CORPORATE STRATEGIES DURING TECHNOLOGICAL TRANSITION IN CHINA'S AUTOMOBILE INDUSTRY: AN EMPIRICAL STUDY FROM A MULTI-LEVEL PERSPECTIVE

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Corporate Strategies during Technological Transition in China's Automobile Industry: An Empirical Study from a Multi-level Perspective

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Abstract

As the world's largest automotive market, China is undergoing a significant technological transition from traditional internal combustion engine vehicles (ICEVs) to electric vehicles (EVs). Such technological transition can fundamentally reshape the automative industry, alter market dynamics, and transform competitive landscapes. To navigate this evolving environment, firms must adopt adaptive strategies that align with changing market demands and technological advancements.

For corporate managers, understanding the key factors influencing strategic decision-making and identifying effective approaches is crucial for sustaining competitiveness and ensuring long-term success during technological transitions. Moreover, technological transitions are inherently complex, involving multiple interconnected levels of evolution. Therefore, the analysis of corporate strategies in this context provides valuable research insights into corporate behaviors in uncertain and complex environments. Thus, drawing upon the multi-level perspective (MLP), we conduct three interconnected studies to examine corporate strategies shaped by key factors at the niche, regime, and landscape levels, within the context of the technological transition from ICEVs to EVs in China's automotive industry.

Study 1 focuses on product technical specification design strategies regarding EV driving range at the niche level. At this level, developing appropriate designs for product technical specifications that effectively address uncertain customer preferences represents the most significant challenge for companies. Using a data set of 393 EV models in 49 Chinese first- and second-tier cities across 28 quarters from 2017 to 2023, we employ a structural model to estimate demand patterns for EVs with varying levels of driving range. Moreover, we collect charging pile density and other market-level data to examine how market elasticities for EV driving range vary across different market

conditions. Our results show that the average driving range elasticity of EVs is 1.441, implying that a 1% increase in the driving range of EVs would lead to approximately a 1.441% increase in demand. Besides, we also find that there exists a complementary relationship between EV driving range and market charging pile density in influencing customer demand for EVs. We further discover that such complementarity might be attributed to the sales distribution by vehicle class of EVs in markets with varying levels of charging pile density. In low charging pile density markets, customers are more likely to purchase subcompact and compact EVs that are better suited for fixed routes and short-distance travel where a smaller driving range is sufficient. However, in high charging pile density markets, the availability of charging infrastructure enables customers to choose medium- and large-sized EVs for long-distance travel and extended commutes where a larger driving range is needed.

Study 2 investigates corporate strategies for participating in emerging technology standardization at the regime level, where path dependence significantly shapes how firms navigate trade-offs between incumbent technologies and emerging alternatives. Adopting a dynamic perspective, we specifically examine how firms' prior participation in incumbent technology standardization affects their subsequent participation in emerging technology standardization, as well as how such impact varies with the level of technological diversification in incumbent technology standardization activities. Using a longitudinal dataset of 217 automotive manufacturers and 466 technology standards in China from 2000 to 2023, our survival analysis reveals that firms with greater participation in incumbent technology standardization are more likely to engage in emerging technology standardization. However, a firm's degree of technological diversification in incumbent technology standardization can create inertia, diminishing the positive effect of prior participation in incumbent technology standardization on emerging technology standardization.

Study 3 examines how market-based deployment policies at the landscape level shape automakers' technology choice and production strategies. At this level, institutional forces are crucial, requiring firms to develop technologies that align with both market demand and regulatory compliance. Specifically, this study examines China's dual-credit policy, a policy designed to promote EV adoption while enhancing fuel efficiency in ICEVs. A key feature of this policy is its credit trading system, which allows firms with surplus credits to sell them to those with deficits, creating a flexible, market-driven approach to compliance. Using a dataset of 15,927 observations covering 906 ICEV models from 2017 to 2018, this study employs a quasi-experimental difference-in-discontinuities (DiDC) design to establish the causal relationship between the implementation of the dual-credit policy and the production volume of ICEVs that exceed fuel consumption standards. Additionally, we investigate how automakers' non-compliance level in both the product market and the credit market moderate this effect. Our findings suggest that the implementation of the dual-credit policy contributes to an increase in the production of excessive fuel consumption ICEVs. Moreover, we find that the strong corporate non-compliance level in both the product market and the credit market of automakers further intensifies this effect.

