Directed Technical Change under Regulation: Evidence from the Chinese Auto Industry *

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Abstract

This paper studies the impacts of China's dual-credit policy (joint management of fuel consumption and new energy vehicle credits) on the electrification of the auto industry. Using a heterogeneous-firm model, newly assembled data, and difference-in-differences designs, we document several findings. First, the policy significantly lowers the relative price of electric vehicles (EVs) compared with gasoline vehicles (GVs). Second, small firms reduce GV production to avoid credit obligations, while larger firms relatively expand it. Third, fuel economy improvement slows as EV production serves as a substitute compliance strategy. Fourth, cannibalization effect discourages incumbents to produce high-quality EVs while newcomers offer superior products. Fifth, innovation shifts toward EV and intelligence-related technologies, weakening path dependence. Finally, EV-focused firms hire more skilled labor and cluster in the most developed regions. Our findings highlight the positive role of the dual-credit policy in directing technical change towards electrification.

Keyword: Electric Vehicle, Dual-Credit Policy, Directed Technical Change, Auto Industry

JEL codes: H23, L50, L62, O14, O25, O30, Q58

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1 Introduction

The development of electric vehicles (EVs) and related technologies is crucial for reducing fossil fuel consumption and carbon dioxide emissions. Beyond their environmental benefits, the rise of EVs is transforming the global automotive industry, with spillover effects on related sectors such as battery manufacturing and artificial intelligence. However, because EVs generate positive externalities, private investment in their development often falls short of the socially optimal level. Designing effective policies to promote EV adoption and innovation has therefore become a global priority. In addition to supportive measures such as subsidies and infrastructure investment, regulatory policies have gained increasing popularity among governments. Yet the impact of such policies on the electrification of the automotive industry remains under-investigated.

This paper studies how the dual-credit policy–the joint regulation of fuel consumption and EV production through a credit trading system–reshapes the supply side of the automotive industry and affects the growth of EVs in China, the world's largest car market and a leading countries in EV development. We focuses on firms' production decisions regarding scale, pricing, and product attributes across gasoline vehicles (GVs) and EVs, and on how credit trading and policy's dual targets redirect innovation and worker allocation.

The dual-credit policy, formally known titled *Parallel Management of New Energy Vehicle (NEV) and Corporate Average Fuel Consumption (CAFC) Credits for Passenger Vehicles*, combines elements of the Corporate Average Fuel Economy (CAFE) regulation in the United States and Europe with California's Zero-Emission Vehicle (ZEV) program. Introduced in September 2017 and implemented in April 2018, it (1) requires CAFC credit, calculated as the gap between firms' average fuel consumption and the compliance level, to be non-negative for every firm after credit trading; (2) introduces a tradable NEV credit scheme and a 1:1 conversion rate from NEV credits to CAFC credits (but not the other way round), allowing firms to outsource

CAFC compliance to those with comparative advantages in generating credits; (3) introduces an NEV credit target for firms whose GV production exceeds a threshold, generating aggregate demand for EVs that redirects production and innovation; (4) sets calculation methods for both credits that create targeted demand for a selected set of car attributes.

To understand the impacts of the dual-credit policy, we build a static model of heterogeneous car manufacturers maximizing profits under two-target regulations. Firms differ in their technology endowment, factor market prices, and existing product mix. They choose the composition of their product fleet, product prices, and product attributes to maximize profits.

The model produces several testable predictions. First, the policy implicitly imposes a larger net tax burden on GVs than on EVs. Second, producing EVs is more effective than lowering GV fuel consumption for meeting CAFC targets, reducing incentives to improve fuel economy. Third, GV production diverges: medium-size producers scale back to avoid NEV credit targets, whereas large producers relatively expand production. Fourth, newcomers build higher-quality EVs than incumbents. Fifth, optimal attribute choices are positively correlated with domain-specific technology endowments. Finally, optimal demand for specific types of talent depends on attribute choices, output elasticities, and wages.

To test these predictions, we conduct the empirical analysis in two steps. First, we examine manufacturers' production responses. We study effects on both the quantity and the quality of cars produced, measuring quality with a set of car attributes. We also distinguish between incumbents and new entrants following the policy shock. In the second step, we explore manufacturers' input responses, focusing on the impacts of the dual-credit policy on innovation and workforce allocation.

The policy is economy-wide, leaving no pure control group. We therefore test model-based predictions with difference-in-differences and event-study designs that define treatment and control groups around policy-defined thresholds and predicted margins of adjustment, based on pre-determined firm characteristics. To establish causality, we assess parallel pre-trends between the treatment and control groups. We also account for concurrent demand-side interventions, including national/local purchase subsidies, tax exemptions, and charging investments, with year fixed effects and additional controls where relevant.

To support the empirical analysis, we use various data sets. First, we draw on administrative records of car production and credits. Second, we compile a new data set that covers the (near) universe of all new cars introduced by manufacturers, and augment it with detailed specification-level data from a leading car information-sharing platform. For innovation, we compile patents filed by car manufacturers, their key shareholders (those holding more than 25% ownership), and all affiliated firms wholly or partially owned by those shareholders. Finally, we collect LinkedIn profiles of China-based users who worked for car manufacturers between 2010 and 2024 to describe workforce allocation within the auto industry.

We document several findings consistent with the model predictions. First, we find that the relative retail price of EVs compared with GVs falls by 48 log points after the policy shock. This sharp decline coincides with a reduction in GV production and a rapid growth in EV production. Decomposing this relative price drop indicates that the credit value directly generated by the policy explains 1/4 of the reduction. Second, firms whose pre-period GV production exceeded the threshold cut their GV output by 26 log points, and among these firms, the reduction is mainly driven by relatively smaller ones. Third, firms with above-median pre-period CAFC levels significantly increase EV production but do not reduce GV fuel consumption more than their below-median counterparts, leading to slower improvement in fuel economy of GVs. Fourth, but of the lack of competition with their own products, newcomers build better EVs than incumbents, especially on attributes valued by consumers but not rewarded in credit calculations. Fifth, after the policy shock, path dependence in innovation becomes much weaker, suggesting that the policy induces firms to work in EV-related and intelligence-related fields rather than those where they hold comparative advantage. Moreover, the policy shock induces newcomers to increase innovation in automobile-related fields, especially EV-related technologies even before they launch their first car. Finally, EV-focused firms are more likely to locate in developed regions with a larger talent supply in EV-related fields.

Our findings suggest that the dual-credit policy accelerates the development of the EV industry and directs innovation toward EV-related fields. The free trading of credits enables the market to select firms with comparative advantages to supply credits. In this sense, the implicit subsidies induced by the policy help circumvent the common criticism of industrial policies that the government may fail to pick the right "winner." That said, even with newcomer entry and talent reallocation enhancing efficiency, the price wedge induced by the policy could still contribute to misallocation and deadweight loss. A comprehensive welfare analysis of the dual-credit policy is left for future research.

This study contributes to several broad strands of literature. First, this paper adds to a recently surging literature on the development of EV. Previous literature investigates multiple demand-side factors that affect EV adoption, including purchase subsidies (Barwick et al., 2024a; Hu et al., 2025; Muehlegger and Rapson, 2022; Remmy, 2024; Sinyashin, 2021), tax exemptions (Allcott et al., 2024), some non-monetary incentives such as released driving and licensing restrictions (Li et al., 2023, 2022; Zhang et al., 2018), charging infrastructure supports (Dorsey et al., 2025; Li et al., 2017; Springel, 2021), and other policies (Davis et al., 2025; Dugoua and Dumas, 2024; Forsythe et al., 2023). A recent research by (Fang et al., 2025) evaluate the complementary effect of high-speed railway on EV adoption. However, the supply-side behavior during the transition from GV to EV is largely under-investigated. A notable exception is the study by Li (2023) that looks at how the compatibility of charging standards affect EV producers' investment in charging infrastructure . This study examines how a key supply-side intervention reshapes firms' production, innovation, and hiring.

Second, this study contributes to the literature on directed technical change, especially directed clean innovation (see Hémous and Olsen, 2021, Popp et al., 2010, and Popp, 2019 for excellent reviews). A large number of theoretical works that analyze the interplay between input prices and directed technical change (Acemoglu, 1998, 2002; Acemoglu et al., 2012, 2016; Loebbing, 2022). Recently, there have been growing empirical results on the causes and consequences of directed technical change (Acemoglu et al., 2023; Aghion et al., 2024; Calel and Dechezleprêtre, 2016; Hanlon, 2015; Hassler et al., 2021; Gugler et al., 2024). Some studies go beyond input price and market size as the drivers of directed technical change, turning to broader settings, such as output price shocks, in triggering directed technical change (Aghion et al., 2016, 2023). This study follows the latter strand of literature and regards the dual-credit policy as generating a wedge between EV and GV prices, which in turn changes the production and innovation behavior of firms.

Third, this study contributes to the literature on regulations in the automotive industry. Given the significant environmental impacts of vehicle use, regulations on fuel economy and emissions are prevalent worldwide. Many studies examine these regulations' effects on automakers' attribute choices (Jacobsen, 2013; Klier and Linn, 2016; Knittel, 2011; Leard et al., 2023), vehicle scrappage (Jacobsen and Van Benthem, 2015; Jacobsen et al., 2023), as well as collusion, gaming, and other strategic behaviors (Alé-Chilet et al., 2025; Anderson and Sallee, 2011; Reynaert, 2021). To the best of our knowledge, the existing literature mainly focuses on the product space that include only gasoline vehicles. In this study, we add electric vehicles as an additional product type in automakers' choice sets, and study the substitution of GVs with EVs as well as the attribute choices of each type. Accordingly, this study bridges the literature on regulation and directed technical change by examining directed changes in the types of products chosen by firms, in addition to R&D or patenting behavior.

Finally, this paper contributes to the literature on the effectiveness of industrial policies. Understanding the efficacy of industrial policies has been an active topic in economics (refer to Juhász et al., 2024 for an extensive review). Recently, Lane (2025) investigates the role of industrial policies, mainly credit and export policies, in advancing industrialization in South Korea. Kantor and Whalley (2025) reviews the effect of public R&D in fostering manufacturing growth by examining the space competition between the US and the Soviet Union. Barwick et al. (2025) discuss the relative performance of different parts of industrial policy, including differential targeting subsidies and consolidation policies, in stimulating shipbuilding in China. Closely related to this paper, Barwick et al. (2024b) analyze the relationship between industrial policies—mainly credit and subsidies—and innovation in EV-related fields. In this study, we regard the dual-credit policy as not only an emissions regulation for cars, but also an industrial policy that targets EV development in China because it induces implicit subsidies toward EVs. Unlike many industrial policies studied in previous literature, regulations like the dual-credit policy do not impose an explicit fiscal burden on the government. In this sense, the role of regulation in directed technical change and accompanying product change sheds light on effective industrial policy design.

The rest of the paper is organized as follows. Section 2 introduces the dual-credit policy. Section 3 builds a theoretical framework and derives testable implications of the impacts of the dual-credit policy. Section 4 introduces the main data sets used in this study. Section 5 shows the results of the first step of the empirical analysis. Section 6 shows the results of the second step of the empirical analysis. Finally, Section 7 concludes.

2 Policy Background

2.1 CAFC regulation before the dual-credit policy

In 2013, the Chinese government introduced the Corporate Average Fuel Consumption (CAFC) methodology, marking the start of fuel-economy regulation for passenger vehicles. The policy targeted a fleet average of 6.9 L/100 km by 2015 and 5.0 L/100 km by 2020.

CAFC credits are computed at the firm–year level as the difference between the target and the firm's actual corporate average fuel consumption. The target is determined by each vehicle's curb weight and the number of seats (see Appendix B.1 for details). If actual fuel consumption exceeds the target, the firm records negative credits; if it is below the target, the firm earns positive credits.

Compliance and enforcement operate at the firm level. Firms with negative credits face administrative penalties, such as restrictions on capacity expansion and the approval of new models and investments. During this period, compliance had to be met internally: inter-firm transfer or trading of CAFC credits was not permitted. Positive CAFC credits could be banked for up to three years.

2.2 NEV credits and Dual-credit framework

Following policy consultations in September 2016 and a draft for comments in June 2017, the government introduced *Parallel Management of New Energy Vehicle and Corporate Average Fuel Consumption Credits for Passenger Vehicles* in September 2017, adding New Energy Vehicle (NEV) credits and linking them to the CAFC system. The policy took effect on 1 April 2018. The NEV credit regulation is similar in spirit to California's Zero-Emission Vehicle (ZEV) program. Each year, a firm's NEV credit target is set in proportion to its total gasoline-vehicle production. Firms generate positive NEV credits by producing battery electric vehicles, plug-in hybrid electric vehicles, and fuel-cell electric vehicles. Each technology has its own credit formula based on vehicle attributes; Appendix B.2 summarizes the rules.

The NEV target applies only to firms whose total gasoline-vehicle production exceeds 30,000 units. However, the target is calculated on total production rather than only the increment above 30,000 units, creating a discontinuity in incentives at the threshold.

Since the dual-credit system's introduction (announced in 2017; implemented in 2018), it has been revised twice—first announced in 2020 (implemented in 2021), and again in 2023. As shown in Appendix B.2, across revisions the government tightened requirements by adjusting per-vehicle crediting rules (e.g., multipliers) and raising effective targets, making compliance progressively more stringent. This pattern suggests policymakers view the dual-credit policy as an ongoing instrument to support EV development.

2.3 Trading, banking, and clearing of credits

Credit deficits for both CAFC and NEV are announced in June of the following year. Firms then have a three-month window to clear their balances. Failure to do so triggers strong administrative penalties (e.g., restrictions on introducing new products, approving new investment projects, and expanding production capacity). In practice, firms almost always clear their balances.[1] Accordingly, we assume firms clear annually or at least plan under that expectation.

CAFC credits are not freely tradable. Transfers are allowed only among "connected firms" as defined by regulation (see Appendix B.3 for details). Positive CAFC credits can offset only negative CAFC credits, not NEV deficits. By contrast, NEV credits are tradable between firms and can offset both NEV and CAFC deficits at a 1:1 rate. Transactions occur bilaterally and are executed on a government-run trading platform rather than through an open marketplace.

Firms may bank both CAFC and NEV credits for future use but cannot borrow credits from future production. While in theory firms could contract over future credits, such arrangements appear rare given the small number of active traders, regulatory uncertainty from evolving credit rules, and limited price transparency. We therefore assume firms do not trade credits in advance. In addition, credits generally cannot be used to offset deficits from prior years, with limited exceptions in 2020–2021. In other words, a given year's negative NEV balance can typically be offset only with NEV credits generated on or before that year. Banking allows firms to smooth compliance costs intertemporally. However, because firm-level records of banking and trading are not observed, we do not model banking behavior empirically and abstract from it in the main analysis.

It is worth noting that only production and imports for domestic sales are included in credit

[1] Public information indicates that uncleared deficits accounted for about 2.1%, 0.5%, and 0.1% in 2019, 2020, and 2021, respectively.

calculations; exports are excluded. This aligns with the policy's objective of reducing domestic fuel consumption and improving local environmental quality. Accordingly, our analysis focuses on domestic production and imports, excluding export volumes.[2]

2.4 Other simultaneous interventions related to EV development

Alongside the dual-credit policy, other concurrent policies aim to promote electric vehicles. These policies and their dynamics may also affect EV production decisions.

First, the government has provided direct purchase subsidies for consumers who buy electric vehicles since 2010. Subsidies are deducted from the price paid by consumers, and producers claim reimbursement from the government afterward. Subsidies are provided by both the central and local governments, with limits on local subsidies to prevent race-to-the-bottom competition. The scope and size of subsidies have changed over time. Initially, subsidies were available only in several pilot regions; in 2016, they became a national policy. At the same time, subsidy levels have decreased over time. The national subsidy from the central government was capped at 60,000 CNY (about 8,400 USD) in 2013 and ended in 2022, while some local governments still provide subsidies at much lower levels. Appendix B.4 provides details on the evolution of national subsidy levels. The post-2017 phase-out suggests that subsidies were not the main driver of EV development after the policy's introduction. In the empirical analysis, we include year fixed effects, which absorb the effects of national subsidies and much of the regional subsidies that are proportional to the national level. In some specifications, we also control explicitly for national subsidy levels.

Second, the government provides national tax exemptions and deductions for EVs. Specifically, EV buyers are exempt from the vehicle and vessel tax and the vehicle purchase tax. The vehicle and vessel tax is determined by engine displacement, ranging from 60 CNY (8.4 USD)

[2]Some firms may respond on the export margin (e.g., reallocating models to export markets), which could affect revenues, profits, and capacity utilization. These adjustments do not directly affect our main outcome variables and are beyond the scope of this paper.

for displacement under 1 L to 5,400 CNY (760 USD) for displacement above 4 L in 2011. The vehicle purchase tax is typically 10% of the price, with a 30,000 CNY (4,200 USD) cap imposed for purchases after 1 January 2024.[3]

Third, the government provides fiscal subsidies and direct investments to build charging infrastructure. Subsidies were provided to several city clusters between 2013 and 2015 and were expanded nationwide after 2016. Subsidy amounts are determined by region and the scale of EV adoption (see Appendix Tables B2 and B3 for details). Local governments also provide their own subsidies toward charging infrastructure.

Understanding the impacts of these simultaneous policies is beyond the scope of this paper. However, we emphasize that these policies do not compromise our main objective of assessing the impact of the dual-credit policy. These other interventions are mostly demand-side, affecting consumer demand for EVs relative to GVs. Throughout, we focus on supply-side dynamics. That is, we compare firms by product fleet, market entry timing, and technological endowments. Although some firms may disproportionately focus on GV or EV production, there are no *ex ante* restrictions on the choice of product mix. Therefore, we treat firms as equally affected by demand-side policies.

3 Theoretical Framework

This section introduces a theoretical framework for consumer choice and firm behavior to understand the impacts of the dual-credit policy. The model builds on existing work about regulations in the automotive industries (Jacobsen, 2013; Reynaert, 2021). In this model, firms choose between different strategies to cope with the regulatory targets for both CAFC credits and NEV credits. We derive several testable implications from the model, which serve as the basis for the empirical analysis in Section 5 and Section 6.

[3] After 1 January 2026, the vehicle purchase tax is no longer waived but is reduced by 50% for EV purchases. The tax reduction is capped at 15,000 CNY (2,100 USD).

3.1 Setup

The market is defined as the domestic market observed in each year y. Because export is not included in the dual-credit policy, here we do not take export into account, assuming that all car manufacturers sell only in the domestic market. There are F firms in the market, denoted by $f \in \{1, 2, ..., F\}$. In this simplified model, we consider each firm as an independent decision maker, abstracting away the affiliation structure of large car manufacturing groups. There are $J + 1$ products in the market, with the outside product denoted by $j = 0$ and different models of vehicles denoted by $j \in \{1, 2, ..., J\}$. Each firm offers part of the J products available in the market. The ownership structure of product is capture by a $J \times J$ matrix Φ_f, where the $j - k$ element equals one is product j and product k belong to the same firm f.

There is a measure of $\mathcal{I}$ consumers in the market. For simplicity, we assume that A is constant across years. Allowing A to vary across years would not affect our results. Consumers make discrete choice among different products to maximize their utility. Quantity of product consumed is not considered because in most cases people buy one car at a time. Consumers are assumed as homogenous in this simplified model. The indirect utility of consumer can be written as:

$$\begin{cases} u_{0y} = \varepsilon_{0y} \\ u_{jy} = x_{jy}\beta^x - \alpha p_{jy} + \xi_j + \tau_y + \varepsilon_{jy}, \quad j = 1, 2, \ldots, J \end{cases}$$

where x_{jy} is the observed car attributes of car j in year y, p_{jy} is the price, ξ_j is the product fixed effect, τ_y is the year fixed effect. ε_{jy} is the idiosyncratic preference shock. Suppose ε_{jy} follows a Type-I extreme value distribution, we have the following logit choice probability of product j:

$$s_{jy} = \frac{\exp\left(-\alpha p_{jy} + \xi_j + \tau_y + x_{jy}\beta^x\right)}{1 + \Sigma_{l=1}^{J} \exp\left(-\alpha p_{ly} + \xi_l + \tau_y + x_{ly}\beta^x\right)}$$

The demand for each product j is:

$$q_{jy} = s_{jy}\mathcal{I}$$

In each period, firms produce different cars to maximize profits. The firm decisions are characterize by the composition of product fleet $\mathbb{J}_f$, as well as the price p_j, and attributes x_j of each product j. At this stage, we first consider the maximizing problem given the product fleet of firms. Under the dual-credit policy, we can write firm's maximization problem as follows:

$$\max_{p_j, e_j, r_j} \tilde{\pi}_f \equiv \sum_j \left(p_j - c_j\right) q_j + F^g\left(Q^g, Q^e\right) + F^e\left(Q^g, Q^e\right)$$

where

$$F^g\left(Q^g, Q^e\right) = \lambda_f^g \left(\underbrace{\frac{\sum_{j=1}^J \bar{e}_j\left(w_j\right) q_j}{\sum_{j=1}^J q_j} \cdot \eta}_{\text{compliance level}} - \underbrace{\frac{\sum_{j=1}^J e_j q_j}{\sum_{j=1}^J q_j W}}_{\text{actual FC}} \right) \cdot Q^g$$

$$F^e\left(Q^g, Q^e\right) = \lambda_f^e \left(\underbrace{\sum_{j \in \mathbb{J}^e} k\left(r_j\right) q_j}_{\text{attribute-based credit}} - \underbrace{\mathbb{1}\left(Q^g \geq 30000\right) \cdot \gamma \cdot Q^g}_{\text{credit target}} \right)$$

We omit the y subscript in the above equations.

