\ all\ countries)}$$

For new entrants, we set w_{ci}^{P} = 1 for the headquarter country and set w_{ci}^{P} =0 for every other country. This scheme assigns all policy exposure to the home market and ignores the firm's filing footprint outside the headquarter country before 2010.

Pre-sample average weights. We recover the geographic footprint that precedes the study window. For every incumbent, we count pre-sample patent families by publication authority and compute country shares same as in pre-sample weights. New entrants have no pre-sample filings in sample countries, so we impute their vector of shares with the headquarter-specific average of incumbent firms. We take all incumbents that share the entrant's headquarter country, average their w_{ci}^{P} across countries and assign that average number to new entrants. This scheme locks exposure to the firm's historical footprint and prevents contemporaneous policy changes from influencing the weights.

Pre-sample by-technology weights. With the concerns that different technologies may experience different policy exposures, we repeat the pre-sample calculation within technology buckets: vehicle and battery technologies. This scheme preserves the advantages of the pre-sample approach while allowing the geographic mapping of policies to follow the technology in which the firm built its early know-how.

In-sample weights. We construct the main weights from the firm's patenting distribution during 2010-2021. These weights track where the firm seeks protection during the study window. The scheme increases power to detect policy effects that move innovation quickly because it aligns the mapping with current markets. The scheme can also reflect portfolio shifts that respond to policy changes, although it raises endogeneity concerns that the pre-sample schemes address.

Appendix H. Two-year Lag Models

To allow time for policy measures to influence firms' innovation decisions, we also estimate models that lag the policy variables by two years. This specification links patent counts in year t to fuel economy standards, financial incentives and other policy indicators in year t – 2. The two-year lag captures the fact that firms need time to adjust their industrial strategies, carry out research projects, and file patent applications after a policy change.

The results for the two-year lag remain very close to those in the one-year lag specification and confirm the robustness of our main findings. Fuel economy standards and financial incentives continue to show positive and statistically significant associations with patenting, and their estimated effects become somewhat larger relative to the one-year lag models. The signs and significance of the interaction terms and knowledge stock variables also stay broadly stable, which suggests that the dynamic pattern of innovation response is consistent across lag lengths. At the same time, the two-year lag requires a longer overlap between policy and patent data and therefore reduces the estimation sample by about 1,100 firms and roughly 3,500 firm-year observations. For this reason, we present the two-year lag results in the appendix and focus on the one-year lag specification in the main text, while using the longer lag as a robustness check on the timing of policy effects.

Table H.1

Main Regression Results with Two-year Lags.

	(1)	(2)	(3)
End-Use Gasoline Price	-0.297	0.575	2.141
	(1.231)	(1.093)	(1.355)
Standard Stringency	0.682^{***}	0.518^{***}	0.044
	(0.144)	(0.133)	(0.198)
Energy Efficiency - Transportation R&D	0.078^{*}	0.098^{**}	-0.146^{*}
	(0.034)	(0.034)	(0.061)
Target Stringency	0.035	0.163^{*}	-0.094
	(0.041)	(0.079)	(0.107)
Financial Incentives	0.175^{***}		0.166^{***}
	(0.041)		(0.038)
Use Benefits	-0.350		-0.269
	(0.572)		(0.583)
Transport Energy-Efficiency R&D × Target Stringency			0.019^{***}
			(0.005)
End-Use Gasoline Price × Target Stringency			-0.173
			(0.118)
Standard Stringency × Target Stringency			0.046^{*}
			(0.022)
Int. knowledge stocks - EVs	0.542^{***}	0.547^{***}	0.547^{***}
	(0.045)	(0.045)	(0.045)
Int. knowledge stocks - batteries	0.429^{***}	0.448^{***}	0.431^{***}
	(0.042)	(0.043)	(0.041)
Int. knowledge stocks - general auto	-0.048	-0.051	-0.051
	(0.035)	(0.036)	(0.035)
Int. knowledge stocks - general electricity	-0.042	-0.048	-0.040
	(0.028)	(0.029)	(0.027)
Ext. knowledge stocks - EVs	-0.220^{*}	-0.187	-0.188
	(0.103)	(0.103)	(0.098)
Ext. knowledge stocks - batteries	0.713^{***}	0.705^{***}	0.631^{***}
	(0.176)	(0.170)	(0.176)
Ext. knowledge stocks - general auto	-0.270^{*}	-0.359^{***}	-0.277^{*}
	(0.110)	(0.095)	(0.110)
Ext. knowledge stocks - general electricity	-0.282	-0.244	-0.217
	(0.205)	(0.202)	(0.198)
Observations	19514	19514	19514
Number of firms	3101	3101	3101
Log-likelihood	-66083	-66761	-65725