This thesis contributes to the literature on corporate strategies during the transition from ICEVs to EVs in the automotive industry in the following aspects. First, at the niche level, we develop an improved and more reliable method for estimating consumer preferences in design of EV driving range during the technological transition. More importantly, the findings highlight the importance of adopting an ecosystem perspective in the design process, revealing a complementary relationship between charging pile density and EV driving range in shaping consumer preferences. Second, at the regime

level, we contribute to the literature on firm participating in technology standardization by shedding light on decision dynamics in the context of technological transitions. We also find a potential downside of diversification that firms deeply engaged in multiple domains within the old technology trajectory may develop inertia. Third, at the landscape level, our study is the first to provide empirical evidence on the unintended consequences resulting from the flexibility embedded in a specific market-based deployment policy (i.e., the China's dual-credit policy). Furthermore, the analysis reveals significant firm-level heterogeneity in how such policies influence firms' technological choices and production decisions.

Keywords: Technological transition; Electric vehicle; Structural demand estimation; Survival analysis; Difference-in-discontinuities; Technical specification design; Technology standardization; Technology choice

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Xinyi Fan, **Xueshu Shan***, Steven Day, & Yongyi Shou. (2022). Toward green innovation ecosystems: Past research on green innovation and future opportunities from an ecosystem perspective. *Industrial Management & Data Systems*, 122(9), 2012-2044.

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Chapter 1 Introduction

1.1 Research Background

1.1.1 Practical Background

In recent years, there is evidence that China is gradually becoming a major source of technological transitions (Wan et al., 2015). This can be attributed to the vast customer market in China, which drives strong demand for technological innovations and product upgrades. To meet the unique demand of the Chinese market, companies compete to develop cost-effective, user-friendly products that are tailored to local needs, thereby driving technological transitions across various industries. Moreover, the Chinese government seeks to actively promote technological transitions through a series of strategic policies and targeted funding initiatives. For example, in January 2024, the Chinese Ministry of Industry and Information Technology issued the "Implementation Opinions on Promoting the Innovation and Development of Future Industries," which specifically emphasized that China should vigorously support technological evolutions to achieve global technological leadership across multiple sectors.

Technological transitions usually can help to achieve resource optimization, improve quality of life, and enhance overall industry efficiency (Akcigit, 2017). For example, the technological transition from internal combustion engine vehicles (ICEVs) to electric vehicles (EVs) in the Chinese automobile industry contributes significantly to addressing energy depletion and environmental pollution issues in China. According to the 2024 report from the Emissions Database for Global Atmospheric Research (EDGAR), China emitted approximately 1,325.96 million tons of CO2 in 2023, ranking first globally and accounting for 33.98% of the global total. The transportation sector is a major contributor to these emissions. Additionally, in 2013, energy consumption in China's transportation sector reached 258 million tons of standard oil, nearly doubling since 2000, with road transportation accounting for 80% of the sector's total energy consumption. In this context, the emergence of EVs which are powered by electricity rather than fuel fossils is of critical significance to the whole society in China (Tran et al., 2012).

However, technological transitions often render existing technological value propositions obsolete, thereby reshaping market dynamics and disrupting established industry structures and competitive landscapes (Hannan & Freeman, 1977; Arend, 1999). Consequently, developing effective response strategies during such transitions is crucial for firms' survival (Hannan & Freeman, 1977; Arend, 1999). Even well-established companies can lose their competitive edge if they fail to adapt to technological transitions. For instance, Toyota, once a leader in setting production standards in the automotive industry, has acknowledged that due to it lags in the development and application of EV technology, it is now facing an unfavorable competitive position in the era of electric cars (Financial Times, 2023). In contrast, emerging firms can leverage a series of strategies to surpass incumbents (Cozzolino et al., 2018). For example, Tesla, which started as a small player in the global automotive market in 2003, has rapidly gained prominence in the EV sector through extensive R&D