Specifically, λ_f^g and λ_f^e are the shadow prices of CAFC and NEV credits, respectively. Here, we do not use the actual transaction prices of credits. In addition, we allow for firm-specific shadow prices even though credits are freely tradable in the market. We define the shadow price in this way for several reasons. First, the price of credit is determined by bilateral deals, which vary across deals. Second, related to the first point, the price of credit is not transparent and is not observed by econometricians. Third, the market size for credits changes across years. It may be the case that the aggregate supply of positive credits exceeds or falls short of aggregate demand. In either case, not all costs and revenues from credits are realized, and the actual transaction price of credits deviates from the shadow price used in a firm's decision-making process. Finally, we treat firms as strategically small such that they take the market supply and demand of credits as given.

CAFC credits are determined by the gap between the average compliance level of fuel consumption and the corporate average fuel consumption. Firms earn positive CAFC credits when the average fuel consumption is lower than the compliance level, and vice versa. The compliance level of fuel consumption is determined by curb weight w_j, target fuel consumption $\bar{e}_j$, and a conversion factor η. The corporate average fuel consumption is the weighted average of fuel consumption e_j, where the weight $W_j = 1$ for gasoline vehicles and $W_j > 1$ for electric vehicles (see Appendix B.1 for details of W_j).

NEV credits are determined by car attributes x_j, including range, battery energy density, and electricity consumption; the volume of gasoline-vehicle production Q_g; and the target factor γ. Appendix B.2 summarizes details of positive NEV credit calculation based on car attributes. $\gamma = 0.1, 0.12, 0.14, 0.16, 0.18, 0.28$, and 0.38 for years 2019 to 2025, respectively (see Figure B4). Notably, only firms with gasoline-vehicle production exceeding 30,000 units are subject to the negative NEV credit. However, the target factor applies to total gasoline-vehicle production rather than only the incremental part above 30,000 units. Therefore, there is a discontinuity in the incentive to produce an extra unit of gasoline vehicle at the threshold.

Take one step backward, the maximization problem regarding the composition of product fleet can be written as:

$$\max \pi_{fy} \equiv \tilde{\pi}_{fy} - C_{fy}$$

where C_{fy} is the transition cost of adjusting the product fleet. We define

$$C_{fy} = S_{fy} \cdot z_{fy} + \tilde{C}_{fy}$$

where z_{fy} is an indicator of firm f introducing EV products for the first time in period y. S_{fy} is a firm-specific lump-sum cost of building EV capacity. $\tilde{C}_{fy}$ is convex, increasing, and non-negative in the incremental number of products compared to the given product fleet (i.e., $\mid \mathbb{J}_{fy} \mid - \mid \mathbb{J}_{f,y-1} \mid$). Under this definition, reducing the number of products save costs for the firm. We assume no extra cost for reducing the number of products from the product fleet.

3.2 Implications

3.2.1 Production, price, and attribute choices

For the profit maximization problem given the product fleet, we first consider the first-order derivative regarding q_j:

$$\frac{\partial \tilde{\pi}_f}{\partial q_j} = p_j - c_j + \lambda_f^g \frac{\partial \mathcal{L}_l^g}{\partial q_j} + \lambda_f^e \frac{\partial \mathcal{L}_f^e}{\partial q_j} \tag{1}$$

where L_f^g and L_f^e are the net credit functions of CAFC credit and NEV credit, respectively. For CAFC credit, we have:

$$\frac{\partial L_f^g}{\partial q_j} = -\bar{e}_j \eta + (1 - W_j \frac{Q}{\tilde{Q}}) \frac{E}{\tilde{Q}} + e_j \frac{Q}{\tilde{Q}}$$

where $\tilde{Q} \equiv \sum_j W_j q_j$ is the weighted production for CAFC calculation, and $E \equiv \sum_j e_j q_j$ is the actual fuel consumption.

For NEV credit, we have:

$$\left.\frac{\partial L_f^e}{\partial q_j}\right|_{Q^g \uparrow \bar{Q}^g} = \begin{cases} k_j, & j \in \text{EV}, \\ 0, & j \in \text{GV}, \end{cases} \quad \left.\frac{\partial L_f^e}{\partial q_j}\right|_{Q^g \downarrow \bar{Q}^g} = \begin{cases} k_j, & j \in \text{EV}, \\ -\gamma, & j \in \text{GV}. \end{cases}$$

Defining τ as the tax burden of the dual-credit policy imposed on one additional unit of product:

$$\tau_j = -\lambda_f^g \frac{\partial L_f^g}{\partial q_j} - \lambda_f^e \frac{\partial L_f^e}{\partial q_j},$$

we draw the following implication:

Implication I: *The tax burden of the dual-credit policy imposed on a gasoline vehicle is always larger than that on an electric vehicle.*

The argument is straightforward. Producing a gasoline vehicle generates an ambiguous impact on the CAFC credit, depending on the vehicle's fuel consumption level. However, it certainly generates negative NEV credits when total gasoline-vehicle production exceeds 30,000 units. By contrast, producing an electric vehicle always lowers average fuel consumption and generates non-negative NEV credits. Moreover, electric vehicles lower average fuel consumption more effectively than any gasoline vehicle with positive fuel consumption. Therefore, the dual-credit policy implicitly taxes gasoline vehicles and subsidizes electric vehicles (Reynaert, 2021), creating a price wedge between these two types of vehicles.

In addition, when we look at the production decisions of firms, we can draw the following two implications:

Implication II: *There is a strong incentive for GV producers to make EVs to reduce CAFC. Compared with the pre-policy period, the incentive to lower fuel consumption for GVs is weaker.*

To see the impact of producing one unit of a gasoline vehicle versus an electric vehicle, consider the case where a firm produces only gasoline vehicles and existing gasoline vehicles have fuel consumption equal to the compliance level. Then we have $Q/\tilde{Q} = 1$, $E/\tilde{Q} = \bar{e}_j\eta$. For a fuel-saving GV with $e_j = 0.9 \times \bar{e}_j\eta$, $\frac{\partial L_f^g}{\partial q_j} = -0.9 \times \bar{e}_j\eta$. For an EV with $e_j = 0$, $\frac{\partial L_f^g}{\partial q_j} = -W_j\bar{e}_j\eta$. In 2017, $W_j = 5$, meaning that producing one EV is equivalent to 50 fuel-saving GVs in reducing CAFC. This example highlights the advantages of producing EVs in driving down CAFC: EVs not only have zero fuel consumption but also have a large weighting factor that amplifies their impact on CAFC.

Implication III: *There is a divergence in gasoline-vehicle production: medium-size producers reduce GV production, while large producers increase it.*

There is a discontinuity ($-\gamma\bar{Q}^g$) in the incentive to produce GVs at the threshold. As shown in Appendix D.1, assuming that increasing GV production is costly, there exists $\tilde{Q}^g > \bar{Q}^g$ such that those with $Q^g < \tilde{Q}^g$ will decrease Q^g to below $\bar{Q}^g$. At the same time, large GV producers may increase GV production to clear the market. The logic is that those who would otherwise buy gasoline vehicles that are no longer available will switch to close substitutes, that is, gasoline vehicles by other producers.

Regarding price and attribute choices, we can derive the following first-order derivatives:

$$\frac{\partial \mathcal{L}}{\partial p} = \underbrace{\left(1 + \lambda_f^g \circ \nabla_{\mathbf{p}} \mathbf{L}^g \circ \Delta_p + \lambda_f^e \circ \nabla_{\mathbf{p}} \mathbf{L}^e \circ \Delta_p\right) \circ \mathbf{q}}_{\text{margin effect}} + \underbrace{\Phi \circ \Delta_p \mathbf{m}}_{\text{market share effect}}$$

$$\frac{\partial \mathcal{L}}{\partial x} = \left(\underbrace{-\mathbf{c}'_x}_{\text{cost effect}} + \underbrace{\lambda_f^g \circ \nabla_{\mathbf{x}} \mathbf{L}^g \circ \Delta_x + \lambda_f^e \circ \nabla_{\mathbf{x}} \mathbf{L}^e \circ \Delta_x}_{\text{credit effect}}\right) \circ \mathbf{q} + \underbrace{\Phi \circ \Delta_x \mathbf{m}}_{\text{market share effect}}$$

where $\nabla_{\mathbf{k}} \mathbf{L}$ is the Jacobian matrix of first-order derivatives of credit function L with respect to $k = p, x$. Δ_k is a $J \times J$ matrix in which the $i - j$ element indicates the derivative of market share s_i with respect to $k_j = p_j, x_j$. $\circ$ is defined as the Hadamard product. Φ is ownership matrix, and $\mathbf{m} = \mathbf{p} - \mathbf{c} - \tau$ is the mark up of J vehicle.

The first-order derivative of price show the trade-off between increased mark up of vehicles and the losses from reduced market shares. The first-order derivative of attributes show the trade-off between increased marginal cost and the benefits from credit earnings and increased market shares (supposing consumers have positive willingness-to-pay for improved attributes). In a multinomial logit type of demand as here, we can write out the elements in Δ as the following:

$$\frac{\partial s_k}{\partial p_j} = \begin{cases} -\alpha s_j \left(1 - s_j\right), & k = j \\ \alpha s_k s_j, & k \neq j \end{cases} \quad \frac{\partial s_k}{\partial x_j} = \begin{cases} \beta^x s_j \left(1 - s_j\right), & k = j \\ -\beta^x s_k s_j, & k \neq j \end{cases}$$

Cannibalization Effect: The increase of market share of vehicle j always happen in accompany with the reduction of market shares of other existing products.

Implication IV: *Newcomers introduce higher-quality EVs, especially in attributes valued by consumers but not accounted for in credit calculation.*

Proof is in Appendix D.1.

Intuitively, from the profit-maximization problem, there are three incentives for producing EVs: (1) reducing CAFC, (2) earning NEV credits, and (3) boosting sales. These map to three distinct impacts on attribute choice. For (1), any EV works the same in reducing CAFC; there is no incentive to improve attributes. For (2), the incentive is to improve only those attributes included in the credit calculation. For (3), there is an incentive to improve all attributes valued by consumers. Because of cannibalization effect, all else equal, newcomers have stronger incentives to produce higher-quality EVs, particularly in attributes valued by consumers but not included in the credit calculation. For incumbents, EVs compete with their own existing GVs, reducing incentives to improve attributes valued only by consumers and not included in the credit calculation. That is, incumbents mainly increase EV production in response to the policy-driven price wedge τ.

3.2.2 Product fleet adjustment

Finally, for the step of choosing the optimal size of product fleet, we can get the following first-order derivative:

$$\frac{\partial \mathcal{L}}{\partial |\mathbb{J}|} = \underbrace{q_k \left[m_k - \mathcal{I}\Phi \circ \Delta_q \mathbf{m} \right]}_{\text{market stealing + cannibalization}} - \underbrace{C'}_{\text{adjustment cost}}$$

where $|\mathbb{J}|$ indicates the measure of product fleet. We denote the added product to be k. The net margin of introducing a new product is the mark up generated from market stealing minus the cannibalization effect from reduced sales of other products that belongs to the same firm, which is measured as the weighted average of mark ups of the affected products with respect to the substitute elasticity. The size of product fleet increases until the net margin of introducing a new product equals to the increase in adjustment cost.

3.2.3 Cost minimization problem

To dig further into the impact of the dual-credit policy on firms' input choices, we now focus on $\mathbf{c}'_x$, a key determinant of firm strategy regarding the attribute choices. We assume that there are multiple types of attributes that are characterized by a. Each type of attribute belongs to a technology domain $s(a)$. Firms solve the cost minimization problem of achieving x^a level of each attribute type a:

$$\min_{\{h_n\}_1^N, m_a} c_a = \sum_n w_{f,n} h_n + r_f m_a$$
$$\text{s.t.} \quad A_{f,s(a)}^{\beta_a} \left(\prod_n h_n^{\gamma_{an}} \right) m_a^{\delta_a} \geq x_a,$$

Notably, there are N types of workers that jointly determine the production of each type of attribute. The output elasticity of type n worker in producing type a attribute is γ_{an}. Firms are heterogeneous in their domain-specific technology $A_{f,s}$ and the factor prices $w_{f,n}$, r_f.

For simplicity, we assume constant return to scale of the production function ($\sum_\tau \gamma_{a\tau} + \delta_a = 1$). Then, with simple algebra (see details in Appendix D.1), we have the optimal cost of achieving x_a to be

$$c_{x_a}^* = K_a \cdot A_{f,s(a)}^{-\beta_a} \cdot r_f^{\delta_a} \cdot \left(\prod_\tau w_{f,\tau}^{\gamma_{a\tau}} \right) \cdot x_a$$

where $K_a \equiv \left(\prod_\tau \gamma_{a\tau}^{-\gamma_{a\tau}} \right) \delta_a^{-\delta_a}$ is a constant.

Accordingly, the optimal factor demand can be written as:

$$h_{a\tau}^* = \frac{\gamma_{a\tau} c_a}{w_{f,\tau}}, \quad m_a^* = \frac{\delta_a c_a}{r_f}$$

Based on results above, we can get the following implications.

Implication V: *The marginal cost of improving a given attribute is negatively correlated with domain-specific technology endowment. Accordingly, the optimal attribute choice is positively correlated with domain-specific technology endowment.*

Implication VI: *The optimal demand for a specific type of talent depends on attribute choice, output elasticity, and wages.*

Furthermore, we argue that firms would locate in places with a larger supply of talent that fits their attribute choices because a larger labor supply implies lower wages, *ceteris paribus*.

4 Data

4.1 Data and Sample Construction

To test the first four implications drawn from the theoretical framework, we assemble several new datasets in this study. Before introducing the data, note that this study focuses on passenger-vehicle production for domestic sales in China. No commercial vehicles and no vehicle exports are included in our data.

We incorporate multiple data sources for analysis. Here we provide a brief introduction to the main data used in this paper on car production and attributes, with more details in Appendix A. There are three main datasets used in this study: (1) a newly built dataset that provides rich administrative information on production and attributes of the (near) universe of new car products in China from 2010 to 2024; (2) extended attributes, prices, and sales for the majority of car products in China from 2010 to 2024 obtained from `autohome.com`; and (3) production, import, and credit records of all active car manufacturers from 2013 to 2024.

For the administrative new-car product dataset, we first collect the Announcements for Vehicle Manufacturers and Products from No.173 to No.392. Each announcement documents which OEM introduces which new product. These announcements provide only the first four parts of the product code for each car product. To identify car products at the trim level, which is identified by the complete six-part product code, we supplement these data with the Road Motor Vehicle Manufacturers and Products Information Inquiry System.[4] In this system, we can search and identify trim-level new car products. More importantly, the website provides product details for each announced car model (see Appendix A). The detail page shows the OEM, brand, release date, production location, weight, size, and supplier information for engineering, batteries (for EVs), and ABS systems. To further supplement the data with performance measures, including fuel consumption, range, battery capacity, etc., we also collect

[4] `https://govs.miit-eidc.org.cn/miitxxgk/gonggao_xxgk/index.html`.

information from the China Automobile Energy Consumption Query System and multiple electric-vehicle catalogues released by the Ministry of Industry and Information Technology. Together, we build a dataset of about 20,000 trim-level car products introduced from 2010 to 2025.

This dataset offers several advantages over existing datasets. First, to the best of our knowledge, this is the first dataset of car products at the trim level. It provides more granular information than the model level because the same model may have different variants and versions over time. For example, the BYD Song Pro PHEV has five variants in 2023 and two variants in 2024, each with different ranges, battery capacities, and prices. With trim-level data, we can distinguish variants and provide a more precise picture of product innovation and upgrading. Second, this dataset offers a complete picture of all new car products in the market because every car product must be announced by the Ministry of Industry and Information Technology to be eligible for sale. This ensures that we do not miss unpopular models with low sales that may not be recorded on car information-sharing platforms. Finally, this dataset focuses on new car products, which is particularly suitable for analyzing automotive innovation and the dynamics of OEMs.

In addition to the above dataset, we collect detailed information on car attributes at the specification level from `autohome.com`, covering 2010–2024. The key advantage of this dataset is that it provides model-month sales and specification-level prices. In addition, it provides information on a much larger set of attributes, especially those related to vehicle intelligence. For example, we can observe whether a specification supports fast charging, whether it is equipped with driver-assistance features, and the vehicle's operating system. This information is valuable for defining a high-quality car. However, this dataset also has drawbacks that prevent us from using it as the main dataset for car products. First, it does not cover the universe of new car products. Second, missing data are more prevalent. Third, in this dataset, models and specifications are not uniquely matched to individual car manufacturers. In Appendix A, we provide more details on linking this dataset with car manufacturers so that we can distinguish newcomers' products from those of incumbents.

Administrative records of annual production, imports, and credits are publicly accessible from annual accounting reports released by the Ministry of Industry and Information Technology.[5] We also observe calculated CAFC and compliance levels of fuel consumption from those reports. Because this list includes all active car manufacturers in the market that are subject to the dual-credit policy, we use these reports to identify firm entry and exit.

4.2 Descriptive Evidence

With the above datasets, we document several stylized facts that characterize the Chinese automobile industry since 2010.

First, Figure 1 shows the dynamics of new car products in China. Before 2014, EVs accounted for only a minimal share of new car products. However, that share has surged over the past decade. By the end of 2024, more than 80% of new vehicles introduced to the market are EVs, especially battery electric vehicles (BEVs). This fact echoes the surge in EV penetration in the automobile industry.

Second, the performance of EVs improved dramatically in the past decade, especially compared with the nearly stagnant attributes of GVs (see Figure 2). Among multiple attributes, the improvements in range and battery capacity are the most remarkable. At the same time, we also observe significant improvements in maximum speed and battery energy density. By contrast, improvements in GVs are not obvious, even for the same attribute like maximum speed. Both EVs and GVs exhibit growth in curb weight, indicating a change in consumer preferences; however, the change for GVs is also less pronounced. Finally, it is worth noting that average fuel consumption remained stable over the last decade, even as the government sought to improve fuel economy over time.

[5] https://www.miit.gov.cn/gyhxxhbwjcx/index.html

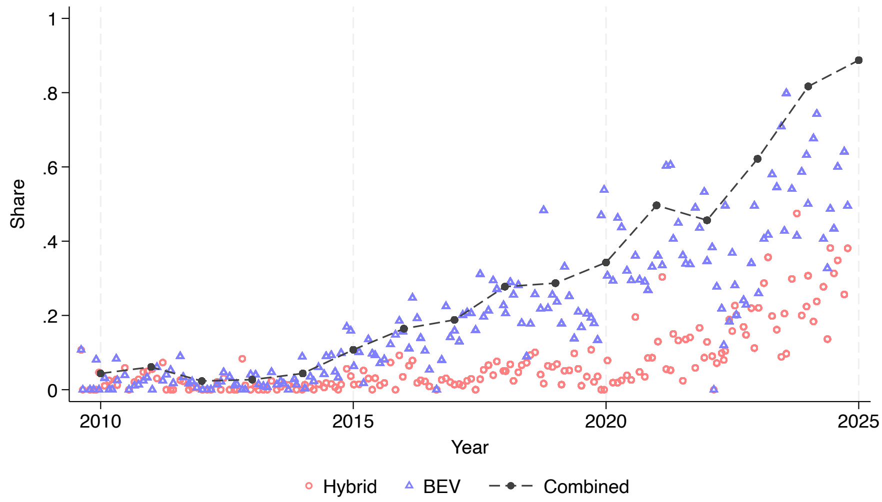
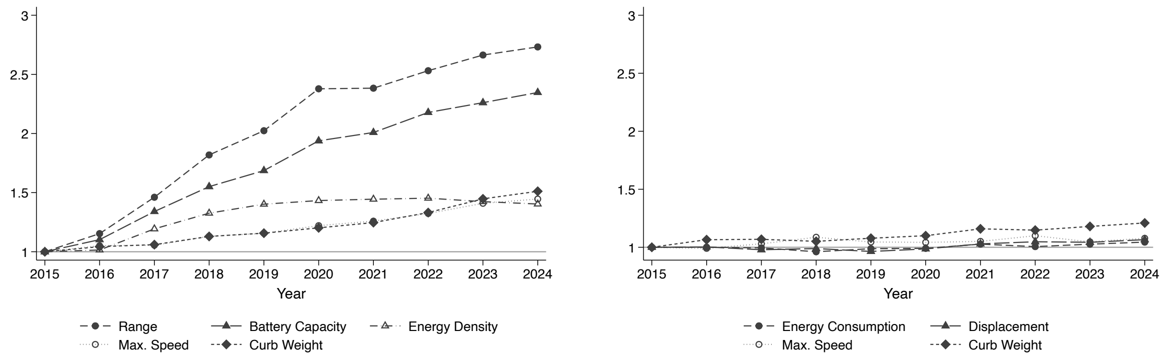


Figure 1: Share of New Products

Notes: Figure shows the dynamics of the share of new trims of battery electric vehicles (BEV), plug-in hybrid vehicles (hybrid) and the sum of these two. Each triangle and each circle is based on the data from one Announcement for Vehicle Manufacturers and Products. The black dots indicate the average of the total share of BEV and hybrid within a calendar year.