Notes: Standard errors in parentheses: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$. All models include year fixed effects and pre-sample controls. Standard errors clustered by firm. Every variable in the log form except for use benefits.

Table H.2

By Technology Regression Results with Two-year Lags.

	(1) Vehicle	(2) Vehicle	(3) Vehicle	(4) Battery	(5) Battery	(6) Battery
End-Use Gasoline Price	-0.341	0.354	2.220	-0.428	0.463	2.201
	(1.463)	(1.323)	(1.587)	(1.245)	(1.116)	(1.383)
Standard Stringency	0.744***	0.574***	0.036	0.700***	0.536***	0.007
	(0.172)	(0.169)	(0.247)	(0.146)	(0.138)	(0.200)
Energy Efficiency -	0.054	0.079	-0.171*	0.076*	0.096**	-0.150*
Transportation R&D	(0.042)	(0.043)	(0.077)	(0.034)	(0.034)	(0.062)
Target Stringency	0.051	0.199	-0.095	0.038	0.167*	-0.098
	(0.058)	(0.115)	(0.133)	(0.042)	(0.083)	(0.111)
Financial Incentives	0.180***		0.167***	0.172***		0.161***
	(0.053)		(0.049)	(0.042)		(0.039)
Use Benefits	-0.770		-0.707	-0.454		-0.365
	(0.714)		(0.728)	(0.605)		(0.614)
Transport Energy-Efficiency			0.019***			0.019***
R&D × Target Stringency			(0.005)			(0.005)
End-Use Gasoline Price ×			-0.177			-0.188
Target Stringency			(0.139)			(0.120)
Standard Stringency × Target			0.050			0.051*
Stringency			(0.026)			(0.022)
Int. knowledge stocks - EVs	0.554***	0.562***	0.560***	0.545***	0.549***	0.549***
	(0.055)	(0.055)	(0.055)	(0.045)	(0.045)	(0.045)
Int. knowledge stocks -	0.404***	0.424***	0.405***	0.420***	0.439***	0.422***
batteries	(0.051)	(0.051)	(0.050)	(0.042)	(0.043)	(0.041)
Int. knowledge stocks -	-0.060	-0.066	-0.063	-0.050	-0.053	-0.053
general auto	(0.038)	(0.038)	(0.038)	(0.036)	(0.036)	(0.036)
Int. knowledge stocks -	-0.036	-0.040	-0.034	-0.043	-0.049	-0.041
general electricity	(0.033)	(0.034)	(0.033)	(0.028)	(0.029)	(0.027)
Ext. knowledge stocks - EVs	-0.214	-0.216	-0.177	-0.218*	-0.191	-0.183
	(0.116)	(0.114)	(0.111)	(0.104)	(0.103)	(0.099)
Ext. knowledge stocks -	0.679**	0.639**	0.589**	0.737***	0.719***	0.658***
batteries	(0.212)	(0.205)	(0.212)	(0.178)	(0.173)	(0.178)
Ext. knowledge stocks -	-0.279*	-0.336**	-0.296*	-0.269*	-0.351***	-0.278*
general auto	(0.129)	(0.111)	(0.128)	(0.112)	(0.097)	(0.112)
Ext. knowledge stocks -	-0.247	-0.181	-0.168	-0.319	-0.275	-0.265
general electricity	(0.263)	(0.259)	(0.257)	(0.209)	(0.207)	(0.202)
Observations	11625	11625	11625	18173	18173	18173
Number of firms	1685	1685	1685	2872	2872	2872
Log-likelihood	-49354	-49873	-49061	-64430	-65060	-64063

Notes: Standard errors in parentheses: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$. All models include year fixed effects and pre-sample controls. Standard errors clustered by firm. Every variable in the log form except for use benefits.