in battery and autonomous driving technologies and eventually surpassed traditional automakers like Ford in market value in recent years (Hardman et al., 2013; Chevalier-Roignant et al., 2019). Similarly, during the electrification process of the Chinese automobile industry, BYD, originally founded in 1995 as a battery manufacturer has strategically expanded into vehicle manufacturing sector. Today, BYD is not only a global leader in EV sales but also pioneers in developing technologies covering the entire industry chain from batteries to complete vehicles.

In summary, firms aiming to navigate technological transitions and secure competitive advantages need a more comprehensive and in-depth understanding of corporate strategies in such transitions. Therefore, this thesis provides a systematic review of these corporate strategies and empirically examines the impact of key factors and internal and external contingencies that influence these strategies. The findings offer valuable insights for business managers to better address the management challenges related to technological transitions.

1.1.2 Theoretical Background

Technological transitions refer to the transformation of frameworks which define relevant technical issues and specific knowledge bodies to address technical challenges (Teece, 2008). These transitions involve not only technological changes but also shifts in social-technological systems (Geels, 2002). During such transitions, firms typically adopt a range of strategies to acquire and sustain competitive advantages (Tushman & Anderson, 1986; Christensen & Rosenbloom, 1995; Chaturvedi & Prescott, 2022). Scholars from various domains within management, such as innovation management

(Christensen & Rosenbloom, 1995), strategic management (Ghita et al., 2006), operations management (Choi et al., 2022), and management information systems (Nault & Vandenbosch, 2000), have given considerable attention to corporate strategies during such transitions.

Technological transitions are inherently complex, involving multi-level structural evolutions that span across technological, market, economic, and social systems (Rip & Kemp, 1998). Thus, to gain a holistic understanding of corporate strategies during technological transitions, this thesis adopts a multi-level perspective (MLP) theoretical framework (Geels, 2004). The MLP framework posits three levels of analysis in technological transitions: *niche*, which refers to protected spaces where the new technology can emerge and develop; *regime*, which refers to the selection environment which includes established players, practices, rules, routines, and infrastructure of the existing technology; and *landscape*, which denotes the broader industry-external context which includes policies, cultural norms, environmental challenges and other factors which shape the overall development direction of the industry (Kemp, 1994; Rip & Kemp, 1998; Kemp et al., 1998; Geels, 2002). For example, according to the MLP framework, the electric vehicle (EV) market represents the *niche* in the electrification of the automobile industry. The traditional internal combustion engine vehicle (ICEV) market system forms the dominant *regime* within the automobile sector. Meanwhile, the broader *landscape* includes factors such as stricter environmental regulations and growing consumer demand for sustainability.

At the *niche* level, firms rely on new technology products to challenge incumbents during technological transitions (Ansari & Krop, 2012; Yu & Hang, 2010; Shao et al., 2017). However, the novelty of new technologies might render it difficult for customers to perceive their value (Rindova & Petkova, 2007). Thus, the existing literature has specifically focused on how firms design their new technology products to alleviate consumer discomfort with innovative technologies and encourage their acceptance (Dell'Era & Verganti, 2011; Simoni et al., 2014; Cautela et al., 2018). Since effective technical specification design hinges on understanding customer preferences, researchers have proposed several human-centered design principles and frameworks for new technology products (Krippendorff, 2006). Based on these principles and frameworks, scholars have conducted a series of experiments and surveys to understand customer preferences.

For example, during the technological transition from ICEVs to EVs in the automotive industry, scholars usually design hypothetical scenarios to simulate customer choice behaviors when faced with EVs that have different feature combinations (Louviere, 2000; Valeri & Danielis, 2015; Li et al., 2020). Through these stated preference studies, scholars have identified that “range anxiety”, which refers to the fear of running out of battery power before reaching the destination or a charging station, is a key barrier preventing customers from perceiving the value of EVs. However, such stated preference data may not reflect actual customer purchasing behaviors (Liao et al., 2017). There is a lack of research that utilizes actual market data and a structural approach to estimate actual customer demand for different new technology product technical specification designs.