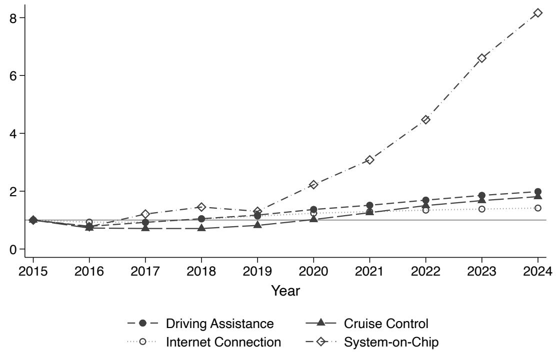
Dynamics of EV Attributes

Dynamics of GV Attributes

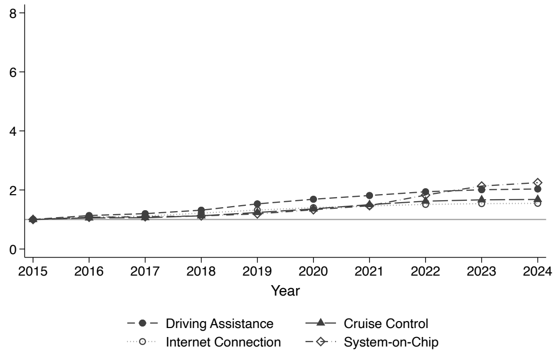
Figure 2: Dynamics of Vehicles' Performance

Notes: Figure shows the dynamics of vehicle attributes. Each marker indicates the average level of a year compared with the average level in 2015 (which is normalized to be 1). Data source: administrative new car product data.

Remarkably, these improvements occur not only in key transportation attributes of EVs but also in attributes that make EVs smart devices like smartphones in the era of intelligence. Notably, the improvement in equipping EVs with a system-on-chip (SoC) far exceeds that for GVs (see Figure 3). A system-on-chip is one of the key features that determines a vehicle's computational capacity, which in turn determines its smartness. The relative advantage in EVs suggests that innovation efforts may have shifted from GV-related fields to EV-related fields.



Dynamics of EV Attributes



Dynamics of GV Attributes

Figure 3: Dynamics of Vehicles' Performance (Cond't)

Notes: Figure shows the dynamics of vehicle attributes. Each marker indicates the average level of a year compared with the average level in 2015 (which is normalized to be 1). Data source: `autohome.com` data.

Third, the automobile market has undergone substantial restructuring since the policy's implementation. Before 2018, few manufacturers left the market, indicating a relatively stable market structure. Afterwards, the number of firms leaving the market increased markedly (see Figure 4).

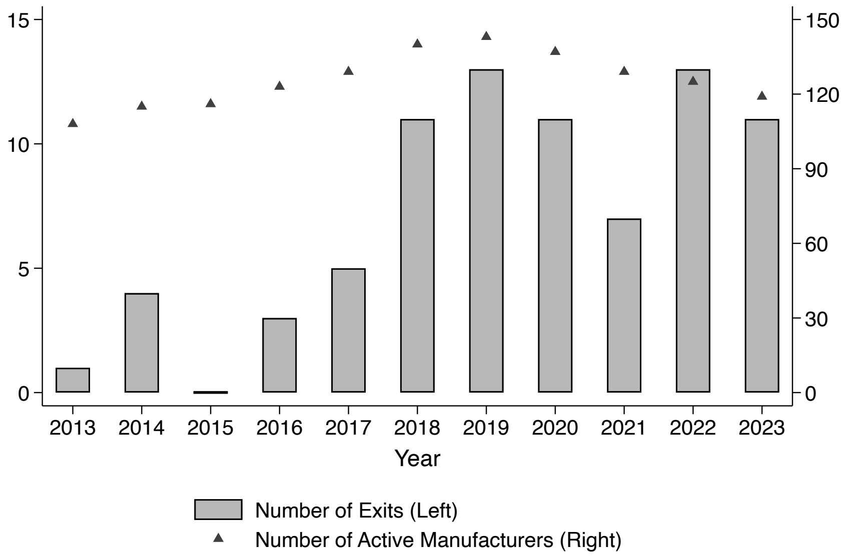


Figure 4: Number of Manufacturers Leaving the Market

Notes: In this figure, bars show the dynamics of the number of manufacturers leaving the market, while triangles show the dynamics in the total number of active manufacturers. For a given bar indicating leaving manufacturers in a year t, it means that this number of manufacturers is last observed in year t in the data. Data source: administrative production records of each original equipment manufacturer.

Accompanying the increase in firms leaving the market are newcomers specializing in EV production. Their market shares have grown rapidly since entry, reaching about 13% of total production in 2024. This is in line with the fact that the main EV producers are newly established domestic car manufacturers. More importantly, their rapid gain in market share echoes our prediction that they have greater incentives in market competition because they are not subject to cannibalization effects.

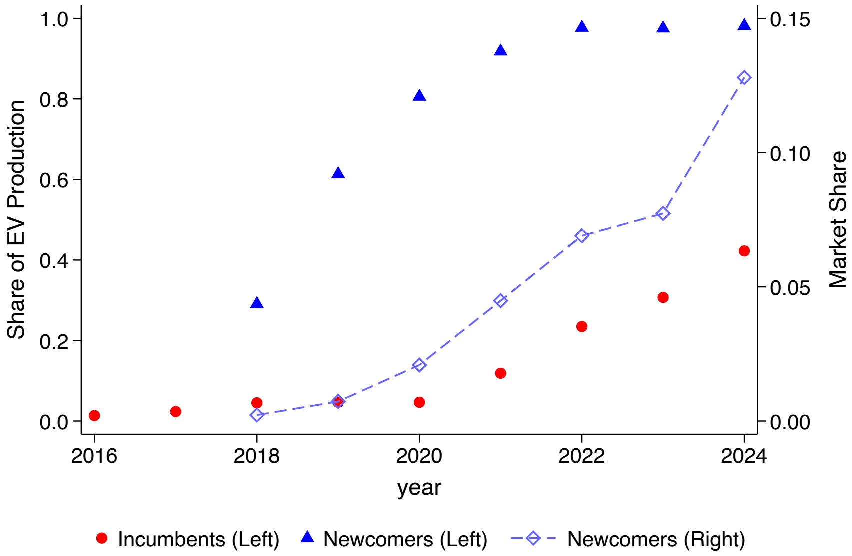


Figure 5: Newcomers after the implementation of Dual-Credit Policy

Notes: Figure shows the dynamics of the share of new car products introduced by newcomers and incumbents, as well as the dynamics in the market share of products produced by newcomers. Data source: administrative production records of each original equipment manufacturer.

5 Empirical Result I: Production Responses to the Policy

In this section, we investigate firms' responses to the dual-credit policy in terms of car production. Specifically, we test Implications I–IV derived in Section 3.

Our main empirical strategy is the difference-in-differences and event-study design to analyze the impacts of the dual-credit policy. Because the policy affects all active car manufacturers, there is no pure "control group." Therefore, we compare different groups of manufacturers or product types based on each question. The identifying assumption is parallel trends in production behavior across firms or products in the absence of the policy shock. We show that this assumption is reasonable in the following subsections.

5.1 Overall Responses

In Implication I, we predict that the dual-credit policy imposes a larger tax burden on gasoline vehicles than on electric vehicles, leading to a price wedge between the two types. We estimate the following model to test this prediction:

$$\ln(p_{jt}) = \sum_{m=-4, m\neq -1}^{6} \gamma_m \cdot EV_j \times t_m + \delta_f + \lambda_t + \beta_X \cdot X_{jt} + \varepsilon_{jt} \tag{2}$$

where p_{jt} is the price of product j in period t. m indicates periods relative to the year of policy shock, defined as 2018, the year of implementation. EV_j is a dummy indicating that car j is an EV. We control for a set of attributes X_{jt}, including curb weight, horsepower, maximum speed, body type (e.g., sedan, SUV, or MPV), cruise control type, parking-assistance type, and indicators for antilock braking, auto hold, hill-start assist, and related features. δ_f denotes firm fixed effects and λ_t denotes year fixed effects. ε_{jt} is the error term. The coefficients of interest are γ_m, which capture the average price gap between GVs and EVs in period m.

Results are shown in Figure 6. Before the policy shock, the relative price between GVs and EVs is stable across years and statistically indistinguishable from the omitted period (2017). This absence of a pre-trend supports the parallel-trends assumption for identifying the causal effect of the dual-credit policy. In the year of policy implementation, the relative price of EVs fell by more than 11 log points (significant at the 10% level). The relative price of EVs continued to decline thereafter, reaching about 59 log points below the pre-policy period.

The price change comes from different channels. First, pass-through from reduced subsidies to reduced price. Second, price wedge rooted from the shadow price of credits. Third, other potential channels including the entry of competitive newcomers, learning-by-doing,

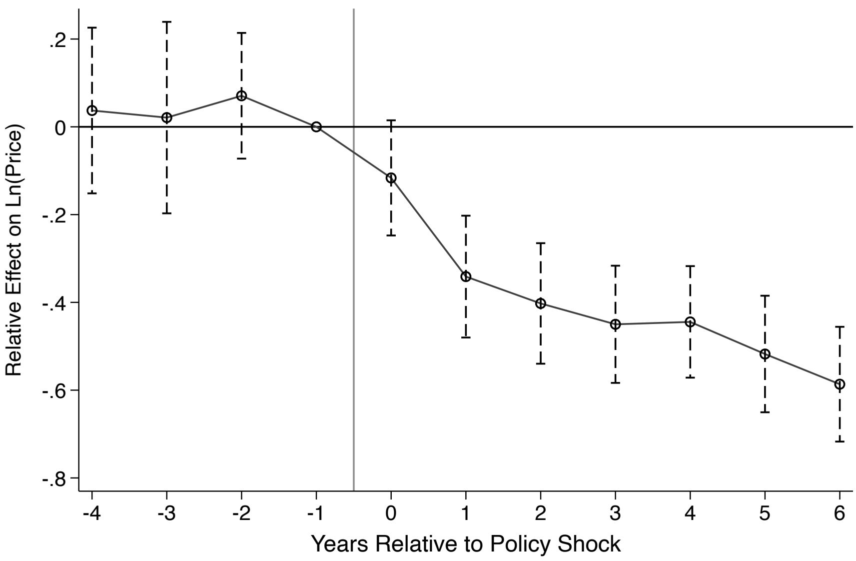


Figure 6: Policy Effect on the Relative Price of EV

Notes: Figure shows the event-study results of the dual-credit policy on the relative price of EVs. The year of policy shock is 2018. Each circle indicates the point estimations of the treatment effect (i.e., the coefficient of $EV_j \times t_m$ in Equations (2)). Each vertical dashed line indicates the 95% confidence interval of the treatment effect.

and technological breakthrough in related-fields. Here, the second one is of interest because it captures the direct impact of the dual-credit policy.[6] To estimate the shadow price of credits, in Appendix E, we follow the usual practice in the literature (Barwick et al., 2024a; Hu et al., 2025) to structurally estimate the markup of vehicles and back out marginal cost and policy-induced price wedge.[7]

Figure 7 shows the decomposition results. The price faced by consumers net of purchase subsidies (referred to as consumer cost) is also decreasing overtime, but with a smaller magnitude in most years after the policy shock. The gap between decrease in MSRP and that of consumer cost indicates that the phase-out of subsidies indeed drives down the relative MSRP of EVs, compared with GVs. Its explanatory power increases overtimes, consistent with the gradual phase-out process. The removal of national subsidy explains about 1/5 of the total

[6] The third channel may also reflect the indirect impacts of the policy, but such indirect impacts are difficult to be clearly quantified. Results in later sections do imply that the policy introduced more competitive newcomers into the market.

[7] One caveat of this practice is that, due to data limitation, we impose homogeneous demand for consumers, which could be too strong to hold.

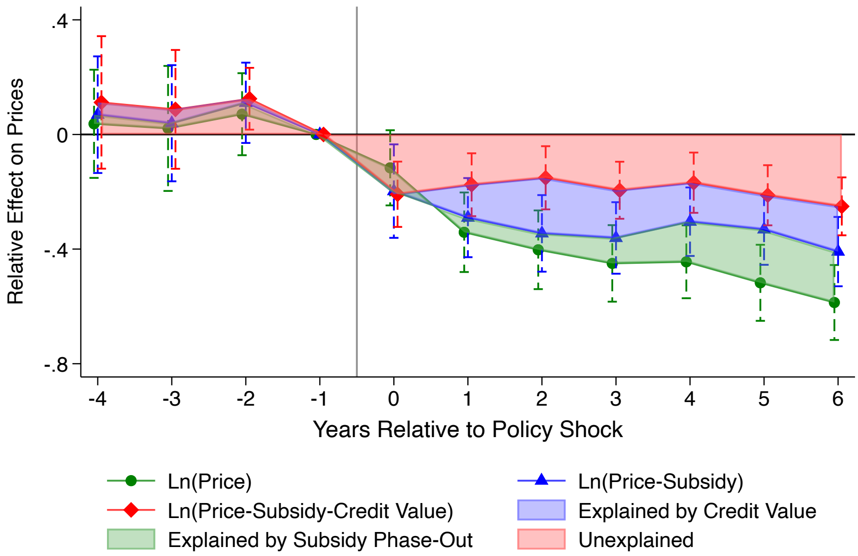


Figure 7: Policy Effect on the Relative Price of EV - Decomposition

Notes: Figure shows the event-study results of the dual-credit policy on the relative price of EVs. The year of policy shock is 2018. Each marker indicates the point estimations of the treatment effect for different dependent variables. Circles indicate effects on the log MSRP. Triangles indicate the effects on the log consumer cost, which is calculated as:

$$\text{Consumer Cost} = MSRP \times \frac{1 + \text{value-added tax rate} + \text{purchase tax rate}}{1 + \text{value-added tax rate}} - \text{Subsidy}$$

Diamonds indicate effects on the log consumer cost net of credit values,where credit values are capture by

$$-\hat{\tau}_j = \hat{\lambda}^g_j \times \text{CAFC credit}_j + \hat{\lambda}^g_j \times \text{NEV credit}_j$$

The gap between circles and triangles (i.e., the green area) indicates the role of subsidy phase-out in explaining the decrease of relative price of EVs. The gap between triangles and diamonds (i.e., the blue area) indicates the role of credit value in explaining the decrease of EV relative price. The gap between diamonds and zero (i.e., the red area) indicates the role of other factors in explaining the decrease of EV relative price. Each vertical dashed line indicates the 95% confidence interval of the treatment effect.

decrease in the post-policy shock period. We can further subtract the shadow value of credits from the consumer cost for each vehicle. Comparing the decrease in the consumer cost and that of the consumer cost net of credit value, we can see that the policy-induced price wedge explains another 1/4 of the decrease in the relative price of EVs. Finally, the consumer cost net of credit value also drops significantly after the policy shock, explaining the rest of decrease in EV price.

5.2 Incumbent Responses

In this subsection, we first focus on the responses of incumbent firms.

5.2.1 Divergence in GV production

In addition to the price wedge created by the dual-credit policy, the threshold for eligibility for the NEV credit target also creates a disincentive for firms above the threshold to produce GVs.

Because there are only about 100 active car manufacturers per year, we do not observe many firms producing close to 30,000 GVs, limiting our ability to detect bunching at the threshold. Instead, we apply an event-study approach similar to Equation (2). Specifically, we first calculate average GV production in the pre-policy period (2013–2017) and classify firms with average GV production above 30,000 as the treatment group. We then test whether these firms are more likely to reduce GV production to below 30,000 units after the policy shock. The empirical model is as follows:

$$\mathbb{1}(Q^g_{ft} > \bar{Q}^g) = \sum_{m=-5, m\neq -1}^{6} \gamma_m \cdot Above_f \times t_m + \delta_f + \lambda_t + \varepsilon_{ft} \tag{3}$$

where $\mathbb{1}(Q^g_{ft} > \bar{Q}^g)$ indicates whether firm f has GV production above 30,000. $Above_f$ indicates whether firm f has pre-period average GV production above 30,000 units. δ_f denotes firm fixed effects, λ_t denotes year fixed effects, and ε_{ft} is the error term.

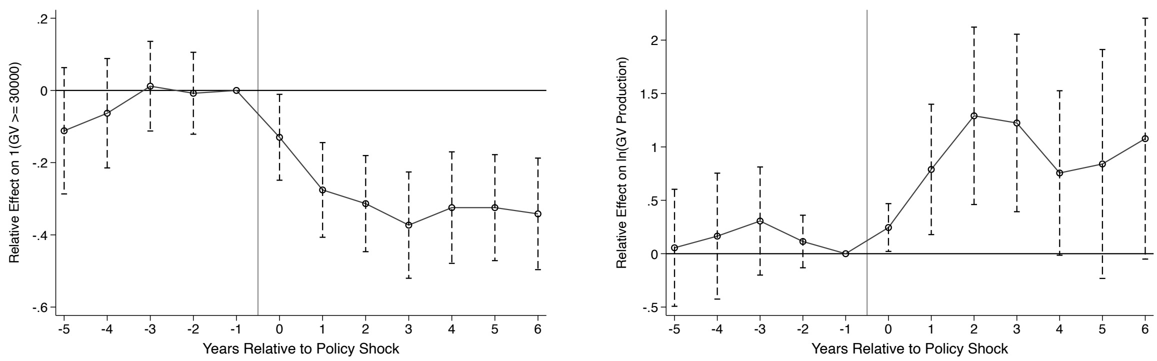
Results are shown in panel A of Figure 8. Before the policy shock, there is no significant pre-trend in the GV production gap between large and smaller manufacturers. After the policy shock, the probability of GV production exceeding 30,000 dropped significantly by more than 30 log points.

In Implication II, we predict that the dual-credit policy leads to a divergence in GV production across firm sizes. That is, while firms with above-threshold pre-period GV production generally reduce GV output, among these above-threshold firms, larger manufacturers may increase GV production relative to smaller ones. We estimate the following model for firms with above-threshold pre-period GV production to test this prediction:

$$\ln(Q^g_{ft}) = \sum_{m=-5, m\neq -1}^{6} \gamma_m \cdot Large_f \times t_m + \delta_f + \lambda_t + \varepsilon_{ft} \tag{4}$$

where $\ln(Q^g_{ft})$ is the log of GV production for firm f in period t. $Large_f$ is a dummy variable indicating if the pre-period average GV production of firm f is above the median level among firms in the regression sample. Other notation follows Equation (3).

Results are shown in panel B of Figure 8. Again, we do not observe any statistically significant pre-trend in GV production. After the policy shock, firms with above-median pre-policy GV production relatively increase their GV production. This result is in line with our prediction in Implication II.



A: GV Production Exceeding Threshold

B: Divergence in GV Production

Figure 8: Policy Effects on GV Production

Notes: The figure shows event-study results of the dual-credit policy on GV production. The policy shock occurs in 2018. Each circle indicates the point estimate of the treatment effect (i.e., the coefficients on $Above_f \times t_m$ and $Large_f \times t_m$ in Equations (3) and (4), respectively). Vertical dashed lines indicate 95% confidence intervals.

5.2.2 Reduced effort in improving fuel economy

Implication III focuses on the policy's impact on attributes of gasoline vehicles. Before the dual-credit policy, CAFC regulation was imposed on individual firms. There was no trading of credits, and firms had to meet the regulatory requirements themselves. After the introduction of the dual-credit policy, firms could compensate credit deficits by purchasing credits from other firms. In this case, CAFC regulation is no longer binding prior to credit trading. This prediction is acknowledged in Figure 9, where we observe clear bunching of firms just meeting the regulatory target before the policy shock, while such bunching disappears thereafter.

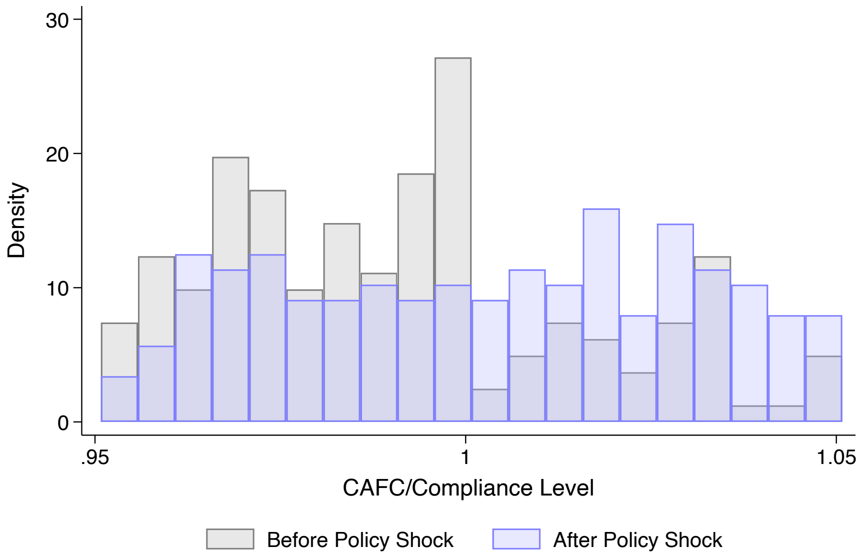


Figure 9: Bunching of Distance to Compliance Level

Notes: This figure shows the densities of the ratio of CAFC to the firm-average compliance level in a ±5% window around the threshold. Gray bars denote the pre-policy period; blue bars denote the post-policy period. Values below 1 indicate compliance; values above 1 indicate shortfall. Both CAFC and firm-average compliance levels are drawn from administrative records.