Appendix I. Additional Robustness Checks

Table I.1

Main Regression Results Using Pre-Sample Weights with Home Country Indicator.

	(1)	(2)	(3)
End-Use Gasoline Price	-0.306	-0.587	-0.120
	(0.531)	(0.316)	(0.851)
Standard Stringency	0.271**	0.226**	0.048
	(0.091)	(0.083)	(0.124)
Transport Energy-Efficiency R&D	0.075*	0.102***	-0.166**
	(0.035)	(0.030)	(0.057)
Target Stringency	0.036**	0.046**	-0.201*
	(0.012)	(0.015)	(0.081)
Financial Incentives	0.059*		0.054*
	(0.024)		(0.024)
Use Benefits	-0.443		-0.241
	(0.447)		(0.447)
Transport Energy-Efficiency R&D × Target Stringency			0.021***
			(0.004)
End-Use Gasoline Price × Target Stringency			0.040
			(0.082)
Standard Stringency × Target Stringency			0.020
			(0.015)
Int. knowledge stocks - EVs	0.545***	0.550***	0.546***
	(0.039)	(0.039)	(0.039)
Int. knowledge stocks - batteries	0.476***	0.491***	0.477***
	(0.037)	(0.036)	(0.036)
Int. knowledge stocks - general auto	-0.044	-0.050	-0.049
	(0.028)	(0.029)	(0.028)
Int. knowledge stocks - general electricity	-0.052*	-0.054*	-0.049
	(0.025)	(0.025)	(0.025)
Ext. knowledge stocks - EVs	-0.077	-0.058	-0.064
	(0.088)	(0.089)	(0.084)
Ext. knowledge stocks - batteries	0.624***	0.629***	0.523**
	(0.185)	(0.180)	(0.181)
Ext. knowledge stocks - general auto	-0.282**	-0.316***	-0.279**
	(0.089)	(0.069)	(0.091)
Ext. knowledge stocks - general electricity	-0.284	-0.302	-0.189
	(0.214)	(0.220)	(0.199)
Observations	22998	22998	22998
Numbers of firms	4227	4227	4227
Log-likelihood	-69521	-69826	-69092

Notes: Standard errors in parentheses: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$. All models include year fixed effects and pre-sample controls. Standard errors clustered by firm. Every variable in the log form except for use benefits.

Table I.2:

By Technology Regression Results Using Pre-Sample Average Weights.