Furthermore, researchers have suggested that the value proposition of a new technology is often dependent on its complements (Teece, 1986; Adner & Kapoor, 2010; Adner, 2017). These factors play a crucial role in determining how effectively the technology can be integrated into the market and its ability to deliver value to customers. For example, customer perceptions of whether the driving range of EVs is sufficient for their needs may largely depend on the level of charging infrastructure in their respective markets (Bonges & Lusk, 2016). Specifically, the availability of charging piles for individuals can shape their purposes of using EVs, which in turn affects their demand for EV driving range. Prior research has explored how complements that enhance the value of emerging technologies shape corporate strategies—such as technology investment decisions (e.g., Kapoor & Lee, 2013; Mantovani & Ruiz-Aliseda, 2016) and patent licensing strategies (e.g., Arora & Ceccagnoli, 2006)—in the context of adopting these technologies during periods of technological transitions. However, when it comes to new technology product technical specification design strategies, there is a lack of research that considers the impact of complements on customer preferences for different new technology product technical specification designs. Thus, we propose our first research gap as follows:

Research Gap 1: At the *niche* level, a core challenge firms face lies in designing technical specifications that align with market demand. Existing research on electric vehicle (EV) technical specification design primarily relies on stated preference data to infer consumer preferences. However, such approaches struggle to effectively capture consumers' actual choice behavior in real market

settings. Moreover, prior studies have rarely systematically examined how the development level of charging infrastructures shapes consumer preferences for EV driving range.

At the *regime* level, whether firms proactively invest in the new technologies is a topic of great interest for management researchers (e.g., Kaplan & Tripsas, 2008; Nadkarni & Barr, 2008; Anand et al., 2010; Kapoor & Adner, 2012; Kotha et al., 2011; Eggers & Kaul, 2018). Specifically, scholars have traditionally focused on corporate strategies such as the level of R&D investment and the timing of market entry for the new technologies (Eggers & Kaplan, 2009; Sosa, 2011; Raffaelli et al., 2019). Recently, participation in emerging technology standardization has emerged as another form of proactive strategy that scholars pay attention to (Blind et al., 2023; Grillo et al., 2024).

On one hand, firms that play a role in emerging technology standardization efforts can influence the direction of industry-wide technological adoption, increase compatibility with their proprietary technologies, and establish early mover advantages (Wen et al., 2020). On the other hand, participation in emerging technology standardization is a resource-intensive endeavor. It requires firms to make substantial investments in R&D, collaborate with standard-setting organizations, and engage in lengthy negotiations with industry stakeholders. These activities may divert managerial and financial resources from existing product lines and technologies (Brem & Nylund, 2024). Given these strategic trade-offs, firms' decisions to participate in emerging technology standardization are far from straightforward. Thus, researchers have increasingly focused on factors that influence firm decisions regarding whether to participate in emerging technology standardization or not (Schott & Schaefer, 2023; Blind et al., 2023; Grillo et al., 2024).

A defining characteristic of firms' strategic decision-making at the regime level of technological transitions is path dependence — the idea that a firm's historical commitments to existing technologies shape both its capabilities and willingness to adopt new ones. However, despite the well-documented role of past investments, routines, and competencies in shaping firm behaviors during technological transitions, most studies on corporate participation in emerging technology standardization have adopted a static perspective. These studies predominantly focus on firm-level attributes at a single point in time, such as technological capabilities, market position, or competitive pressures (e.g., Zhang et al., 2024; Blind & Mangelsdorf, 2016), while overlooking the long-term influence of firms' prior engagement in existing technology standardization efforts for existing technologies.

Research Gap 2: At the *regime* level, the existing research on firm participation in emerging technology standardization has mostly adopted a static perspective. There is a lack of a dynamic perspective that considers how firms' past engagements in standardization for existing technologies influence their subsequent participation in emerging technology standardization.