With credit trading, firms' optimal strategy equates the marginal cost of compliance among three strategies: improving the fuel economy of GVs, producing more EVs, and buying credits from others. Substitution effect across strategies predicts that firms will put less effort into improving the fuel economy of GVs.

To test this prediction, we first calculate each firm's ratio of CAFC to the compliance level in the pre-policy period based solely on GV fuel consumption. We then classify firms with a ratio above the median (i.e., higher fuel consumption relative to the compliance level) as the treatment group and those below the median as the control group. Finally, we estimate the following empirical models:

$$
\begin{aligned}
Y_{ft} &= \beta_0 + \beta_1 \cdot HighCAFC_{ft} \times Post_t + \delta_f + \lambda_t + \varepsilon_{ft} \\
Y_{j(f)t} &= \beta_0 + \beta_1 \cdot HighCAFC_{ft} \times Post_t + \beta_X X_{jt} + \delta_f + \lambda_t + \varepsilon_{jt}
\end{aligned}
\tag{5}
$$

We estimate two models, one at the firm level and the other at the product level. For the firm-level regression, we consider two outcomes Y_{ft}: the share of EVs in total production and the ratio of CAFC to the firm-average compliance level based on GVs. For the product-level regression, we also consider two outcomes $Y_{j(f)t}$: an indicator for j being an EV and the fuel consumption of j, conditional on j being a gasoline vehicle. We control for firm, year, and product fixed effects, and product characteristics accordingly.

Results are shown in Table 1. As shown in columns (1) and (3), firms with pre-period CAFC above the median, compared with those below, experience a larger increase in the share of EV production and introduce more new EVs following the policy shock. At the same time, these firms do not put more effort into improving the fuel economy of GVs (see columns (2) and (4)).

Consequently, the steady decline in GV fuel consumption slows significantly after the policy shock (see Appendix Figure F1). This result does not imply that the dual-credit policy worsens environmental outcomes, because EV adoption reduces fuel consumption. A precise and comprehensive accounting of the environmental impacts of the dual-credit policy involves not only GV fuel consumption and EV electricity use, but also the impacts of vehicle manufacturing and electricity production, which is beyond the scope of this research.

5.3 Newcomer Responses

All the empirical results above focus on the responses of incumbents. However, as shown in Figure 5, car manufacturers entering the market after the policy shock are important. Neglecting newcomers' production behavior would not provide a complete picture of how the dual-credit policy affects the market.

Table 1: Policy Impacts on Compliance Strategy

	Firm-level		Product-level	
VARIABLES	(1) Share of EV	(2) CAFC/ Compliance	(3) EV	(4) Fuel Consumption
Above-median pre-period Real CAFC $\times$ Post	0.067**	-0.006	0.130***	0.210
	(0.032)	(0.024)	(0.040)	(0.147)
Observations	931	1,219	16,876	12,311
R-squared	0.695	0.716	0.337	0.434
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Notes: Table shows the estimation result of Equation (5). In column (2), CAFC are calculated based solely on gasoline vehicles. Numbers of observations differ between columns (1) and (2) because the production of EV is only available after 2016 while the calculation of CAFC and compliance level are available from 2013 onwards. Numbers of observations differ across columns (3) and (4) because in column (4) we only focus on gasoline vehicles. Robust standard errors clustered at the firm level are in parentheses. ***, **, and * denote significance at the 1, 5, and 10 percent level, respectively.

In Implication III, we propose that newcomers have greater incentives to improve car attributes because they are not subject to cannibalization effects like incumbents. To test this prediction, we leverage two datasets with detailed car-attribute information. For the main dataset assembled from multiple administrative sources, we calculate product-level credits according to the NEV credit formula and compare products accordingly. Further, we compare the driving-related performance of EVs—range, battery capacity, battery energy density, maximum speed, electricity consumption, etc. For the `autohome.com` dataset, while it has more missing attribute information, it provides a much larger set of attributes related to advanced technologies and vehicle intelligence, such as fast-charging support, numbers of cameras and sensors for autonomous driving, system-on-chip, and operating-system performance. These measures are not included in credit calculations but are important for evaluating the quality and attractiveness of EVs.

We estimate the following model:

$$Y_{j(f)t} = \beta_0 + \beta_1 \cdot Newcomer_f + \beta_X X_{jt} + \lambda_t + \varepsilon_{jt} \tag{6}$$

where $Y_{j(f)t}$ denotes the attributes mentioned above; $Newcomer_f$ indicates whether firm f entered the market in or after 2018. X_{jt} is a vector of basic attributes, including curb weight and its square, body type, battery type, and log price for the `autohome.com` sample. We also control for year fixed effects λ_t.

We estimate an OLS regression on repeated cross-sectional data without using a panel structure or a DiD approach. This is because there are no pre-period data for newcomers, and newcomer status is time-invariant. Therefore, the coefficient of interest β_1 is correlational, not causal. It reflects both endogenous selection into entry and the incentive effect from the absence of cannibalization. Suppose the policy shock endogenously induces firms with a comparative advantage in EVs to enter; newcomers will tend to have a lower marginal cost of making EVs and will thus choose higher attribute levels, *ceteris paribus*. We cannot distinguish these two sources of variation with reduced-form analysis. The results therefore provide suggestive evidence of the incentive effect. That said, as shown below, the differential effects between attributes that affect NEV credit calculation but are not salient to consumers, and those not included in credit calculation but more salient to consumers, are in line with our prediction in Implication III and highlight the incentive effect.

Results using administrative data are shown in Table 2. Newcomers make EVs with comparable NEV credit per vehicle to those made by incumbents (col. (1)). However, EVs made by newcomers offer significantly longer range (col. (2)), even when additional range does not yield extra NEV credits (col. (3)). For electricity consumption, which is not salient to consumers, EVs made by newcomers do not have an advantage (col. (4)). An interesting comparison lies in columns (5) and (6): the energy density of cars is comparable between newcomers and incumbents, but battery capacity is 4 log points larger for EVs made by newcomers. The differential results between attributes that affect NEV credit calculation but are not salient to consumers and attributes that are not included in credit calculation but are more salient to consumers are in line with our prediction in Implication III, highlighting the incentive effect.

Finally, we find that newcomers make EVs with a higher maximum speed. Maximum speed can be regarded as a measure of EV driving performance because there is a trade-off between maximum speed and range. Newcomers make EVs with both longer range and higher maximum speed, which shows their advantages in EV-related technology.

Table 2: Incumbents vs. Newcomers on Car Attributes

VARIABLES	(1) NEV Credit	(2) Range	(3) Range $>$ limit	(4) EC	(5) ED	(6) Capacity	(7) Max. Speed
Newcomers	0.0901	0.0589***	0.0591*	-0.00553	-0.0118	0.0404**	0.0435**
	(0.0578)	(0.0216)	(0.0338)	(0.0139)	(0.0102)	(0.0201)	(0.0177)
Observations	3,561	5,145	3,571	3,383	5,102	5,102	5,553
R-squared	0.858	0.915	0.532	0.648	0.765	0.919	0.818
Car Category	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Battery Type	Yes	Yes	Yes	Yes	Yes	Yes	No
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The table shows estimation results for Equation (6) using the administrative new-car product data. Observations are at the trim level. Dependent variables in columns (2) and (4)–(7) are log-transformed. "Range $>$ limit" is a dummy indicating that range is above the upper bound, so higher range does not yield additional NEV credits. "EC" stands for electricity consumption; "ED" stands for battery energy density; "Capacity" stands for battery energy capacity. The number of observations differs across columns because of missing data. Robust standard errors clustered at the firm level are in parentheses. ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively.

Results using the `autohome.com` data are shown in Table 3. EVs made by newcomers have faster 0–100 acceleration; have more cameras and sensors for autonomous driving; are more likely to support fast charging; are more frequently equipped with a system-on-chip (SoC); and offer greater operating system (OS) storage.

5.4 Direct Evidence of Production Responses

So far, our empirical results rely on either a difference-in-differences design or a cross-sectional comparison. Both are subject to potential endogeneity concerns. Specifically, simultaneous shocks could contaminate the effects of the dual-credit policy. In this subsection, we leverage exogenous shocks to the dual-credit policy to provide more direct evidence on the policy's effects, highlighting the role of specific policy margins in firms' behavior and outcomes.

Table 3: Incumbents vs. Newcomers on Car Attributes

VARIABLES	(1) 0-100 Acceleration	(2) Camera	(3) Sensor	(4) Fast Charging	(5) SoC	(6) OS Storage
Newcomers	-0.392**	0.746***	0.375*	0.0474*	0.0716**	28.28**
	(0.175)	(0.247)	(0.212)	(0.0271)	(0.0335)	(11.21)
Observations	3,210	3,336	3,252	6,118	6,118	1,044
R-squared	0.730	0.523	0.599	0.550	0.382	0.370
Car Category	Yes	Yes	Yes	Yes	Yes	Yes
Energy Type	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The table shows estimation results for Equation (6) using the `autohome.com` data. Observations are at the specification level. Dependent variables in columns (2) and (3) are counts. The dependent variable in column (4) is a dummy indicating whether an EV supports fast charging. "SoC" stands for system-on-chip. The number of observations differs across columns because of missing data. Robust standard errors clustered at the model level are in parentheses. ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively.

5.4.1 COVID shock and switch to EV production

First, we leverage the exogenous COVID shock on car manufacturers to show that the dual-credit policy generates a strong incentive for firms to switch to EV production, conditional on the implicit subsidy toward EVs.

In 2020, COVID severely affected production, sales, and innovation in the automotive industry, resulting in a large deficit in CAFC credits. As shown in Appendix Figure C2, market-level CAFC credits turned negative for the first time in 2020.

This large credit deficit implies that the prices of both CAFC and NEV credits would rise sharply in 2020. To help firms recover from the COVID shock and ease their credit-balance burden, in February 2021 the Chinese government unexpectedly allowed firms to use NEV credits generated in 2021 to compensate for 2020 NEV credit deficits. Although only NEV credits were explicitly affected by this intervention, the offsetting rules between CAFC and NEV credits imply that the intervention also affects CAFC credit balances.

Given expectations of high credit prices, firms hit hard by the COVID shock had strong incentives to increase EV production in 2021, earn more NEV credits, and reduce credit costs.

If there were no credit-trading system, and if CAFC credit deficits cannot be compensated by NEV credits, there would be no such adjustment. Therefore, observing this adjustment points to the dual-credit policy's design. Moreover, firms' adjustments in 2021 are plausibly exogenous for two reasons: first, the COVID shock is exogenous to firms; second, permission to use 2021 NEV credits to offset 2020 deficits was unexpected.

To detect firms' production adjustments, we estimate the relationship between the change in CAFC credits between $t-2$ and $t-1$ ($\Delta CAFC_{t-1}$) and the change in EV production between $t-1$ and t (ΔEV_t). In years other than 2021, we expect a negligible relationship because credits in t cannot offset negative credits in $t-1$. In 2021, however, we expect a strong negative relationship between the two.

Results are shown in Table 4. Comparing columns (1) and (2), the coefficient is significantly negative in 2021 but is not significantly different from zero in other years. In columns (3)–(5), the coefficient of interest is the interaction between lagged ΔCAFC and an indicator for 2021. Across three specifications with different controls, we consistently find a significantly negative interaction coefficient. These results align with our prediction and suggest that a positive NEV credit price induces firms to switch to EV production.

Table 4: Adjustment in EV Production

	(1)	(2)	(3)	(4)	(5)
Sample	In 2021	Not in 2021	All	All	All
VARIABLES	ΔEV	ΔEV	ΔEV	ΔEV	ΔEV
Lag ΔCAFC	-0.0645***	0.0137	0.0142	0.0137	0.0273
	(0.0111)	(0.0122)	(0.0142)	(0.0122)	(0.0389)
Lag ΔCAFC × Yr2021			-0.0729***	-0.0782***	-0.0464**
			(0.0188)	(0.0166)	(0.0232)
Observations	76	312	388	388	217
R-squared	0.616	0.027	0.104	0.124	0.747
Firm FE	No	No	No	No	Yes
Year FE	No	Yes	No	Yes	Yes

Notes: Table shows the estimation result of firms' EV production change between periods t and $t-1$ with respect to the change in CAFC credits between $t-1$ and $t-2$. Observations are at firm-year level. In column (1), we only look use the data in 2021. In column (2), we use the data excluding year 2021. In columns (3) to (5), we use the whole sample. Robust standard errors clustered at the firm level are in parentheses. ***, **, and * denote significance at the 1, 5, and 10 percent level, respectively.

5.4.2 Policy revisions and attribute choices

Second, we leverage policy revisions in 2021 and 2023 to evaluate how the credit-calculation rules affect firms' attribute choices. Specifically, we expect firms to improve attributes included in the credit calculation when the criteria are tightened.

The empirical strategy is as follows. First, for any given EV, we calculate its NEV credits under the three versions of the credit-calculation formula (i.e., the 2018, 2021, and 2023 versions, defined by implementation year).

Second, under each set of criteria, we calculate the distance between the credit and the upper bound, measured as

$$\widetilde{Distance}_j^m = (NEV_j^m - \overline{NEV}^m)/\overline{NEV}^m$$

where NEV_j^m is the NEV credit of EV j evaluated under the credit-calculation criteria in month m, and $\overline{NEV}^m$ is the upper bound of NEV credit per vehicle in month m.

Third, to convert the data into a panel structure, we average the distance and car attributes in each month m and estimate the following empirical model:

$$\bar{x}_{f,m} - \bar{x}_{f,m-12} = \beta\left(\widetilde{Distance}_{f,m-12}^m - Distance_{f,m-12}\right) + \delta_f + \varepsilon_{fm} \tag{7}$$

where $\widetilde{Distance}_{f,m-12}^m$ is the counterfactual distance of all products of firm f in month $m-12$ evaluated under the month-m criteria. $x_{f,m}$ and $Distance_{f,m}$ are the average attribute and distance for firm f in month m under the month-m criteria. Specifically, we compute $x_{f,m}$ and $Distance_{f,m}$ using data from $[m-6, m]$ to avoid having too few observations at the monthly level. To avoid potential contamination, we use only data starting seven months after each formula change.

The logic is that, holding attributes fixed, a larger reduction in credits after a formula change implies stronger incentives for firms to improve those attributes. With firm fixed effects, these responses are exogenously driven by changes in the calculation formula. Results are shown in Table 5. For range, energy capacity, energy density, and electricity consumption—attributes included in the credit calculation—all coefficients are negative, and three are large in magnitude and significant at the 1% level. Placebo attributes such as maximum speed and vehicle length are unaffected.

Table 5: Adjustment in Attributes with Respect to Policy Changes

VARIABLES	(1) ΔRange	(2) ΔCapacity	(3) ΔED	(4) ΔEC	(5) ΔSpeed	(6) ΔLength
ΔDistance	-0.334***	-0.264***	-0.164***	-0.0753	0.0240	-0.0162
	(0.0784)	(0.0844)	(0.0318)	(0.0805)	(0.0236)	(0.0138)
Observations	4,863	4,861	4,861	2,759	4,933	4,559
R-squared	0.163	0.151	0.155	0.164	0.147	0.201
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Table shows the estimation result of Equation (7). Dependent variables are calculated at firm level. "ED" means energy density of battery, "EC" means electricity consumption. "speed" stands for maximum speed of an EV. Numbers of observations are different across columns because of missing data. Robust standard errors clustered at the firm level are in parentheses. ***, **, and * denote significance at the 1, 5, and 10 percent level, respectively.

6 Empirical Result II: Input Responses to the Policy

To further test Implications V–VI, we turn to firms' input markets. Specifically, we focus on technology and human capital.

6.1 Innovation

6.1.1 Data

Technology and innovation are measured by patents in this study. To measure innovation at the firm level, we collect all patents filed through the China National Intellectual Property Administration (CNIPA) from Google Patents, covering 1985–2024.

Car manufacturers are often part of large conglomerates. For example, SAIC Volkswagen Automotive Co., Ltd. and SAIC Maxus Automotive Co., Ltd. are subsidiaries of SAIC Motor Corporation Limited (formerly Shanghai Automotive Industry Corporation). While each car manufacturer produces vehicles as the final product, they may not conduct all innovations themselves; many innovations related to car manufacturing occur outside the manufacturer. To measure manufacturers' innovation more accurately, we use patent data for all car manufacturers, their key shareholders, and affiliated firms.

Compared with collecting patents only for car manufacturers, covering the full network of shareholders and affiliates provides two advantages. First, ignoring affiliates would miss a large share of relevant patents. For example, much battery-related innovation is done by NIO Battery Technology (Anhui) Co., Ltd., rather than by NIO Technology (Anhui) Co., Ltd. As shown in Appendix Figure A2, about 70% of all patents are held by affiliates rather than manufacturers; the proportion is similar when focusing on car-manufacturing domains. Second, for newcomers who enter after the dual-credit policy, including affiliates of the key shareholders allows us to observe pre-policy innovation, enabling an event-study design to analyze how their innovation responds to the policy shock.

In practice, key shareholders are those who directly or indirectly hold 25% or more of a manufacturer's shares. Affiliated firms are those held by car manufacturers and their key shareholders. To identify key shareholders and affiliates, we manually collect OEM ownership structure data from `tianyancha.com`, a leading Chinese platform for firm registration information. Appendix A shows a sample page from `tianyancha.com`.

In sum, we leverage more than 1.5 million patents for the network defined above. This dataset should capture manufacturers' innovation behavior but does not necessarily include all car-related innovations.[8]

Following prior literature, we categorize patents into EV-related and GV-related based on International Patent Classification (IPC) and Cooperative Patent Classification (CPC) codes (Aghion et al., 2016; Barwick et al., 2024b). In addition, we define intelligence-related patents

[8]For example, research institutions and universities also hold many car-related patents.

related to vehicle intelligence, human–device interaction, and autonomous driving. To our knowledge, this is the first study to categorize intelligence-related patents. We view this as a valuable addition to the literature, as vehicles are now not only transportation devices but also smart devices that provide multimedia entertainment and incorporate AI for autonomous driving.

In practice, EV-related patents cover the EV production process, including battery technology, charging systems, electric powertrain, and vehicle control systems based on electric power. GV-related patents cover the GV production process, including fuel systems, internal combustion engines, transmission technologies, exhaust treatment, and vehicle control systems based on fuel power. Intelligence-related patents cover vehicle intelligence (but not general AI), including autonomous driving, head-up displays, human–vehicle interaction systems, and V2X networking. While intelligence-related features are more prevalent among EVs, we do not treat them as exclusive to EVs; rather, they are general technologies that apply to both EVs and GVs. See Appendix Table A1 for all IPC and CPC codes used to define EV-, GV-, and intelligence-related patents.

6.1.2 Empirical strategy

Implications V and VI suggest that firms would turn to EV production after the policy shock. Accordingly, we predict that after the implementation of the dual-credit policy, innovation in EVs—relative to GVs—will increase, and this increase will occur regardless of a firm's existing technology endowment. Empirically, the dual-credit policy will lead to weaker path dependence in innovation and a convergence in innovation trajectories. We estimate the following model to test this prediction using a Poisson pseudo-maximum-likelihood method:

$$Pat_{ft} = \exp\left(\beta_0 + \beta_1 \cdot K_{f,t-1} \times Pre_t + \beta_2 \cdot K_{f,t-1} \times Post_t + \lambda_f + \tau_t + \varepsilon_{ft}\right) \tag{8}$$

where Pat_{ft} is the number of patents firm f applied for in period t. $K_{f,t-1}$ is firm f's patent stock in period $t-1$, which measures technology endowment and knowledge. The correlation between lagged patent stock and new patents captures path dependence in innovation. We allow for differential path dependence between pre- and post-policy-shock periods, measured by β_1 and β_2, respectively. Pre_t equals one for $t < 2018$; $Post_t$ equals one for $t \geq 2018$. We expect $\beta_1 > \beta_2$.

Moreover, Implication V indicates that newcomers start working on automobile-related innovation prior to market entry. The logic is as follows: newcomers induced to enter the market have no incentives to conduct automobile-related innovation while they remain out of the market; after the policy shock, they switch to automobile-related innovation because it lowers marginal cost. Only newcomers who would have entered in the absence of the dual-credit policy may have been preparing in advance. To gauge the prevalence of these "ever-newcomers," we estimate the following event-study model:

$$S_{ft} = \beta_0 + \sum_{t=2013, t\neq 2017}^{2024} \beta_t \cdot Newcomer_f \times T_t + \lambda_f + \tau_t + \varepsilon_{ft} \tag{9}$$

where S_{ft} is the share of automobile-related patent stock among all patents. Automobile-related patents include the three types defined above (EV-, GV-, and intelligence-related). The coefficient of interest is β_t. We expect β_t to be significantly positive after the policy shock (i.e., $t > 2017$), even though these firms are not yet in the market.

6.1.3 Results

Table 6 reports estimates of Equation (8). For each patent type, the correlation between lagged patent stock and the number of new patents is larger in the pre-period than in the post-period. Specifically, for EV-related and intelligence-related innovation, path dependence vanishes in the post-period, which is in line with the dual-credit policy pushing the industry toward these fields. The coefficient for GV-related patents remains positive and is significant at the 10% level, as expected because firms focusing on EV production would not switch to GV-related innovation.