	(1) Vehicle	(2) Vehicle	(3) Vehicle	(4) Battery	(5) Battery	(6) Battery
End-Use Gasoline Price	-0.200	-0.555	-0.619	-0.347	-0.631	-0.128
	(0.646)	(0.411)	(1.070)	(0.543)	(0.323)	(0.871)
Standard Stringency	0.332**	0.282*	0.136	0.273**	0.227**	0.035
	(0.125)	(0.114)	(0.154)	(0.094)	(0.085)	(0.125)
Transport Energy-Efficiency R&D	0.060	0.090*	-0.214**	0.073*	0.101***	-0.169**
	(0.043)	(0.037)	(0.076)	(0.036)	(0.031)	(0.058)
Target Stringency	0.036*	0.046*	-0.272**	0.036**	0.046**	-0.206*
	(0.015)	(0.021)	(0.099)	(0.012)	(0.016)	(0.083)
Financial Incentives	0.051		0.045	0.059*		0.054*
	(0.028)		(0.028)	(0.025)		(0.025)
Use Benefits	-0.566		-0.302	-0.452		-0.245
	(0.567)		(0.565)	(0.454)		(0.455)
Transport Energy-Efficiency R&D × Target Stringency			0.024***			0.021***
			(0.005)			(0.004)
End-Use Gasoline Price × Target Stringency			0.108			0.037
			(0.101)			(0.084)
Standard Stringency × Target Stringency			0.019			0.022
			(0.018)			(0.015)
Int. knowledge stocks - EVs	0.598***	0.602***	0.597***	0.547***	0.551***	0.548***
	(0.049)	(0.049)	(0.048)	(0.039)	(0.039)	(0.039)
Int. knowledge stocks - batteries	0.428***	0.442***	0.428***	0.471***	0.486***	0.472***
	(0.044)	(0.043)	(0.043)	(0.037)	(0.037)	(0.036)
Int. knowledge stocks - general auto	-0.075*	-0.082**	-0.080**	-0.045	-0.051	-0.050
	(0.030)	(0.031)	(0.030)	(0.028)	(0.029)	(0.028)
Int. knowledge stocks - general electricity	-0.031	-0.032	-0.028	-0.053*	-0.055*	-0.050*
	(0.029)	(0.030)	(0.029)	(0.025)	(0.025)	(0.025)
Ext. knowledge stocks - EVs	-0.102	-0.092	-0.097	-0.082	-0.063	-0.067
	(0.097)	(0.099)	(0.092)	(0.089)	(0.089)	(0.084)
Ext. knowledge stocks - batteries	0.577**	0.559**	0.445*	0.638***	0.642***	0.540**
	(0.217)	(0.209)	(0.214)	(0.188)	(0.182)	(0.183)
Ext. knowledge stocks - general auto	-0.288**	-0.299***	-0.290**	-0.280**	-0.313***	-0.277**
	(0.099)	(0.078)	(0.100)	(0.089)	(0.070)	(0.091)
Ext. knowledge stocks - general electricity	-0.209	-0.223	-0.068	-0.306	-0.324	-0.219
	(0.257)	(0.264)	(0.248)	(0.217)	(0.223)	(0.202)
Observations	13780	13780	13780	21671	21671	21671
Number of firms	2196	2196	2196	3934	3934	3934
Log-likelihood	-50550	-50761	-50146	-68019	-68318	-67594

Notes: Standard errors in parentheses: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$. All models include year fixed effects and pre-sample controls. Standard errors clustered by firm. Every variable in the log form except for use benefits.

Table I.3

Main Regression Results Using Pre-Sample Average Weights.

	(1)	(2)	(3)
End-Use Gasoline Price	1.072	1.078	0.218
	(0.800)	(0.852)	(1.227)
Standard Stringency	0.302*	0.255*	0.065
	(0.129)	(0.124)	(0.168)
Transport Energy-Efficiency R&D	0.083*	0.106***	-0.196**
	(0.033)	(0.029)	(0.062)
Target Stringency	0.030	0.048	-0.287**
	(0.023)	(0.035)	(0.088)
Financial Incentives	0.042		0.037
	(0.030)		(0.029)
Use Benefits	-0.842		-0.698
	(0.506)		(0.493)
Transport Energy-Efficiency R&D × Target Stringency			0.024***
			(0.004)
End-Use Gasoline Price × Target Stringency			0.102
			(0.106)
Standard Stringency × Target Stringency			0.027
			(0.020)
Int. knowledge stocks - EVs	0.542***	0.543***	0.543***
	(0.039)	(0.039)	(0.039)
Int. knowledge stocks - batteries	0.473***	0.485***	0.474***
	(0.037)	(0.036)	(0.036)
Int. knowledge stocks - general auto	-0.043	-0.050	-0.046
	(0.027)	(0.029)	(0.027)
Int. knowledge stocks - general electricity	-0.049	-0.050*	-0.046
	(0.025)	(0.025)	(0.024)
Ext. knowledge stocks - EVs	-0.069	-0.069	-0.060
	(0.087)	(0.091)	(0.082)
Ext. knowledge stocks - batteries	0.670***	0.593***	0.595***
	(0.168)	(0.169)	(0.160)
Ext. knowledge stocks - general auto	-0.361***	-0.341***	-0.356***
	(0.081)	(0.073)	(0.080)
Ext. knowledge stocks - general electricity	-0.232	-0.198	-0.169
	(0.202)	(0.210)	(0.184)
Observations	22998	22998	22998
Log-likelihood	-69462	-69653	-69006

Notes: Standard errors in parentheses: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$. All models include year fixed effects and pre-sample controls. Standard errors clustered by firm. Every variable in the log form except for use benefits.