At the *landscape* level, deployment policies have become a critical factor influencing firms' technological decision-making, as they can significantly enhance the competitiveness of specific technologies through institutional arrangements (Peters et al., 2012; Schmidt et al., 2016). Depending on the policy-implementing body, deployment policies are generally categorized into two types: government-based deployment policies and market-based deployment policies (Hoppmann et al., 2013). Government-based policies—such as stringent regulations on incumbent technologies and direct subsidies for emerging technologies—have long been considered an important driver of technological innovation. However, these policies often face considerable challenges in implementation (Majumdar & Marcus, 2001; Hu et al., 2021; Li et al., 2018; Li et al., 2020). In contrast, market-based deployment policies offer a more flexible approach by leveraging market mechanisms to incentivize technological transitions. Rather than mandating firm behavior directly, these policies create structured market environments within which firms make strategic decisions.

China's dual-credit policy represents a typical market-based deployment policy in the country's automotive industry technological transition. It consists of two credit systems: the Corporate Average Fuel Consumption (CAFC) credit, which requires automakers to reduce the average fuel consumption of conventional ICEVs based on fuel consumption targets set by the government; and the New Energy Vehicle (NEV) credit, which mandates a minimum production share of NEVs. The two credit types are calculated separately. Prior to the dual-credit policy, firms with negative CAFC credits could only comply by improving the fuel efficiency of ICEVs and adjusting their ICEV production portfolios. Notably, the dual-credit policy provides a credit trading mechanism, allowing firms to purchase NEV credits to offset their CAFC credit deficits, thereby providing flexibility in navigating the technological transition.

Although the dual-credit policy is designed to accelerate improvements in fuel efficiency of ICEVs, its effectiveness remains a subject of debate among scholars. Some studies argue that such market-based deployment policies can effectively incentivize firms to phase out fuel-inefficient technologies by sending clear price signals (e.g., Jaffe et al., 2005; Aldy & Stavins, 2012). In contrast, others suggest that these policies may produce unintended consequences (e.g., Aghion et al., 2009; Schmidt et al., 2016). Given that market mechanisms often prioritize short-term profitability, firms may continue to invest in more profitable, fuel-inefficient technologies. These divergent findings highlight the need for further investigation into the actual effectiveness of the dual-credit policy.

Much of the existing research on the role of market-based deployment policies relies on theoretical models or scenario-based simulations. While valuable for illustrating general mechanisms, these approaches fall short of capturing firms' real-world strategic responses. So far, empirical studies based on observed firm behavior remain limited, hindering a nuanced understanding of how firms respond to market-based deployment policies amid technological transitions in practice. Moreover, while some research has considered the potential heterogeneity in firms' responses to market-based deployment policies, these discussions have largely focused on heterogeneity caused by differences in policy designs, with limited investigation of firm-level mechanisms that explain different responses.

Research Gap 3: At the *landscape* level, market-based deployment policies offer firms greater flexibility in achieving compliance. As a representative example, the effectiveness of China's dual-credit policy in driving a shift in technology

choices and production strategies for ICEVs toward greater fuel efficiency remains a subject of ongoing debate. Moreover, the existing literature rarely provides systematic empirical analyses of firm-level heterogeneity in such market-based deployment policy responses.

1.2 Research Questions and Framework

To address the identified gaps in the existing literature, this thesis seeks to answer the following research questions (RQs):

RQs of Study 1: At the niche level, 1) How does the design of the driving range of EVs affect customer preferences? 2) How does the density of EV charging piles in a market affect the relationship between the driving range design of EVs and customer preferences?

RQs of Study 2: At the regime level, 1) How does a firm's participation in incumbent technology standardization influence its subsequent participation in emerging technology standardization during a technological transition? 2) How do the levels of technological and network diversification in firms' participation in incumbent technology standardization moderate the effect of their participation in incumbent technology standardization on their participation in emerging technology standardization during a technological transition?