Table 6: Path Dependence in Innovation

VARIABLES	(1) EV-related	(2) GV-related	(3) Intelligence-related
l.Stock of EV-related Patents×Pre	0.156**		
	(0.0729)		
l.Stock of EV-related Patents×Post	-0.0394		
	(0.0267)		
l.Stock of GV-related Patents×Pre		0.240***	
		(0.0720)	
l.Stock of GV-related Patents×Post		0.182*	
		(0.0980)	
l.Stock of Intelligence-related Patents×Pre			0.275**
			(0.107)
l.Stock of Intelligence-related Patents×Post			-0.0394
			(0.0591)
Observations	6,502	3,957	3,454
Firm	Yes	Yes	Yes
Year	Yes	Yes	Yes

Notes: Table shows the estimation result of Equation (9). Dependent variables are the number of different types of patents applied in a year. "Pre" means before 2018. "Post" means on or after 2018. Robust standard errors clustered at the firm level are in parentheses. ***, **, and * denote significance at the 1, 5, and 10 percent level, respectively.

Figure 10 shows that newcomers increase innovation in car-related fields immediately after the policy shock, prior to market entry. This result indicates that the policy induces newcomers to switch to car-related innovation. It also suggests that "ever-newcomers" are not prevalent in the data. Instead, newcomers are incentivized by the policy shock to participate in the automotive industry. Finally, as shown in Appendix Figure F2, newcomers mainly turn to EV-related innovations and relatively reduce GV-related innovations.

6.2 Talent

Finally, we turn to the labor input margin, evaluating how the dual-credit policy affects the allocation of talent across firms. Following Implication VI, we hypothesize that firms prioritize

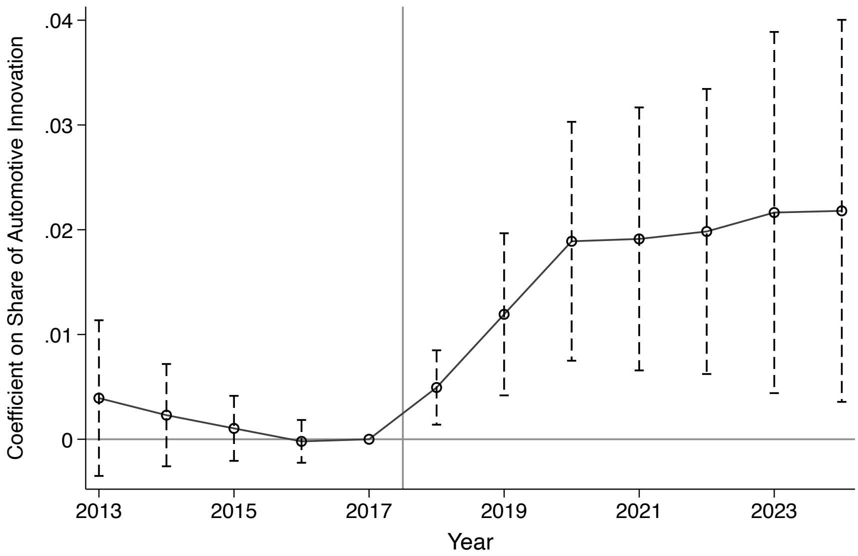


Figure 10: Event Study of Car-related Innovation of Newcomers

Notes: The figure shows event-study results of the dual-credit policy on newcomers' car-related innovation. The policy shock occurs in 2018. Each circle indicates the point estimate of the treatment effect (i.e., the coefficient on $Newcomer_f \times T_t$ in Equation (9)). Vertical dashed lines indicate 95% confidence intervals.

hiring specific types of talent according to product composition and attribute choices. Given the stark differences across firms in product fleets, we test this hypothesis by examining talent allocation across firms.

6.2.1 Data

The data for this analysis come from LinkedIn profiles registered in China and captured in a June 2025 snapshot. To construct the sample, we first identify all car companies and car groups in the Chinese automotive market based on the list of original equipment manufacturers. In total, we identify 55 groups. We then focus on profiles that worked in at least one of those groups during 2010–2024. The final sample includes 173,320 user profiles and 420,322 job-spell records. From these records, we identify employers and job positions and reconstruct individual job histories. Finally, we observe education, gender, and ethnicity for individuals when the information is available in the profile.

6.2.2 Empirical Strategy

To test how talent allocation responds to firms' production composition, we compare worker composition between groups that mainly focus on GV production and those that mainly focus on EV production. Specifically, we calculate the share of new EV trims among all new products for each group and define those with a share above the median as EV-focused groups and the others as GV-focused groups. We then run the following regression at the individual job-spell level:

$$Y_{i(f)t} = \sum_{t=2012, t\neq 2017}^{2024} \gamma_t \cdot EV\_Focused_f \times T_t + \alpha_i + \lambda_t + \varepsilon_{it} \tag{10}$$

where each observation is a job spell for individual i working in firm f starting in period t. $Y_{i(f)t}$ is an indicator that the job is a high-skill position. γ_t is the coefficient of interest, capturing the gap between EV-focused and GV-focused groups in period t.

Similarly, we estimate a model where the dependent variable indicates whether the worker has a Master's degree or higher. Because education is time-invariant for workers, we cannot include worker fixed effects as above. Instead, we control for firm fixed effects.

Finally, we run a similar regression where the dependent variable indicates whether the job is located in a first-tier city in China (Beijing, Shanghai, Guangzhou, or Shenzhen). These four cities are the most developed in China and host the largest concentrations of high-skilled and highly educated workers. Because the dependent variable is largely time-invariant at the firm level, we instead control for observed worker characteristics, including education, gender, and ethnicity.

6.2.3 Results

Figure 11 shows the results of estimating Equation (10). After the policy shock, EV-focused firms offer more high-skilled positions than GV-focused firms. This is in line with our prediction when high-skilled positions are technologically closer to EV-related and intelligence-related innovations.

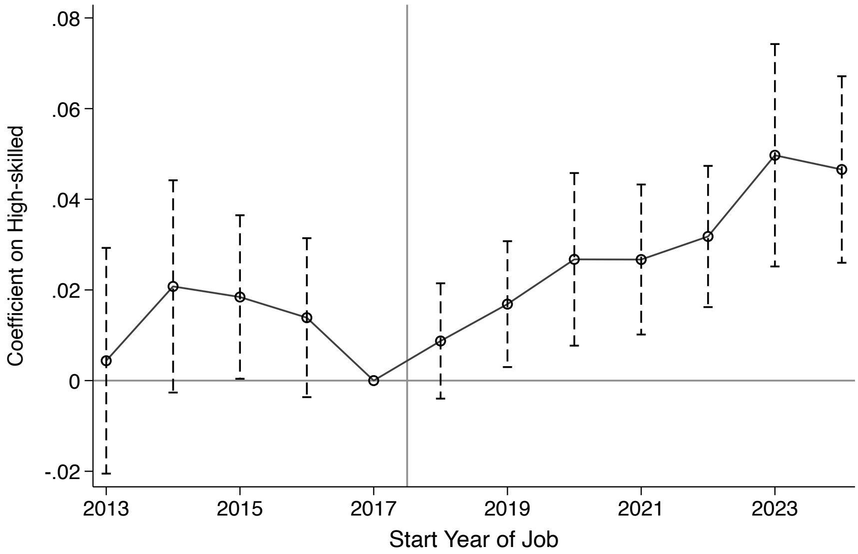


Figure 11: Job Spells of High-Skilled Positions

Notes: Figure shows the event-study results of the dual-credit policy on EV-focused firms offering high-skilled positions. The year of policy shock is 2018. Each circle indicates the point estimations of the treatment effect (i.e., the coefficient of $EV\_Focused_f \times T_t$ in Equations (10))). Each vertical dashed line indicates the 95% confidence interval of the treatment effect.

Similarly, Figure 12 shows that EV-focused firms hire relatively more highly educated workers after the policy shock.

Finally, the job spells of EV-focused firms become more concentrated in developed regions with a larger supply of high-skilled talent, as shown in Figure 13. Notably, before the policy shock, GV-focused firms offered relatively more positions in first-tier cities over time; the policy shock reverses this trend. Controlling for worker fixed effects yields qualitatively similar results.

7 Conclusion

This paper documents how China's dual-credit policy directed technical change in the automotive sector toward vehicle electrification. Combining administrative production records, new-vehicle specifications, and rich innovation and talent data, we document several key transitions induced by the policy: First, the dual-credit policy creates a significant price wedge

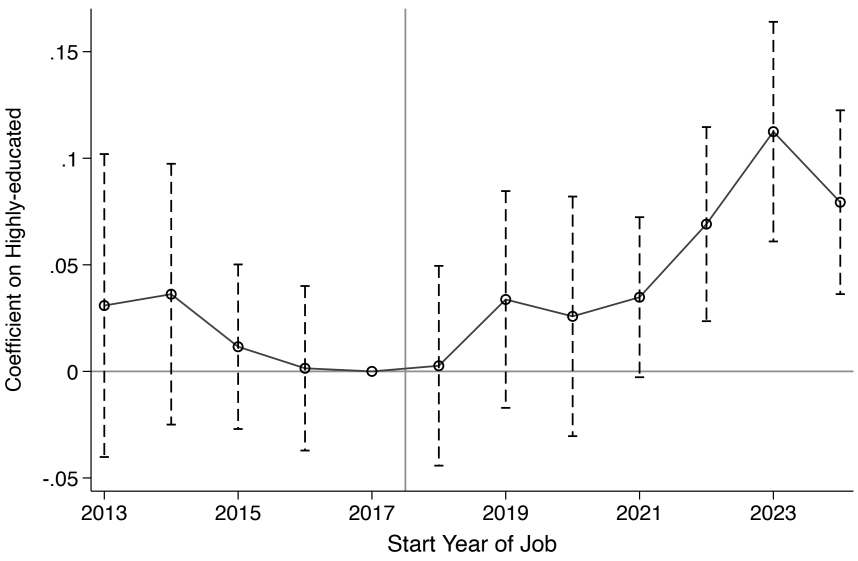


Figure 12: Job Spells of Highly Educated Workers

Notes: Figure shows the event-study results of the dual-credit policy on EV-focused firms hiring highly-educated workers with at least a Master's degree. The year of policy shock is 2018. Each circle indicates the point estimations of the treatment effect. Each vertical dashed line indicates the 95% confidence interval of the treatment effect.

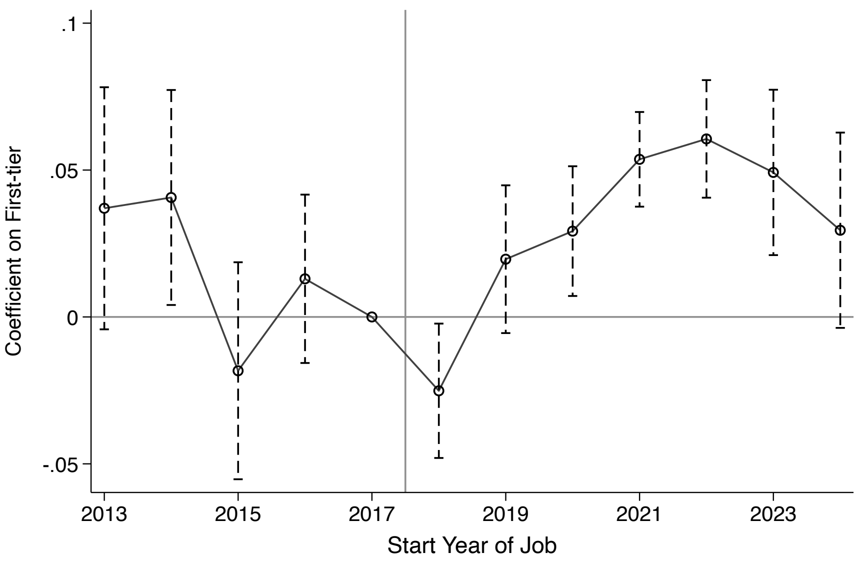


Figure 13: Job Spells in First-Tier Cities

Notes: Figure shows the event-study results of the dual-credit policy on EV-focused firms offering jobs in the four first-tier cities–Beijing, Shanghai, Guangzhou, and Shenzhen. The year of policy shock is 2018. Each circle indicates the point estimations of the treatment effect. Each vertical dashed line indicates the 95% confidence interval of the treatment effect.

between EVs and GVs that shifts demand (and thus supply) toward EVs. Second, because of the NEV-target threshold, relatively small firms with GV production above the threshold reduced GV production, while larger firms relatively increased it. Third, the turn toward EVs substitutes for effort to reduce GV fuel consumption. Fourth, cannibalization generates negative incentives for incumbents to produce high-quality EVs, whereas newcomers' EVs exhibit higher quality in driving performance and intelligence. Taken together, the dual-credit policy plays a significant role in the transition from GVs to EVs, as well as the shift from incumbents to newcomers.

These production transitions are accompanied by shifts in technological innovation and talent allocation within the industry. Innovation was redirected toward EV and intelligence-related technologies, weakening path dependence in innovation. This shift was mirrored in the labor market, where EV-focused firms increasingly hired high-skilled, highly educated workers and concentrated activity in top-tier cities.

The results highlight the power of targeted regulatory policies to align private incentives with climate and industrial objectives. The introduction of credit trading enables the market to select players with comparative advantages. Cannibalization, combined with a new product type with distinct technological requirements, further enhances newcomers' advantages in competition with incumbents.

References

Acemoglu, D. (1998). Why Do New Technologies Complement Skills? Directed Technical Change and Wage Inequality. *The Quarterly Journal of Economics*, 113(4):1055–1089.

Acemoglu, D. (2002). Directed Technical Change. *Review of Economic Studies*, 69(4):781–809.

Acemoglu, D., Aghion, P., Barrage, L., and Hémous, D. (2023). Climate Change, Directed Innovation, and Energy Transition: The Long-run Consequences of the Shale Gas Revolution. Technical Report w31657, National Bureau of Economic Research, Cambridge, MA.

Acemoglu, D., Aghion, P., Bursztyn, L., and Hemous, D. (2012). The Environment and Directed Technical Change. *American Economic Review*, 102(1):131–166.

Acemoglu, D., Akcigit, U., Hanley, D., and Kerr, W. (2016). Transition to Clean Technology. *Journal of Political Economy*, 124(1):52–104.

Aghion, P., Bergeaud, A., Lequien, M., and Melitz, M. J. (2024). The Heterogeneous Impact of Market Size on Innovation: Evidence from French Firm-Level Exports. *Review of Economics and Statistics*, 106(3):608–626.

Aghion, P., Bénabou, R., Martin, R., and Roulet, A. (2023). Environmental Preferences and Technological Choices: Is Market Competition Clean or Dirty? *American Economic Review: Insights*, 5(1):1–19.

Aghion, P., Dechezleprêtre, A., Hémous, D., Martin, R., and Van Reenen, J. (2016). Carbon Taxes, Path Dependency, and Directed Technical Change: Evidence from the Auto Industry. *Journal of Political Economy*, 124(1):1–51.

Allcott, H., Kane, R., Maydanchik, M., Shapiro, J., and Tintelnot, F. (2024). The Effects of "Buy American": Electric Vehicles and the Inflation Reduction Act. Technical Report w33032, National Bureau of Economic Research, Cambridge, MA.

Alé-Chilet, J., Chen, C., Li, J., and Reynaert, M. (2025). Colluding Against Environmental Regulation. *Review of Economic Studies*, page rdaf024.

Anderson, S. T. and Sallee, J. M. (2011). Using Loopholes to Reveal the Marginal Cost of Regulation: The Case of Fuel-Economy Standards. *American Economic Review*, 101(4):1375–1409.

Barwick, P. J., Kalouptsidi, M., and Zahur, N. B. (2025). Industrial Policy Implementation: Empirical Evidence from China's Shipbuilding Industry. *Review of Economic Studies*, page rdaf011.

Barwick, P. J., Kwon, H.-S., and Li, S. (2024a). Attribute-based Subsidies and Market Power: an Application to Electric Vehicles. Technical Report w32264, National Bureau of Economic Research, Cambridge, MA.

Barwick, P. J., Kwon, H.-S., Li, S., Wang, Y., and Zahur, N. (2024b). Industrial Policies and Innovation: Evidence from the Global Automobile Industry. Technical Report w33138, National Bureau of Economic Research, Cambridge, MA.

Calel, R. and Dechezleprêtre, A. (2016). Environmental Policy and Directed Technological Change: Evidence from the European Carbon Market. *Review of Economics and Statistics*, 98(1):173–191.

Davis, L., Li, J., and Springel, K. (2025). Political Ideology and U.S. Electric Vehicle Adoption. Technical Report w33591, National Bureau of Economic Research, Cambridge, MA.

Dorsey, J., Langer, A., and McRae, S. (2025). Fueling Alternatives: Gas Station Choice and the Implications for Electric Charging. *American Economic Journal: Economic Policy*, 17(1):362–400.

Dugoua, E. and Dumas, M. (2024). Coordination dynamics between fuel cell and battery technologies in the transition to clean cars. *Proceedings of the National Academy of Sciences*, 121(27):e2318605121.

Fang, H., Li, M., Wang, L., and Yang, Z. (2025). High-Speed Rail and China's Electric Vehicle Adoption Miracle. Technical Report w33489, National Bureau of Economic Research, Cambridge, MA.

Forsythe, C. R., Gillingham, K. T., Michalek, J. J., and Whitefoot, K. S. (2023). Technology advancement is driving electric vehicle adoption. *Proceedings of the National Academy of Sciences*, 120(23):e2219396120.

Gugler, K., Szücs, F., and Wiedenhofer, T. (2024). Environmental Policies and directed technological change. *Journal of Environmental Economics and Management*, 124:102916.

Hanlon, W. W. (2015). Necessity Is the Mother of Invention: Input Supplies and Directed Technical Change: Directed Technical Change. *Econometrica*, 83(1):67–100.

Hassler, J., Krusell, P., and Olovsson, C. (2021). Directed Technical Change as a Response to Natural Resource Scarcity. *Journal of Political Economy*, 129(11):3039–3072.

Hu, Y., Yin, H., and Zhao, L. (2025). Subsidy Phase-Out and Consumer Demand Dynamics: Evidence from the Battery Electric Vehicle Market in China. *Review of Economics and Statistics*, 107(2):458–475.

Hémous, D. and Olsen, M. (2021). Directed Technical Change in Labor and Environmental Economics. *Annual Review of Economics*, 13(1):571–597.

Jacobsen, M. R. (2013). Evaluating US Fuel Economy Standards in a Model with Producer and Household Heterogeneity. *American Economic Journal: Economic Policy*, 5(2):148–187.

Jacobsen, M. R., Sallee, J. M., Shapiro, J. S., and Van Benthem, A. A. (2023). Regulating Untaxable Externalities: Are Vehicle Air Pollution Standards Effective and Efficient? *The Quarterly Journal of Economics*, 138(3):1907–1976.

Jacobsen, M. R. and Van Benthem, A. A. (2015). Vehicle Scrappage and Gasoline Policy. *American Economic Review*, 105(3):1312–1338.

Juhász, R., Lane, N., and Rodrik, D. (2024). The New Economics of Industrial Policy. *Annual Review of Economics*, 16(1):213–242.

Kantor, S. and Whalley, A. (2025). Moonshot: Public R&D and Growth. *American Economic Review*, 115(9):2891–2925.

Klier, T. and Linn, J. (2016). The effect of vehicle fuel economy standards on technology adoption. *Journal of Public Economics*, 133:41–63.

Knittel, C. R. (2011). Automobiles on Steroids: Product Attribute Trade-Offs and Technological Progress in the Automobile Sector. *American Economic Review*, 101(7):3368–3399.

Lane, N. (2025). Manufacturing Revolutions: Industrial Policy and Industrialization in South Korea. *The Quarterly Journal of Economics*, 140(3):1683–1741.

Leard, B., Linn, J., and Zhou, Y. C. (2023). How Much Do Consumers Value Fuel Economy and Performance? Evidence from Technology Adoption. *The Review of Economics and Statistics*, 105(1):158–174.

Li, G., Walls, W., and Zheng, X. (2023). Differential license plate pricing and electric vehicle adoption in Shanghai, China. *Transportation Research Part A: Policy and Practice*, 172:103672.

Li, J. (2023). Compatibility and Investment in the U.S. Electric Vehicle Market. Working Paper.

Li, S., Tong, L., Xing, J., and Zhou, Y. (2017). The Market for Electric Vehicles: Indirect Network Effects and Policy Design. *Journal of the Association of Environmental and Resource Economists*, 4(1):89–133.

Li, S., Zhu, X., Ma, Y., Zhang, F., and Zhou, H. (2022). The Role of Government in the Market for Electric Vehicles: Evidence from China. *Journal of Policy Analysis and Management*, 41(2):450–485.

Loebbing, J. (2022). An Elementary Theory of Directed Technical Change and Wage Inequality. *The Review of Economic Studies*, 89(1):411–451.

Muehlegger, E. and Rapson, D. S. (2022). Subsidizing low- and middle-income adoption of electric vehicles: Quasi-experimental evidence from California. *Journal of Public Economics*, 216:104752.

Popp, D. (2019). Environmental Policy and Innovation: A Decade of Research. *International Review of Environmental and Resource Economics*, 13(3-4):265–337.

Popp, D., Newell, R. G., and Jaffe, A. B. (2010). Energy, the Environment, and Technological Change. In *Handbook of the Economics of Innovation*, volume 2, pages 873–937. Elsevier.