Table I.4

By Technology Regression Results Using Pre-Sample Average Weights.

	(1) Vehicle	(2) Vehicle	(3) Vehicle	(4) Battery	(5) Battery	(6) Battery
End-Use Gasoline Price	1.725	1.744	0.608	1.031	1.021	0.175
	(0.989)	(0.981)	(1.460)	(0.790)	(0.857)	(1.244)
Standard Stringency	0.362*	0.298	0.100	0.302*	0.255*	0.057
	(0.171)	(0.164)	(0.210)	(0.132)	(0.126)	(0.171)
Transport Energy-Efficiency R&D	0.051	0.087*	-0.244**	0.082*	0.106***	-0.202**
	(0.041)	(0.036)	(0.080)	(0.033)	(0.030)	(0.063)
Target Stringency	0.038	0.061	-0.305**	0.031	0.048	-0.293**
	(0.032)	(0.052)	(0.107)	(0.024)	(0.036)	(0.091)
Financial Incentives	0.039		0.034	0.041		0.036
	(0.037)		(0.036)	(0.031)		(0.030)
Use Benefits	-1.288*		-1.169*	-0.872		-0.717
	(0.597)		(0.575)	(0.511)		(0.500)
Transport Energy-Efficiency			0.025***			0.024***
R&D × Target Stringency			(0.006)			(0.005)
End-Use Gasoline Price ×			0.126			0.104
Target Stringency			(0.125)			(0.109)
Standard Stringency × Target			0.026			0.028
Stringency			(0.025)			(0.021)
Int. knowledge stocks - EVs	0.596***	0.589***	0.598***	0.544***	0.544***	0.545***
	(0.050)	(0.049)	(0.050)	(0.039)	(0.039)	(0.040)
Int. knowledge stocks - batteries	0.415***	0.433***	0.416***	0.468***	0.480***	0.469***
	(0.044)	(0.042)	(0.043)	(0.037)	(0.036)	(0.036)
Int. knowledge stocks - general	-0.072*	-0.080**	-0.076**	-0.043	-0.051	-0.047
auto	(0.029)	(0.030)	(0.029)	(0.028)	(0.029)	(0.027)
Int. knowledge stocks - general	-0.025	-0.027	-0.023	-0.049*	-0.050*	-0.047
electricity	(0.029)	(0.029)	(0.028)	(0.025)	(0.025)	(0.024)
Ext. knowledge stocks - EVs	-0.106	-0.120	-0.097	-0.072	-0.072	-0.062
	(0.092)	(0.100)	(0.088)	(0.087)	(0.091)	(0.082)
Ext. knowledge stocks - batteries	0.637**	0.501*	0.544**	0.681***	0.600***	0.609***
	(0.196)	(0.198)	(0.189)	(0.169)	(0.171)	(0.162)
Ext. knowledge stocks - general	-0.373***	-0.324***	-0.373***	-0.359***	-0.338***	-0.354***
auto	(0.092)	(0.082)	(0.091)	(0.081)	(0.073)	(0.080)
Ext. knowledge stocks - general	-0.134	-0.064	-0.043	-0.248	-0.211	-0.193
electricity	(0.244)	(0.257)	(0.229)	(0.204)	(0.213)	(0.186)
Observations	13340	13340	13340	21084	21084	21084
Log-likelihood	-50210	-50476	-49830	-67967	-68162	-67508

Notes: Standard errors in parentheses: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$. All models include year fixed effects and pre-sample controls. Standard errors clustered by firm. Every variable in the log form except for use benefits.

Table I.5

Main Regression Results Using In-Sample Weights without Chinese Firms.