RQs of Study 3: At the landscape level, 1) How does the market-based mechanism of the dual-credit policy influence automakers' production of fuel-inefficient ICEVs? Furthermore, how do firms' levels of non-compliance in both the product and credit markets moderate such influence of this market mechanism on their technology choice and production strategies?

Figure 1.1 illustrates the comprehensive research framework and the connections between the three research questions in our thesis.

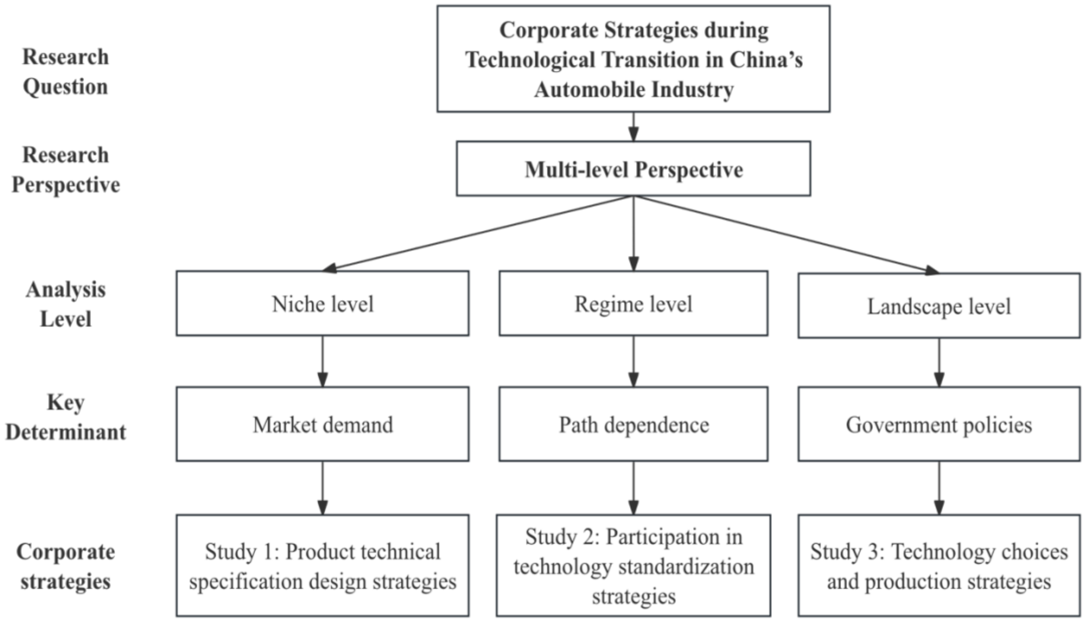

Figure 1.1 The framework of the thesis

1.3 Research Methods

We adopt different research methods to address the RQs in our three studies:

(1) Structural demand estimation

Study 1 adopts structural demand estimation approach to estimate customer preferences for key technical specification designs of new technology products during technological transitions. This method enables researchers to utilize aggregate market data rather than individual stated preference data to show customer preferences. Specifically, it applies the utility maximization principle to derive market share functions for different products based on mean utility functions (Berry, 1994). This approach has been widely applied in various fields, such as marketing (e.g., Sudhir, 2001; Narayanan et al., 2005), information systems (e.g., Dong et al., 2021), and operations management (e.g., McKie et al., 2018) in top management journals (such as Management Science, Manufacturing & Service Operations Management, and Information Systems Research).

In this study, we gather product-level data on electric passenger vehicle (EV) sales and their attributes, as well as market-level data on charging pile density and other geographic information from multiple sources. We finally obtain a sample of 67,648 observations of 393 EV models in 49 Chinese first- and second-tier cities across 28 quarters from 2017 to 2023. Following Berry (1994), we rigorously derive the function that captures the relationship between EV driving range design and market share as our main effects model. Next, we integrate the hierarchical linear model (HLM) approach into the structural demand estimation model to derive a function that captures the interaction between EV driving range design and market charging pile density. To address the endogeneity of price, we employ the two-stage least squares (2SLS) method to estimate both the main effects model and the interaction model using our sample data. Additionally, we conduct a series of analyses to compute market elasticities for EV driving range based on the estimated coefficients. Finally, we perform multiple robustness checks to ensure the reliability and validity of our findings.