Remmy, K. (2024). Adjustable product attributes, indirect network effects, and subsidy design: The case of electric vehicles. Technical Report DP19639, CEPR Press, Paris & London.

Reynaert, M. (2021). Abatement Strategies and the Cost of Environmental Regulation: Emission Standards on the European Car Market. *The Review of Economic Studies*, 88(1):454–488.

Sinyashin, A. (2021). Optimal Policies for Differentiated Green Products: Characteristics and Usage of Electric Vehicles. Technical report.

Springel, K. (2021). Network Externality and Subsidy Structure in Two-Sided Markets: Evidence from Electric Vehicle Incentives. *American Economic Journal: Economic Policy*, 13(4):393–432.

Zhang, X., Bai, X., and Zhong, H. (2018). Electric vehicle adoption in license plate-controlled big cities: Evidence from Beijing. *Journal of Cleaner Production*, 202:191–196.

APPENDIX

Table of Contents

A Data Appendix

A.1 Data construction for step I analysis

We assemble multiple administrative data sources in constructing the sample that covers the near universe of all new car products from 2010 to 2024.

The basis of this data set is the government-released announcements of motor vehicle manufacturers and products. In each announcement, we can find a list of new products released by manufacturers. While in this new product list, products are listed with their model code instead of trim code, we can identify the trim that is newly released by further checking the Road Motor Vehicle Manufacturers and Products Information Inquiry System. Figure A1 shows a sample page and its translation from the Road Motor Vehicle Manufacturers and Products Information Inquiry System. It shows the detailed information of an FAW model with trim code CA6463BEV, including identifiers, dimensions, weights, performance data, key intermediate input suppliers, production location, and others.

Second, we supplement some other performance data of electric vehicles from (1) the Catalogues of Recommended Models for the Promotion and Adoption of NEVs, available from 2017 to 2022, (2) the Catalogues of Energy-Efficient Vehicles and NEVs Eligible for Vehicle and Vessel Tax Reduction, available from 2012 onwards, and (3) the Catalogues of NEVs Exempt from Vehicle Purchase Tax, available from 2014 onwards. In these catalogues, we observe the identifier, dimension, curb weight, range, battery capacity, battery weight, battery type, electricity consumption, battery type, motor power, and others. Compared with the announcement data, these catalogues essentially enrich the performance measures available for our analysis, enabling us to back out the NEV credit for each trim.

Third, we augment this data by combining the data from the China Automobile Energy Consumption Query System,[9] which provides information about vehicle energy consumption

[9]Refer to https://yhgscx.miit.gov.cn, last accessed: 26 September, 2025.

产品号	ZPUG16E801W	产品ID	W9150403
批次	329	发布日期	20200306
企业名称	中国第一汽车集团有限公司	产品商标	一汽牌
生产地址	长春		
车辆型号	CA6463BEV	车辆名称	纯电动多用途乘用车
外形尺寸长	4639	外形尺寸宽	1880
外形尺寸高	1640		
总质量	2230	整备质量	1810
额定载客(含驾驶员)	5	接近角/离去角	20° /27°
最高车速	170	轴荷	1103/1127
前悬后悬	919/910		
底盘型号及企业	承载式车身		
钢板弹簧片数	-/-		
轴数	2	轴距	2810
前轮距	1615	后轮距	1615
轮胎数	4		
轮胎规格	225/65 R17,225/55 R19		
转向形式	方向盘		
车辆识别代号(VIN)	LFBGEV07×××××××××		
燃料种类	纯电动	油耗	
排放依据标准			
发动机生产企业	株洲中车时代电气股份有限公司	发动机型号	CAM210PT2
排量		发动机功率	140
是否免检	1	防抱死系统	有
其它	选装尾部标识,无天窗,侧面标识,轮辋.储能装置的种类:三元锂离子蓄电池;储能装置单体的生产企业:宁德时代新能源科技股份有限公司;ABS系统生产厂家:博世汽车部件(苏州)有限公司;ABS系统型号:EV7111		
停产日期		停售日期	

A: Original Chinese version

Product code	ZPUG16E801W	Product ID	W9150403
Batch	329	Release date	20200306
Manufacturer	China FAW Group Co., Ltd.	Brand	FAW
Location	Changchun		
Trim code	CA6463BEV	Car category	Pure Electric Multi-Purpose Passenger Vehicle
Length	4639	Width	1880
Height	1640		
Total weight	2230	Curb weight	1810
Passenger	5	Angle	20° /27°
Max. speed	170	Load	1103/1127
Overhang	919/910		
Chassis	Bearing type car body		
Leaf springs	-/-		
Axles	2	Wheelbase	2810
Front track	1615	Rear Track	1615
Wheels	4		
Tire Spec.	225/65 R17,225/55 R19		
Steering control	Steering wheel		
VIN	LFBGEV07×××××××××		
Fuel type	Pure electric	Fuel consum.	
Emission std.			
Engine Manuf.	Zhuzhou CRRC Times Electric	Engine model	CAM210PT2
Displacement		Motor power	140
Inspection exem.	1	ABS	Yes
Other	Optional configurations: logo without luminous effect, non-privacy glass, without side logo, side decoration plate; Battery type: ternary lithium-ion battery; Battery manufacturer: Contemporary Amperex Technology Co., Ltd.; ABS system supplier: Bosch Automotive Systems (Suzhou) Co., Ltd.; ABS system model: EV7111		
End of prod.		End of sales	

B: English translation

Figure A1: Sample Page of Trim Information

Notes: Data Source: Road Motor Vehicle Manufacturers and Products Information Inquiry System. In Panel B, the translation is done by the authors.

from 2010 onwards. Specifically, we are able to observe administrative records of fuel consumption of gasoline vehicles, which is crucial for analyzing the impact of the dual-credit policy on fuel economy of vehicles.

Across these data sources, we use the trim code as the unique identifier to merge the data. Trim code of vehicles in China is regulated under the Rules of Designating Trim Codes of Automobiles and Trailers and the Technical Conditions for Determining the Same Trim of Automobile Products. Take a trim code $TSL7000BEVAR0$ as an example. It consists of several parts:

$$\underbrace{TSL}_{\text{OEM Code}} \quad \underbrace{7}_{\text{Vehicle Category Code}} \quad \underbrace{00}_{\text{Main Parameter Code}} \quad \underbrace{0}_{\text{Product Serial Number}} \quad \underbrace{BEV}_{\text{Classification code}} \quad \underbrace{AR0}_{\text{Customized Code}}$$

where TSL stands for Tesla, 7 is the category code for sedan, 00 is the displacement for sedan, which is 0 for EVs, 0 following is the serial number, indicating it is the first product among this type. BEV indicates battery electric vehicle, and $AR0$ is freely determined by firms. This trim code indicates a specific trim of Tesla Model 3. We define the first four parts up to product serial number of a trim code as the model code, which captures the same series of product. For example, every Model 3 has the same $TSL7000$ model code in our data.

Together, we observe 2,665 unique model codes and 19,855 unique trim codes in our data for the period from 2010 to 2024, produced by 156 original equipment manufacturers.

However, in this dataset, we lack two key variables to analyze the market outcomes of cars: prices and sales. To add this important information, we turn to `autohome.com`, one of the leading online platforms and forums of the Chinese auto market. It provides rich information of cars on the market.

Collecting the public data available on the website, we assemble a comprehensive dataset of cars from 2010 to 2024, with a extensive set of characteristics, including price, sales, dimensions, weight, fuel consumption, driving performance, suppliers, and importantly, intelligence-related measures.

There are several differences in the way of data recording between the `autohome.com` and the administrative new car product data. Specifically, the `autohome.com` data is at the specification level, which is even more granular than at the trim level because some specifications only differ in terms of exterior or interior decorations, which is not sufficient to be designated a new trim code. In sum, we collect data for 2,475 unique models and 45,268 specifications. Noting that the `autohome.com` data also covers many imported foreign brand cars, the coverage of models is slightly lower than the administrative new car product data. It is worth noting that there are only identifiers for models and specifications defined by the platform, which is not directly mapped to the trim code. Moreover, the name of producers in this data is different from the official firm name of original equipment manufacturers as in the administrative records. Because of the ambiguity in the `autohome.com` data, we do not consider forming a 1-to-1 mapping at the most granular level. Instead, we identify the original equipment manufacturers in the data so that we can distinguish incumbents and newcomers. We manage to match 137 original equipment manufacturers, covering 1,685 models and 35,828 specifications.

A.2 Data construction for step II analysis

Patent Data

We combine two data sources in constructing the patent data used in this study. The first one is the patent application records from the China National Intellectual Property Administration (CNIPA). We identify all the patents application filled by the manufacturers, the key shareholders, and the affiliated firms. We start from the CNIPA system because it offers the query function that helps us to precisely identify each firm with their Chinese name. Starting from Google Patent may include some noise in this step of identification. We supplement the patent records with Google Patent, which provides the full text contents, Cooperative Patent Classification (CPC) code, legal status and corresponding timeline, as well as citations of patents.

Figure A2 shows the dynamics of the number of patent applications filled in each year, as well as the share of patents that are applied by manufacturers. We can see that the total number increases rapidly in the pass decade except for 2024. This is inline with the fact that with the electrification process of vehicles, many innovations take place in the automobile industry. At the same time, the share of patents applied by manufactures started decreasing after 2018. In general, the manufacturers only account for a small share of patents among the car manufacturing groups, highlighting the importance of including affiliated firms into account.

To identify the key shareholders of manufacturers and the affiliation network of firms, we leverage the ownership structure data from `tianyancha.com`, one of the leading business information platforms of Chinese companies that provides company registration data, legal filings, financial records, and corporate relationships. Figure A3 shows a sample page of ownership structure of a car manufacturer in `tianyancha.com`. We identify a key shareholder as a firm

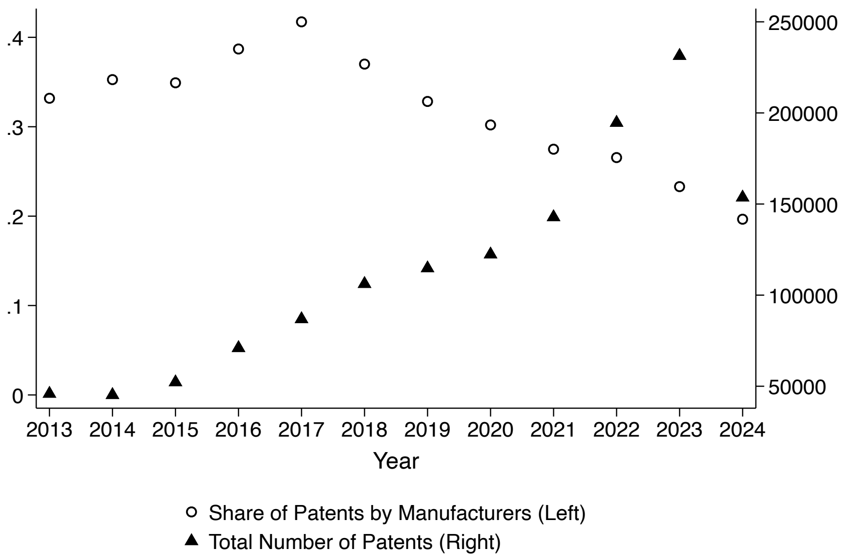


Figure A2: Share of Patents by Manufacturers

Notes: Figure shows the total number of patents and the share of patents applied by manufacturers across years.

that directly or indirectly hold more than 25% of shares, echoing the definition of connected firms in the dual-credit policy. Then, we include all affiliated firms of these key shareholders, defined as firms whose shares are directly or indirectly hold by the key shareholders. It is worth noting that, in `tianyancha.com`, we can only observe ownership structure up to three layers of indirect shareholding. Therefore, we assume that firms that are indirectly linked through more than three intermediate firms are not affiliated with each other.

We identify three types of innovation in this study, namely EV-related, GV-related, and intelligence-related innovations. The identification of the first two is based on previous literature. The identification of the last one is based on inquiry with a leading Large Language Model (LLM) about "the key information tech technologies applied in the auto industry". Then, we search for the corresponding CPC code based on the key words of technologies. Table A1 summarizes the CPC and IPC codes used to categorized innovations.

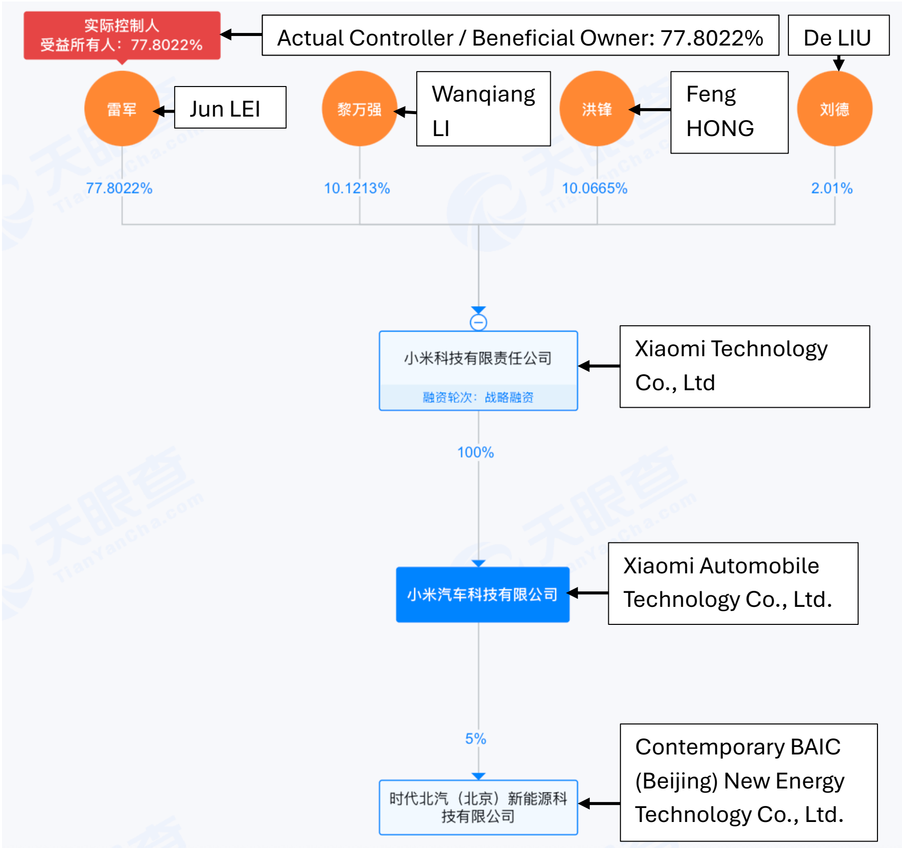


Figure A3: Sample Page of `tianyancha.com`

Notes: Figure shows the sample page of ownership structure of a company on `tianyancha.com`.

Table A1: IPC and CPC Codes in Innovation Categorization

IPC Code	CPC Code	Description
	EV-related Innovation	
B60K1		Arrangement or mounting of electrical propulsion units in vehicles.
B60K6		Arrangement or mounting of hybrid propulsion units.
B60K7		Arrangement or mounting of auxiliary drives or power take-offs.
B60L3		Electric propulsion using power supplied within the vehicle (e.g. batteries).
B60L7/1, 20		Electric propulsion with power supply external to the vehicle, such as trolley wires or inductive systems.

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IPC Code	CPC Code	Description
B60L11		Electric propulsion with energy recovery (e.g. regenerative braking).
B60L15		Methods or apparatus for reducing energy consumption in electric propulsion.
B60W10/08, 24, 26,28		Control systems for hybrid or electric vehicles, including torque distribution, braking coordination, and power flow management.
B60W20		Control systems specially adapted for hybrid vehicles.
B60L11/18		Regenerative braking with control of returned energy storage.
B60L1		Electric propulsion using external sources of power along a fixed track (railway, tram, trolley).
B60L50		Electric propulsion details of power supply means for road vehicles.
B60L53		Electric propulsion details concerning charging equipment and methods.
B60L55		Electric propulsion details concerning electric energy storage in vehicles.
B60L58		Electric propulsion details concerning wireless energy transfer for vehicles.
B60W60		Control systems specially adapted for hybrid or electric vehicles with energy management strategies.
H01M8		Fuel cells and related structures.
H01M10/02, 04, 052, 0525		Secondary (rechargeable) batteries, especially lithium-ion structures, electrodes, and electrolytes.
H01M50		Constructional details of electrochemical cells (e.g. casings, current collectors, connectors).
		GV-related Innovation
B60K5		Arrangement or mounting of internal combustion engines in vehicles.
B60K6		Arrangement or mounting of hybrid propulsion units.
B60K13		Arrangement in connection with combustion air intake or gas exhaust of propulsion units
B60K15		Arrangement in connection with fuel supply of combustion engines

Continued on next page

IPC Code	CPC Code	Description
B60S5/02		Supplying fuel to vehicles
B60W10/06		Conjoint control of vehicle sub-units, including control of combustion engines
B60W20		Control systems specially adapted for hybrid vehicles
F02B		Internal-combustion piston engines
F02D		Controlling combustion engines
F02F		Cylinders, pistons, or casings for combustion engines
F02M		Supplying combustion engines with fuel or air
F02N		Starting of internal combustion engines
F02P		Ignition systems for internal combustion engines.
		Intelligence-related Innovation
	B60K37	Dashboards (as road-vehicle superstructure sub-units)
	B60L2260	Indexing for operating modes of electric propulsion
	B60R11/02	Arrangements for holding or mounting articles, for radio sets, television sets, telephones, or the like
	B60W30	Purposes of road vehicle drive control systems
	B60W50	Details of control systems for road vehicle drive control
	B60W60	Drive control systems specially adapted for autonomous road vehicles
	B62D25/14	Dashboards as superstructure sub-units
	G02B27/01	Head-up displays
	G05B13	Adaptive control systems, including artificial intelligence applied to control.
	G06F3/0481	Touch-sensitive input devices, particularly touchscreens as user interfaces.
	G08G1/0968	Systems involving transmission of navigation instructions to the vehicle
	H04W4/02	Wireless communication services for location-based applications (e.g. navigation).

Notes: Table shows the IPC and CPC codes for classifying patens into EV-related innovations, GV-related innovations, and intelligence-related innovations. Following previous literature, we treat hybrid (non-plug-in) patents as GV-related innovations.

LinkedIn Profiles

LinkedIn is one of the leading online platforms where individuals and organizations connect, share career information, and explore job opportunities. Individual profiles on LinkedIn provide rich information about people's education background, job history, and details about specific tasks, experience, and skills. Given this advantage, LinkedIn profiles have been increasingly used in economics research. In this study, we use LinkedIn profiles to capture individuals who have ever worked for leading car manufacturers in China, which enables us to look at the labor market consequences of the transition in the auto industry.

While LinkedIn has left China since 2019, there are still many China-based users remain active on the platform. Moreover, Chinese users can still register for a LinkedIn profile. In sum, there are more than 16 million China-based user profiles on LinkedIn, which is sufficiently large. However, even with a large user group, LinkedIn does not cover the universe of workforce. In particular, LinkedIn is more representative for high-tech industries. In recent years, auto industry increasingly incorporates IT- and AI-related technologies. Therefore, we argue that LinkedIn profiles should also have a good representativeness for the auto industry. When we look at the auto industry, many engineers, technicians, designers, and managers are included. Restricting our focus on China-based users who have ever worked for car manufacturers during 2010 to 2024 gives us a total sample of 173,320 user profiles and 420,322 job spell records.

It is worth noting that LinkedIn records car manufacturers in a way different than identifying each individual original equipment manufacturer. To enable comparisons across results, we categorize 209 car manufacturing firms listed on LinkedIn into 55 groups and the "other" that covers all the original equipment manufacturers in our baseline datasets. Further, we divide groups into EV-focused and GV-focused groups based on the share of EV products among all new products introduced. Specifically, those with a share of EV products above the median are defined as EV-focused, while the others are defined as GV-focused.

B Additional Details of the Policy Background

B.1 Calculation of CAFC

The target levels of fuel consumption are set according to the national standards entitled "Fuel consumption evaluation methods and targets for passenger cars". The national standards are managed by the government and are drafted by leading research institutions in the field as well as some leading automakers. The standards are updated periodically. Within the studied period, there are three versions of this national standard, which became effective on the 1 January of 2012, 2016, and 2021.

The target levels are determined by curb weight and the number of seats. Figure B1 shows the target levels of litre of fuel consumed per 100 kilometer of driving across different versions of standards. It is worth noting that in the 2021 version of the standard, the evaluation method was changed from the New European Driving Cycle (NEDC) to Worldwide harmonized Light vehicles Test Cycle (WLTC). The latter one is considered to be closer to real-world driving conditions. In general, the fuel consumption under WLTC is about 10% higher than that under NEDC.

The compliance level is set above the target level when a standard is newly come into force, and gradually converge to the target level overtime. Figure B2 shows the compliance-target ratio across years.