	(1)	(2)	(3)
End-Use Gasoline Price	-0.538	0.126	0.107
	(1.195)	(1.088)	(1.257)
Standard Stringency	0.400**	0.301**	0.308
	(0.123)	(0.105)	(0.160)
Transport Energy-Efficiency R&D	-0.047	-0.051	-0.125
	(0.037)	(0.037)	(0.072)
Target Stringency	0.010	0.050	0.011
	(0.028)	(0.033)	(0.094)
Financial Incentives	0.087**		0.087**
	(0.028)		(0.030)
Use Benefits	0.388		0.412
	(0.532)		(0.534)
Transport Energy-Efficiency R&D × Target			0.007
Stringency			(0.005)
End-Use Gasoline Price × Target Stringency			-0.030
			(0.115)
Standard Stringency × Target Stringency			-0.003
			(0.024)
Int. knowledge stocks - EVs	0.630***	0.634***	0.633***
	(0.050)	(0.050)	(0.050)
Int. knowledge stocks - batteries	0.378***	0.384***	0.378***
	(0.040)	(0.040)	(0.040)
Int. knowledge stocks - general auto	-0.096**	-0.095**	-0.098**
	(0.036)	(0.035)	(0.035)
Int. knowledge stocks - general electricity	0.005	0.003	0.006
	(0.027)	(0.027)	(0.027)
Ext. knowledge stocks - EVs	-0.281**	-0.230**	-0.265**
	(0.089)	(0.087)	(0.087)
Ext. knowledge stocks - batteries	0.335	0.350	0.323
	(0.212)	(0.189)	(0.217)
Ext. knowledge stocks - general auto	0.284*	0.232	0.265*
	(0.126)	(0.124)	(0.125)
Ext. knowledge stocks - general electricity	-0.306	-0.321	-0.291
	(0.241)	(0.229)	(0.246)
Observations	17098	17098	17098
Numbers of firms	2535	2535	2535
Log-likelihood	-44852	-45040	-44815

Notes: Standard errors in parentheses: *** p < 0.001, ** p < 0.01, * p < 0.05. All models include year fixed effects and pre-sample controls. Standard errors clustered by firm. Every variable in the log form except for use benefits.

Table I.6

Main Regression Results Using In-Sample Weights with an exponent of 1 on GDP.

	(1)	(2)	(3)
End-Use Gasoline Price	0.554	1.340	0.864
	(1.283)	(1.092)	(1.472)
Standard Stringency	0.266***	0.147	0.099
	(0.079)	(0.081)	(0.173)
Transport Energy-Efficiency R&D	0.079*	0.090**	-0.208**
	(0.031)	(0.030)	(0.074)
Target Stringency	0.070*	0.182**	-0.070
	(0.031)	(0.064)	(0.100)
Financial Incentives	0.130***		0.123***
	(0.034)		(0.033)
Use Benefits	0.101		0.127
	(0.617)		(0.621)
End-Use Gasoline Price × Target Stringency			0.024***
			(0.006)
Transport Energy-Efficiency R&D × Target Stringency			-0.012
			(0.117)
Standard Stringency × Target Stringency			0.004
			(0.017)
Int. knowledge stocks - EVs	0.540***	0.543***	0.545***
	(0.040)	(0.039)	(0.039)
Int. knowledge stocks - batteries	0.472***	0.483***	0.473***
	(0.036)	(0.036)	(0.035)
Int. knowledge stocks - general auto	-0.048	-0.047	-0.052
	(0.029)	(0.029)	(0.029)
Int. knowledge stocks - general electricity	-0.050*	-0.054*	-0.050*
	(0.025)	(0.025)	(0.024)
Ext. knowledge stocks - EVs	-0.140	-0.098	-0.113
	(0.090)	(0.087)	(0.085)
Ext. knowledge stocks - batteries	0.569**	0.586***	0.494**
	(0.174)	(0.172)	(0.169)
Ext. knowledge stocks - general auto	-0.214*	-0.299***	-0.215*
	(0.093)	(0.077)	(0.091)
Ext. knowledge stocks - general electricity	-0.216	-0.196	-0.162
	(0.212)	(0.211)	(0.200)
Observations	22998	22998	22998
Numbers of firms	4227	4227	4227
Log-likelihood	-68930	-69328	-68498

Notes: Standard errors in parentheses: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$. All models include year fixed effects and pre-sample controls. Standard errors clustered by firm. Every variable in the log form except for use benefits.