As shown in Section 3, the calculation of CAFC credit is based on the following equation, which compares the weighted average fuel consumption of cars sold and the average compliance level determined by the above standards.

$$CAFC\ Credit = \left(\underbrace{\frac{\sum_{j=1}^{J} \bar{e}_j \left(w_j\right) q_j}{\sum_{j=1}^{J} q_j} \cdot \eta}_{\text{compliance level}} - \underbrace{\frac{\sum_{j=1}^{J} e_j q_j}{\sum_{j=1}^{J} q_j W}}_{\text{actual FC}} \right) \cdot Q^g$$

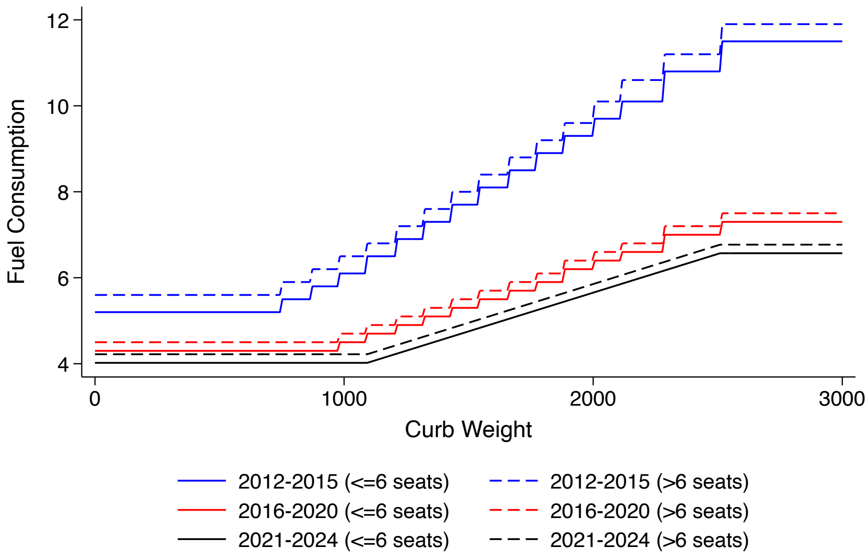


Figure B1: Target Level of Fuel Consumption

Notes: Figure shows the target levels of litre of fuel consumed per 100 kilometer of driving across different versions of standards. In the 2021 version of fuel consumption target, the evaluation method changed from NEDC to WLTC.

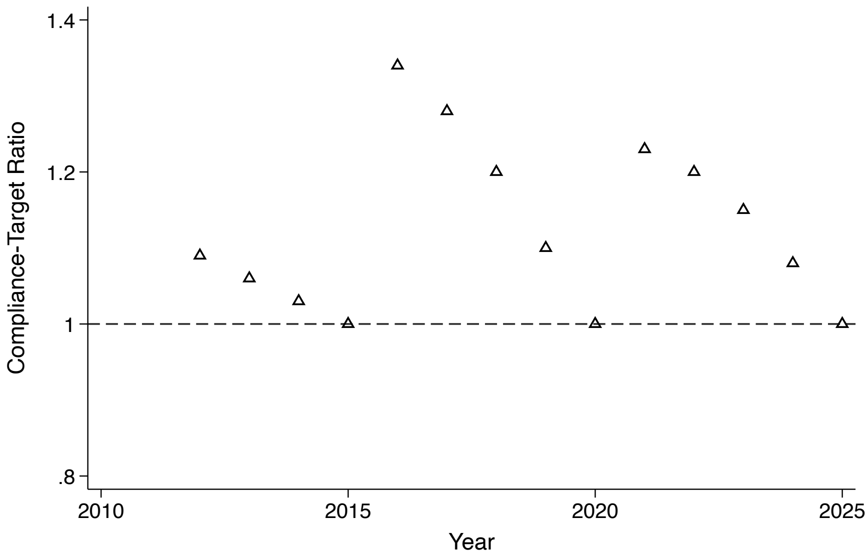


Figure B2: Compliance-Target Ratio

Notes: Figure shows the Compliance-target Ratio across years.

where the weighting factor W is favoring energy-saving GVs and EVs. Table B1 shows the values of W across years and car categories.

Table B1: Weighting Factor W

W	2012-2015	2016-17	2018-19	2020	2021	2022	2023	2024
BEV/PHEV/FCEV	5	5	3	2	2	1.8	1.6	1.3
Energy-saving GV	3	3.5	2.5	1.5	1.4	1.3	1.2	1.1

Notes: Table shows the values of W across years and car categories. "BEV" stands for battery electric vehicle. "PHEV" stands for plug-in hybrid electric vehicle. "FCEV" stands for fuel cell electric vehicle. "Energy-saving GV" stands for GVs with fuel consumption <2.8L/100km under the 2012 and 2016 standards, and <3.2L/100km under the 2021 standard.

B.2 Calculation of NEV credit

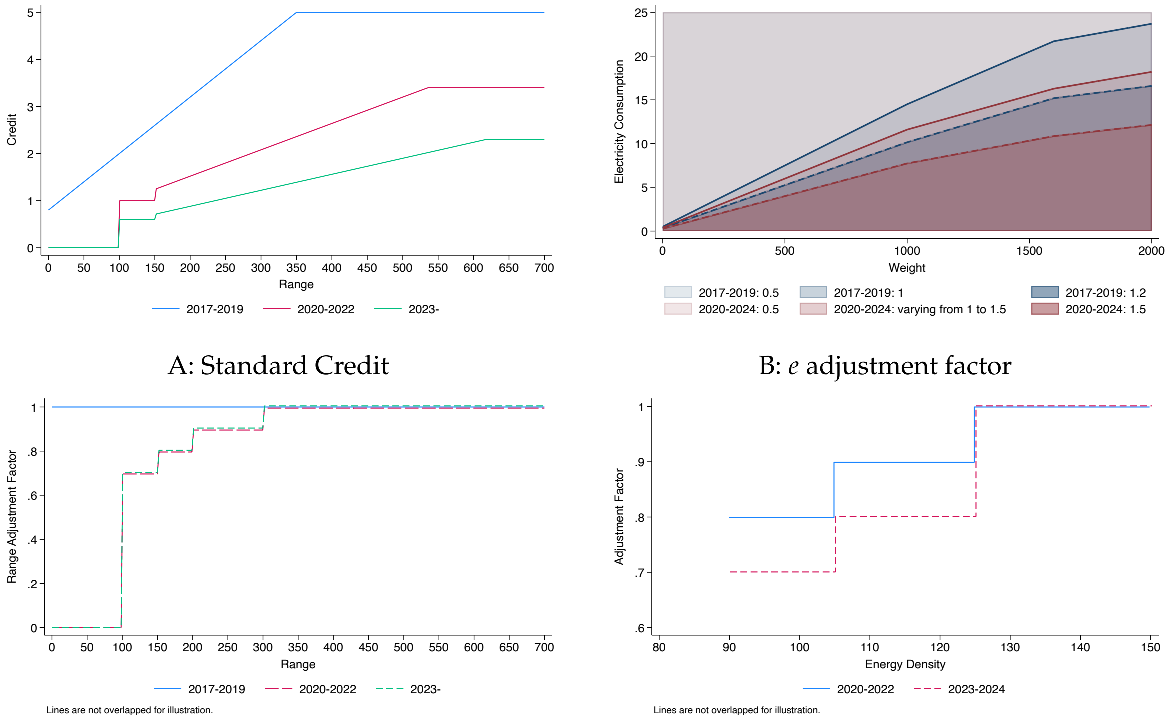
Throughout this study, we do not take fuel cell electric vehicles into account because it is still an immature technology with limited market practices. Here, we focus on the calculation of NEV credit for battery electric vehicles and plug-in hybrid electric vehicles.

For battery electric vehicles, the NEV credit is determined by curb weight (w), range (r), battery energy density (d), and electricity consumption level (c). The calculation is based on the following equation:

$$NEV\ Credit = \begin{cases} \underbrace{k_1(r)}_{\text{standard credit}} * \underbrace{\zeta_1(c,w)}_{e \text{ adjustment factor}}, & \text{2017 version} \\ k_1(r,w) * \zeta_1(c,w) * \underbrace{\zeta_2(r)}_{r \text{ adjustment factor}} * \underbrace{\zeta_3(d)}_{d \text{ adjustment factor}}, & \text{2020 and 2023 versions} \end{cases}$$

Figure B3 summarizes the calculation criteria across different versions of the dual-credit policy. In general, the criteria become more and more stringent overtime, leading to a decrease of per vehicle credit.

Except for the positive credit calculation formula, the government also adjust ratio of the NEV credit target on GV production overtime (see Figure B4). Before 2024, it increases by 2% each year. Afterwards, it increases by 10% each year and is assumed to keep increasing in 2026 and 2027 at the time of research.



A: Standard Credit

B: e adjustment factor

C: r adjustment factor

D: d adjustment factor

Figure B3: NEV Credit Calculation

Notes: Figure shows the rules of calculating each component in NEV credit formula. Panel A shows the relationship between range and the standard credit. Panel B shows the space of electricity consumption and curb weight of EVs. ζ_1 is determined by these two factors. Specifically, for the 2017 version, satisfying the electricity consumption target gives you a $\zeta_1 = 1$ or $\zeta_1 = 1.2$, depending on which target is achieved. For the 2020 and 2023 version, meeting the target gives you $\zeta_1 \geq 1$, where the actual ζ_1 depends on the electricity consumption level and is capped at 1.5. Panel C shows the relationship between ζ_2 and range. Panel D shows the relationship between ζ_3 and energy density of battery.

B.3 Credit Clearance and Connected Firms

CAFC credits are only allowed to be transferred between "connected firms" defined by the government. Firms are connected when they meet at least one of the following conditions:

1. A domestic car manufacturer and another domestic manufacturer in which it directly or indirectly holds 25% or more of shares.

2. Two domestic car manufacturers that are both directly or indirectly held 25% or more by the same domestic third party.

3. An authorized importer of cars from a foreign manufacturer and a domestic manufacturer in which that foreign manufacturer directly or indirectly holds 25% or more of

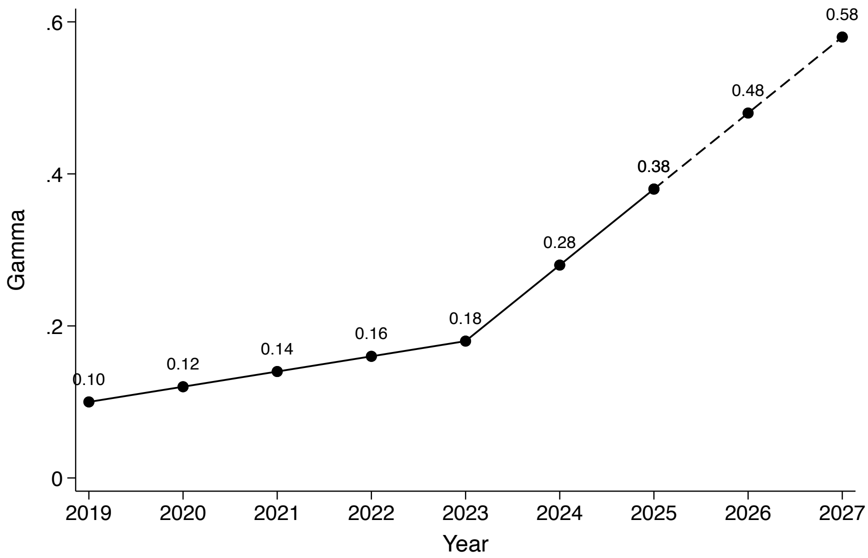


Figure B4: γ Over time

Notes: Figure shows the dynamics of γ across years. Dashed line indicates the proposed levels in the new draft for comment, which is not yet determined or come into force.

shares.

Among the about 200 active manufacturers that are ever observed in the market, we can identify 23 connected sets connecting 118 manufacturers as shown in Figure B5 based on the ownership structure data from `tianyancha.com`. A lot of manufacturers are part of the few large groups, including Shanghai Automotive Industry Corporation (SAIC), First Automotive Works (FAW), Guangzhou Automobile Group (GAC), Dongfeng Automobile Company (DFAC), Beijing Automotive Group (BAIC), Changan Automobile, Chery, and Geely. BYD and Great Wall Motor are also major automakers in China. However, compared with the groups listed in text, they do not have a large connected network of original equipment manufacturers.

B.4 Contemporary policies

Purchase subsidies in general decrease over time, except that in 2018, those with a range over 400km witnessed an increase in subsidy level.

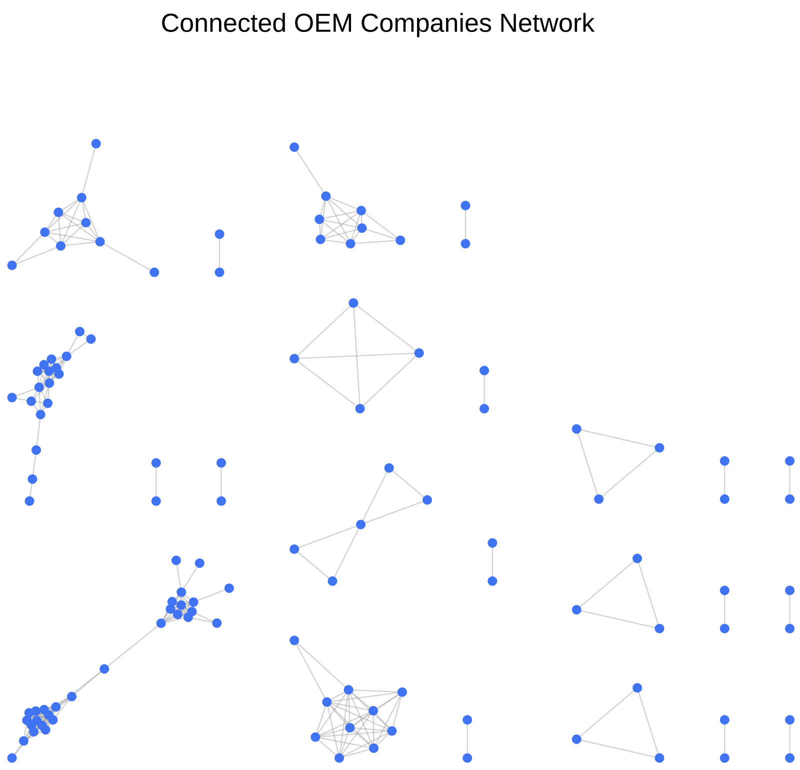


Figure B5: Connected Sets of Manufacturers

Notes: Figure shows the connected sets of manufacturers. Each dot stands for one manufacturer.

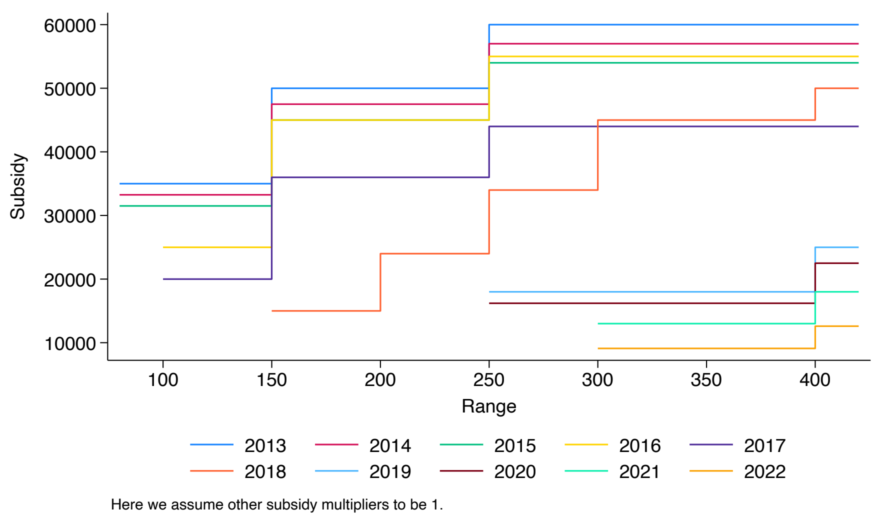


Figure B6: Purchase Subsidies for EVs

Notes: Figure shows the dynamics of purchase subsidies of new energy vehicles.

Table B2: Subsidy by Region and Year

Region	2013		2014		2015	
	Promotion Volume (Q)	Subsidy (mil. RMB)	Promotion Volume (Q)	Subsidy (mil. RMB)	Promotion Volume (Q)	Subsidy (mil. RMB)
Key Clusters	$2500 \leq Q < 5000$	20	$5000 \leq Q < 7000$	27	$10000 \leq Q < 15000$	50
	$5000 \leq Q < 7000$	30	$7000 \leq Q < 10000$	38	$15000 \leq Q < 20000$	70
	$7000 \leq Q < 10000$	45	$10000 \leq Q < 15000$	55	$20000 \leq Q < 25000$	90
	$Q \geq 10000$	75	$Q \geq 15000$	90	$Q \geq 25000$	120
Other Regions	$1500 \leq Q < 2500$	10	$3000 \leq Q < 5000$	18	$5000 \leq Q < 7000$	24
	$2500 \leq Q < 5000$	20	$5000 \leq Q < 7000$	27	$7000 \leq Q < 10000$	34
	$5000 \leq Q < 7000$	30	$7000 \leq Q < 10000$	38	$10000 \leq Q < 15000$	50
	$Q \geq 7000$	50	$Q \geq 10000$	67	$Q \geq 15000$	80

Notes: "Key Clusters" include Beijing-Tianjin-Hebei region, Yangtze River Delta, and Pearl River Delta.

Table B3: Subsidy by region and year (Cont'd)

Year	Key regions for air pollution control		Central provinces and Fujian Province		Other provinces	
	Q	Subsidy (mil. RMB)	Q	Subsidy (mil. RMB)	Q	Subsidy (mil. RMB)
2016	$Q \geq 30000$	$\min\left(120, 90 + \frac{Q-30000}{2500} \times 7.5\right)$	$Q \geq 18000$	$\min\left(120, 54 + \frac{Q-18000}{1500} \times 4.5\right)$	$Q \geq 10000$	$\min\left(120, 30 + \frac{Q-10000}{800} \times 2.4\right)$
2017	$Q \geq 35000$	$\min\left(140, 95 + \frac{Q-35000}{3000} \times 8\right)$	$Q \geq 22000$	$\min\left(140, 59.5 + \frac{Q-22000}{2000} \times 5.5\right)$	$Q \geq 12000$	$\min\left(140, 32.5 + \frac{Q-12000}{1000} \times 2.8\right)$
2018	$Q \geq 43000$	$\min\left(160, 104 + \frac{Q-43000}{4000} \times 9.5\right)$	$Q \geq 28000$	$\min\left(160, 67 + \frac{Q-28000}{2500} \times 6\right)$	$Q \geq 15000$	$\min\left(160, 36 + \frac{Q-15000}{1200} \times 3\right)$
2019	$Q \geq 55000$	$\min\left(180, 115 + \frac{Q-55000}{5000} \times 10\right)$	$Q \geq 38000$	$\min\left(180, 80 + \frac{Q-38000}{3500} \times 7\right)$	$Q \geq 20000$	$\min\left(180, 42 + \frac{Q-20000}{1500} \times 3.2\right)$
2020	$Q \geq 70000$	$\min\left(200, 126 + \frac{Q-70000}{6000} \times 11\right)$	$Q \geq 50000$	$\min\left(200, 90 + \frac{Q-50000}{4500} \times 8\right)$	$Q \geq 30000$	$\min\left(200, 54 + \frac{Q-30000}{2500} \times 4.5\right)$

Notes: "Key regions" include Beijing, Shanghai, Tianjin, Hebei, Shanxi, Jiangsu, Zhejiang, Shandong, Guangdong, and Hainan provinces.

C Additional Descriptive Results

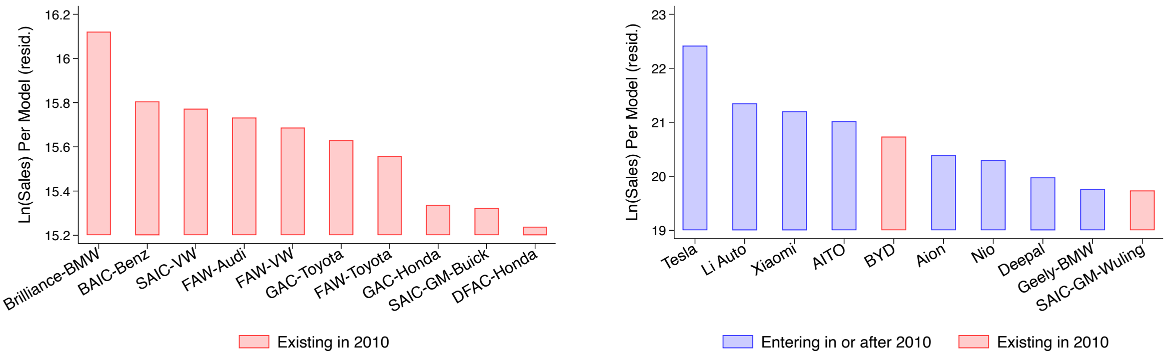
C.1 Estimating Manufacturer Fixed Effect in Model Sales

We leverage the monthly national model sales from `autohome.com` data to estimate the following empirical model:

$$\ln(Y_{jt}) = \beta_X X_{jt} + \gamma_f + \delta_t + \varepsilon_{jt}$$

where Y_{jt} is the yearly sales of model j introduced in year t. We control for car category and fuel type of cars, as well as manufacturer fixed effects and year fixed effects in the model. γ_f is the coefficient of interest, which captures the residualized average sales per model of each manufacturer. It indicates the "popularity" of products made by each manufacturer in the market. We do not control for many car attributes because we would like to capture the difference between manufacturers, taking into account their endogenous price choices and attribute choices. Therefore, we are not trying to establish any causal linkage between sales and manufacturers. But rather, we try to compare the average sales between manufacturers within the same category of cars and the same year, in an aggregate way that we weight the comparisons by their contributions to sales variance.