Table I.7

By Technology Regression Results Using In-Sample Weights with an exponent of 1 on GDP.

	(1) Vehicle	(2) Vehicle	(3) Vehicle	(4) Battery	(5) Battery	(6) Battery
End-Use Gasoline Price	0.533	1.183	0.914	0.489	1.312	0.919
	(1.494)	(1.284)	(1.674)	(1.302)	(1.107)	(1.500)
Standard Stringency	0.301**	0.178	0.113	0.273***	0.152	0.078
	(0.100)	(0.103)	(0.230)	(0.080)	(0.082)	(0.178)
Transport Energy-Efficiency	0.064	0.075*	-0.234*	0.079*	0.090**	-0.210**
R&D	(0.038)	(0.038)	(0.093)	(0.031)	(0.031)	(0.076)
Target Stringency	0.079	0.193*	-0.074	0.071*	0.187**	-0.071
	(0.043)	(0.087)	(0.125)	(0.032)	(0.067)	(0.105)
Financial Incentives	0.126**		0.117**	0.131***		0.124***
	(0.042)		(0.040)	(0.035)		(0.034)
Use Benefits	-0.165		-0.179	0.136		0.167
	(0.706)		(0.711)	(0.653)		(0.655)
Transport Energy-Efficiency			0.024***			0.024***
R&D × Target Stringency			(0.007)			(0.006)
End-Use Gasoline Price ×			-0.015			-0.025
Target Stringency			(0.138)			(0.120)
Standard Stringency × Target			0.006			0.007
Stringency			(0.021)			(0.017)
Int. knowledge stocks - EVs	0.589***	0.593***	0.596***	0.542***	0.544***	0.547***
	(0.050)	(0.049)	(0.049)	(0.040)	(0.039)	(0.039)
Int. knowledge stocks -	0.425***	0.434***	0.426***	0.467***	0.477***	0.468***
batteries	(0.044)	(0.043)	(0.043)	(0.036)	(0.036)	(0.035)
Int. knowledge stocks - general	-0.077*	-0.078*	-0.082**	-0.049	-0.048	-0.053
auto	(0.032)	(0.031)	(0.031)	(0.030)	(0.029)	(0.029)
Int. knowledge stocks - general	-0.033	-0.034	-0.032	-0.051*	-0.055*	-0.050*
electricity	(0.029)	(0.029)	(0.028)	(0.025)	(0.025)	(0.024)
Ext. knowledge stocks - EVs	-0.146	-0.125	-0.115	-0.146	-0.103	-0.117
	(0.103)	(0.097)	(0.097)	(0.090)	(0.087)	(0.086)
Ext. knowledge stocks -	0.523*	0.521*	0.435*	0.574**	0.592***	0.503**
batteries	(0.208)	(0.206)	(0.203)	(0.176)	(0.174)	(0.171)
Ext. knowledge stocks -	-0.210	-0.277**	-0.221*	-0.207*	-0.294***	-0.209*
general auto	(0.109)	(0.090)	(0.106)	(0.094)	(0.078)	(0.092)
Ext. knowledge stocks -	-0.170	-0.132	-0.095	-0.229	-0.208	-0.184
general electricity	(0.271)	(0.268)	(0.261)	(0.216)	(0.214)	(0.203)
Observations	13780	13780	13780	21671	21671	21671
Number of firms	2196	2196	2196	3934	3934	3934
Log-likelihood	-50112	-50366	-49730	-67419	-67814	-66989

Notes: Standard errors in parentheses: *** p < 0.001, ** p < 0.01, * p < 0.05. All models include year fixed effects and pre-sample controls. Standard errors clustered by firm. Every variable in the log form except for use benefits.