For comparison, we estimate the above equation and control for price. By doing so, we partial out the impact of different manufacturers have different price strategies. The estimated manufacturer fixed effects would be closer to a "competitiveness" or "attractiveness" measures given the same price. Results are shown in Figure C1. The take-away messages are identical to those drawn from the main text: (1) In the EV market, new manufacturers are taking place of incumbents. (2) In the EV market, domestic manufacturers are replacing joint-ventures to hold the leading positions. Moreover, we can see that the estimated fixed effects are smaller for GV manufactures than for EV manufacturers, indicating that, with price considered, EVs have higher sales per model than GVs.



A: Top-10 GV Manufacturers

B: Top-10 EV Manufacturers

Figure C1: Top Manufacturers in the Automobile Market (Controlling for Price)

Notes: Figure shows top manufacturers of gasoline vehicles (GVs) and electric vehicles (EVs) in the market. The y-variable is the residualized sales per model captured by the estimates of manufacturer fixed effects. Log-transformed price, body type, energy type, and year fixed effects are controlled for in this regression. The estimation is based on `autohome.com` data.

C.2 Dynamics of CAFC and NEV Credits

Throughout the years, the total supply of credits in the market are in general positive, with the exception of 2020 when COVID hit the auto industry (see Figure C2). While the aggregate supply is positive, credit price is not zero because individual firms with negative credit would still need to reach bilateral agreement with credit sellers. Nonetheless, rapidly increasing aggregate supply drives down the price of credits.

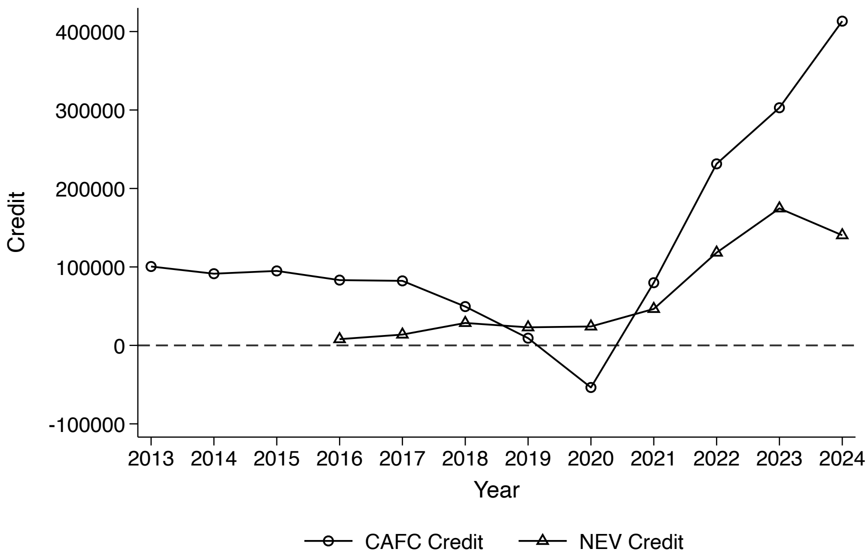


Figure C2: Dynamics of CAFC and NEV Credits

Notes: Figure shows the aggregate number of CAFC and NEV credits in the market across years. All the credits are recorded before credit trading.

D Additional Details of the Model

D.1 Proofs

D.1.1 Divergence in GV production with discontinuity in NEV credit target

First, consider a small number $\varepsilon > 0$, then the net profit of producing $\bar{Q}^g + \varepsilon$ instead of $\bar{Q}^g$ can be written as:[10]

$$\int_0^{\bar{Q}+\varepsilon} (p_j - c_j)dj - \gamma(\bar{Q}^g + \varepsilon) - \int_0^{\bar{Q}} (p_j - c_j)dj \xrightarrow{\varepsilon \to 0} -\gamma \bar{Q}^g < 0$$

Therefore, firms with GV productions just above the threshold would choose to reduce their GV productions. Given the fact that marginal profit $p_j - c_j > \gamma, \forall j$, we have

$$\frac{\partial \left(\int_{\bar{Q}}^{\bar{Q}+\varepsilon} (p_j - c_j)dj - \gamma(\bar{Q}^g + \varepsilon) \right)}{\partial \varepsilon} > 0$$

$$\Rightarrow \exists \varepsilon \text{ s.t. } \int_0^{\bar{Q}+\varepsilon} (p_j - c_j)dj - \gamma(\bar{Q}^g + \varepsilon) - \int_0^{\bar{Q}} (p_j - c_j)dj = 0$$

D.1.2 Cannibalization and the choice of attributes

Based on the first-order derivative, regarding a given attribute x, we have the following first order condition (FOC):

$$0 = -c'(x_j) + \underbrace{\left([\lambda_f^g \circ g^x]_j + [\lambda_f^e \circ e^x]_j \right) q_j}_{\text{credit term}} + [(\Phi \circ \Delta_x)\, m]_j\,,$$

where $g^x = \frac{\partial L^g}{\partial x}$, $e^x = \frac{\partial L^e}{\partial x}$.

For simplicity, assume the attribute is not included in credit calculation, $\left([\lambda_f^g \circ g^x]_j + [\lambda_f^e \circ e^x]_j \right) q_j \rightarrow$

[10]Here we slightly abuse the notation that j stands for each car sold instead of each car product as in the main text.

0. Consider a newcomer with $s_j = 0$ and $q_j \approx 0$, we have

$$c'(x_j^N) = \beta^x \, s_j(x^N) \, (1 - s_j(x^N)) \, m_j(x^N)$$

wher N stands for "newcomers".

Consider an incumbent making the decision about x, we have

$$c'(x_j^I) = \beta^x \, s_j(x^I) \, (1 - s_j(x^I)) \, m_j(x^I) - \beta^x \, s_j(x^I) \sum_{l \in \mathcal{F}_f \setminus \{j\}} s_l(x^I) \, m_l(x^I)$$

where I stands for "incumbents".

For $m_j > 0, \forall j$; and x satisfying $\beta^x > 0$, that is, x is an attribute valued by consumers, we have

$$c'(x_j^N) > c'(x_j^I)$$

at the optimum. Based on the regular assumption that $c''(\cdot) > 0$, we have

$$x_j^N > x_j^I$$

D.1.3 Solving cost minimization problem

Given the cost minimization problem:

$$\begin{aligned}
\min_{\{h_n\}_1^N, m_a} \quad & c_a = \sum_n w_{f,n} h_n + r_f m_a \\
\text{s.t.} \quad & A_{f,s(a)}^{\beta_a} \left(\prod_n h_n^{\gamma_{an}} \right) m_a^{\delta_a} \geq x_a,
\end{aligned}$$

we can write down the Lagrangian:

$$\mathcal{L} = \sum_n w_{f,n} h_n + r_f m_a - \lambda \left(A_{f,s(a)}^{\beta_a} \left(\prod_n h_n^{\gamma_{an}} \right) m_a^{\delta_a} - x_a \right)$$

Then we have FOCs:

$$
\begin{aligned}
\frac{\partial \mathcal{L}}{\partial h_{a\tau}}: &\quad w_{f,\tau} = \lambda \gamma_{a\tau} \frac{A_{f,s(a)}^{\beta_a} \prod_n h_n^{\gamma_{an}} m_a^{\delta_a}}{h_{a\tau}} = \lambda \gamma_{a\tau} \frac{x_a}{h_{a\tau}} \\
\frac{\partial \mathcal{L}}{\partial m_a}: &\quad r_f = \lambda \delta_a \frac{x_a}{m_a}
\end{aligned}
$$

$$
\Rightarrow h_{a\tau}^* = \frac{\lambda \gamma_{a\tau} x_a}{w_{f,\tau}}, \quad m_a^* = \frac{\lambda \delta_a x_a}{r_f}
$$

Plugging it back to the cost function, we have:

$$
c_a^* = \sum_\tau w_{f,\tau} h_{a\tau}^* + r_f m_a^* = \lambda x_a \left(\sum_\tau \gamma_{a\tau} + \delta_a \right) = \lambda x_a \Rightarrow \lambda = \frac{c_a^*}{x_a}
$$

Therefore, we have

$$
h_{a\tau}^* = \frac{\gamma_{a\tau} c_a^*}{w_{f,\tau}}, \quad m_a^* = \frac{\delta_a c_a^*}{r_f}
$$

$$
c_{x_a}^* = K_a \cdot A_{f,s(a)}^{-\beta_a} \cdot r_f^{\delta_a} \cdot \left(\prod_\tau w_{f,\tau}^{\gamma_{a\tau}} \right) \cdot x_a
$$

where $K_a \equiv \left(\prod_\tau \gamma_{a\tau}^{-\gamma_{a\tau}} \right) \delta_a^{-\delta_a}$.

E Model Estimation

In this section, we provide details about estimating the model outlined in 3. The purpose of the estimation is to get $\lambda^{g,e}$, the shadow price of credits, which speaks to the direct impacts of the dual-credit policy. The procedure consists of three steps. First, we estimate the coefficients in the utility function, especially the coefficient of price α. Second, we calculate the markup of vehicles based on price elasticity, and back out the sum of marginal cost c and credit burden τ. Finally, we regress the sum of c and τ on a set of car attributes and the credits to get the coefficient of credits, which stands for the shadow price λ.

E.1 Demand side

Based on the multinomial Logit model we have, we can write down the following equation for estimation:

$$\ln s_{jy} - \ln s_{0y} = x_{jy}\beta^x - \alpha p_{jy} + \xi_j + \tau_y + \varepsilon_{jy} \tag{11}$$

It is worth noting that, p_{jy} here should be the actual cost faced by consumers. Following Barwick et al. (2024a), we take taxation and subsidies into account. Specifically, we use the consumer cost below when estimating α:

$$\text{Consumer Cost} \equiv \tilde{p} = MSRP \times \frac{1 + \text{value-added tax rate} + \text{purchase tax rate}}{1 + \text{value-added tax rate}} - \text{Subsidy}$$

As documented in the literature, price is endogenous in the demand equation because price may be correlated with unobserved quality that is related to sales. Following Barwick et al. (2024a), we consider the following two instruments: (1) national purchase subsidies for EVs. The national purchase subsidies are largely determined by the stair-wise function of range of EVs, and the formula changes across years. This generates sufficient variations for identification. (2) purchase tax for cars. Purchase tax is normally 10% of the list price of vehicles.

However, there are several policy shocks that generates variations for identification. Specifically, from 1 October 2015 to 31 December 2016, the tax rate was reduced to 5% for cars with displacement below 1600 ml. In 2017, the tax rate was set at 7.5% for cars with displacement below 1600 ml. Also, as stated in Section 2, EVs are exempted from purchase tax. The identification assumption is that Because of the calculation method, both instruments are strong predictors of $\tilde{p}$.

Estimation results are shown in Table E1. In our preferred specification in column (2), the coefficient of $\ln(\tilde{p})$ is estimated to be -2.293, which is comparable to the number in Hu et al. (2025). This point estimate result is robust to changing the model into a nested Logit model where consumers first choose whether to buy the outside good or EVs or GVs, then they choose a specific product.

Table E1: Demand Estimation

VARIABLES	(1) $\ln(s_j/s_0)$	(2) $\ln(s_j/s_0)$	(3) $\ln(s_j/s_0)$	(4) $\ln(s_j/s_0)$
$\ln(\tilde{p})$	-1.254***	-2.293***	0.118	-2.027***
	(0.162)	(0.444)	(0.0721)	(0.571)
$\ln(s_{j\|g})$			0.940***	0.0731
			(0.00780)	(0.0967)
Range	0.00121*	0.000927	0.00426***	0.00120
	(0.000708)	(0.000654)	(0.000854)	(0.000764)
Weight	0.000681	0.00154***	-0.000722***	0.00130**
	(0.000540)	(0.000510)	(0.000189)	(0.000510)
Power	0.00181	0.00316*	-0.000187	0.00280
	(0.00165)	(0.00174)	(0.000576)	(0.00177)
Fuel Consumption	-0.00312	-0.00556	0.00346**	-0.00514
	(0.0157)	(0.0162)	(0.00158)	(0.0149)
Observations	12,902	12,902	12,900	12,900
R-squared	0.009	0.003	0.941	0.144
Model	MNL	MNL	Nested	Nested
Estimation	OLS	IV	OLS	IV
Product FE	Yes	Yes	Yes	Yes
Firm-Quarter-Market	Yes	Yes	Yes	Yes

Notes: Table shows the estimation result of Equation (11). "MNL" stands for multinomial Logit model. "Nested" stands for nested Logit model where consumers first choose whether to buy the outside good or EVs or GVs, then they choose a specific product. $\ln(s_{j|g})$ indicates the log share of product j within product nest $g = EV, GV$. Robust standard errors clustered at the market level are in parentheses. ***, **, and * denote significance at the 1, 5, and 10 percent level, respectively.

E.2 Supply side

From the FOC of firms regarding vehicle price in Section 3, we can write down the following:

$$\mathbf{p} - \mathbf{c} - \tau = \left(\Phi \circ \Delta_p\right)^{-1}(-\mathbf{s})$$

where we assume that price does not directly affect the credits of vehicles. Given the elements in Δ_p satisfying

$$\frac{\partial s_k}{\partial p_j} = \begin{cases} -\alpha s_j \left(1 - s_j\right), & k = j \\ \alpha s_k s_j, & k \neq j \end{cases}$$

and the fact that $\hat{\alpha} = -2.293/p$, we can calculate the margins of vehicles. It is worth noting that, to back out the marginal cost and the tax burden of credit τ, we use the price faced by producers in the calculation, which is defined as follows:

$$\text{Producer Price} = MSRP \times \frac{1 - \text{consumption tax rate}}{1 + \text{value-added tax rate}}$$

Results indicate that markup takes up about 44% of the price.

E.3 Credit values

With the sum of marginal cost and the tax burden of credits, we can divide them by estimating the following equation:

$$(c + \tau)_{jy} = \beta_0 + \beta_X X_j + \beta_{\lambda,g} CAFC + \beta_{\lambda,e} NEV + \gamma_{jy} + \eta_{yr} + \delta_m + \varepsilon_{jy}$$

where $CAFC$ and NEV indicate CAFC and NEV credits, respectively. The logic is that, with attributes X_j and a set of fixed effects that affect the marginal cost controlled for, we can identify the coefficients of credits, which would then capture the shadow prices $\lambda^{g,e}$. The Results in

Table E2 suggests that the average value of an NEV credit is around 5,880 CNY while that for a CAFC credit is around 3,420 CNY. The fact that NEV credit is more valuable is consistent from the policy setting.

Table E2: Supply Estimation

VARIABLES	(1) MC	(2) MC
NEV credit	-0.588***	
	(0.0536)	
CAFC credit		-0.342***
		(0.116)
Speed	-0.0108***	-0.00598***
	(0.00153)	(0.00184)
Power	0.0218***	0.0417***
	(0.00117)	(0.00245)
Weight	0.00762***	0.0101***
	(0.000447)	(0.000404)
Range	0.00185***	
	(0.000313)	
Fuel Consumption		-0.524***
		(0.104)
Observations	13,269	162,368
R-squared	0.901	0.898
Sample	EV	GV
Firm-Year	Yes	Yes
Year Released	Yes	Yes
Market	Yes	Yes

Notes: Table shows the estimation result of estimating the cost equation. "MC" stands for marginal cost. Robust standard errors clustered at the market level are in parentheses. ***, **, and * denote significance at the 1, 5, and 10 percent level, respectively.

We also consider the dynamics of credit prices and calculate the average credit value per vehicle from 2018 to 2024. Figure E1 shows that the average credit value for EV is always positive while that for GV is always negative. The change in credit values for EV is generally mapped (inversely) to the market dynamics of aggregate credit surplus/deficit.

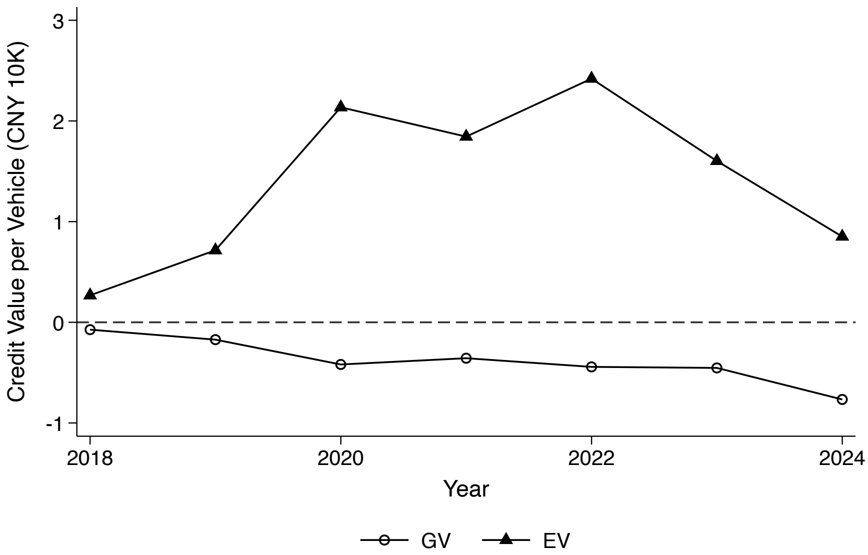


Figure E1: Dynamics of CAFC and NEV Credit Values Per Vehicle

Notes: Figure shows the average credit value per vehicle for EVs and GVs across years.

F Additional Empirical Results

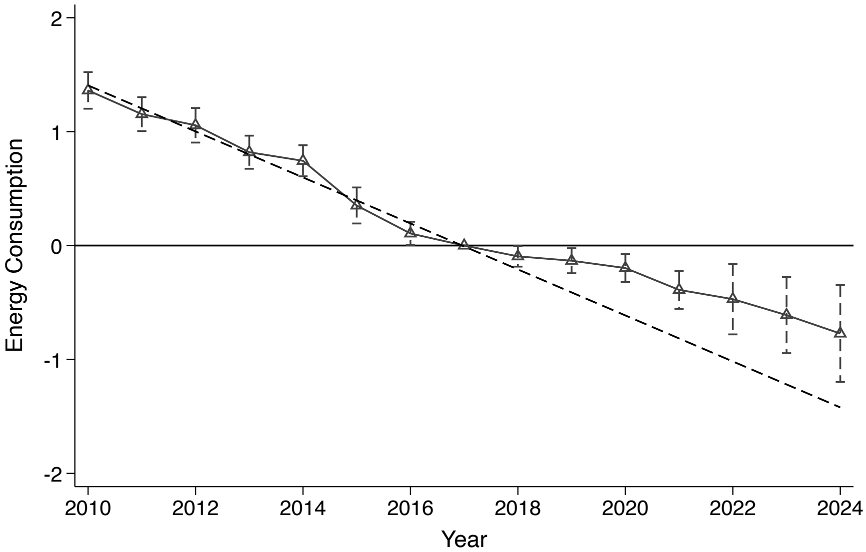
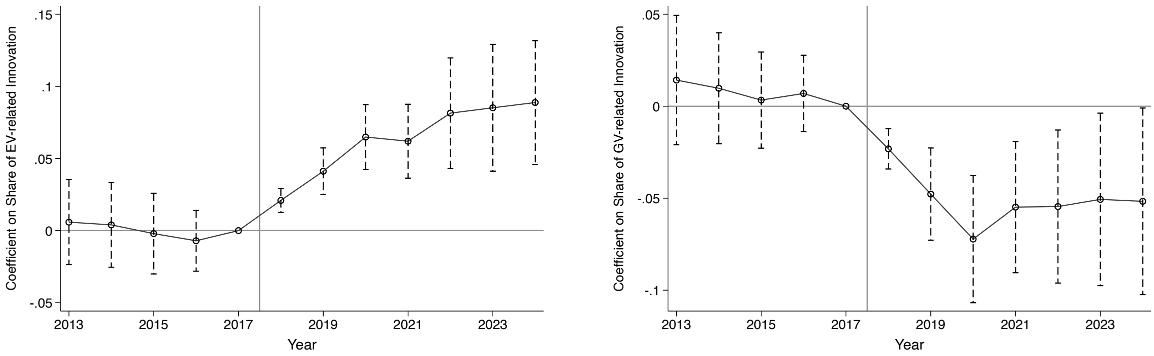


Figure F1: Decrease of Fuel Consumption Overtime

Notes: Figure shows the decrease of fuel consumption of gasoline vehicles across years. Each dot stands for the estimation of coefficient δ_t in the following equation:

$$FC_{jt} = \sum_{t \neq 2017} \delta_t + \beta_X X_{jt} + \gamma_f + \lambda_b + \varepsilon_{jt}$$

where FC_{jt} is the fuel consumption level of product j introduced in year t. δ_t captures the relative level of fuel consumption in year t compared with the baseline year 2017. We control for curb weight and its square term, firm fixed effects γ_f, and brand fixed effects λ_b in the equation. We estimate the equation with the administrative new car product data. Capped spikes indicate the 95% confidence interval. Robust standard errors are clustered at the firm level.



A: EV-related Innovation

B: GV-related Innovation

Figure F2: Event Study of Innovation of Newcomers

Notes: Figure shows the event-study results of the dual-credit policy on EV-related and GV-related innovation of newcomers. The year of policy shock is 2018. Each circle indicates the point estimations of the treatment effect (i.e., the coefficient of $newcomers_f \times T_t$ in Equations (9))). Each vertical dashed line indicates the 95% confidence interval of the treatment effect.