(2) Survival analysis

In Study 2, as our dependent variable is whether and when manufacturing firms in the automobile industry participate in emerging technology standardization, we adopt survival analysis to test our hypotheses. Different from logistic regression models, survival analysis is a statistical approach designed to analyze time-to-event data, focusing not only on whether an event occurs but also on when it occurs (Cox, 1972). Besides, it accounts for right-censored data in our study (Hosmer et al., 1999). Besides, since manufacturing firms can participate in emerging technology standardization more than once, we adopt the Anderson-Gill (AG) version of the proportional hazard model to handle the occurrence of repeated events (Andersen & Gill, 1982).

Specifically, we compile our dataset from multiple authoritative sources, including the National Standard Information Public Service Platform, the National Enterprise Credit Information Publicity System, and the Incopat Global Patent Database. Our final sample consists of 217 automotive manufacturers and 466 automotive technology standards from 2000 to 2023. Following prior research, we construct appropriate measurements of our variables and utilize this data sample to measure them. Next, we test our hypotheses using the AG version of the proportional hazard model. Besides, we have also conducted several checks to test the robustness of our results.

(3) Difference-in-discontinuities (DiDC)

Study 3 employs difference-in-discontinuities (DiDC) design, a quasi-experimental econometric method that integrates elements of both Difference-in-Differences (DiD) and Regression Discontinuity Design (RDD). The DiDC design enables us to simultaneously account for both temporal and threshold variations in policy implementation, making it particularly well-suited for examining the impact of the dual-credit policy on corporate technology choice and production decisions. Compared to standard RDD, DiDC is advantageous in contexts where multiple confounding treatments exist at the threshold, as it leverages temporal variations to enhance causal inference. Moreover, it relaxes the strict parallel trends assumption required in DiD, allowing for potential differences between treatment and control groups before policy implementation. In this study, the DiDC design is used to estimate the causal effect of the dual-credit policy on the production volume of fuel-inefficient ICEV model years while controlling for pre-existing policy effects from the fuel consumption standard GB27999-2014.

To conduct our empirical analysis, we compile a dataset covering 15,927 observations of 1,452 ICEV model years produced between January 2017 and December 2018. Production data for ICEVs are obtained from a leading automotive industry research firm in China. Additionally, we collect vehicle specifications—including fuel consumption, size, curb weight, and price—from reputable automotive information platforms and official automaker websites. We restrict our analysis to ICEV model years registered after the year of 2016 to isolate the impact of the dual-credit policy from earlier fuel consumption regulations. To implement the DiDC estimation, we select ICEV model years for which the standardized deviation of actual fuel consumption from the target value falls within a bandwidth of 0.2 around zero, eliminating models with excessive deviations from the threshold. This results in a final sample of 12,897 observations across 1,163 ICEV model years. The DiDC estimator is derived by performing local linear regressions on either side of the threshold, both before and after the policy implementation, allowing us to quantify the effect of the dual-credit policy on the production volume of fuel-inefficient ICEV models.

1.4 Structure of the Dissertation

This dissertation is organized into six chapters: Introduction, Literature review, Study 1, Study 2, Study 3 and Conclusions. The specific contents are as follows:

Chapter 1 sets the stage by elaborating on the practical and theoretical background, formulating the research questions, and introducing the research methods.

Chapter 2 presents a comprehensive review of existing literature, identifies the gaps in current research. This chapter synthesizes two streams of research: general studies on corporate strategies during periods of technological transition, and industry-specific studies that examine such decisions within the automotive sector.

Chapter 3 investigates how firms optimize technical specification designs to meet consumer preferences at the niche level of technological transition in the automative industry. It introduces a structural demand estimation model to quantify the elasticity of market demand with respect to a major EV technical specification—driving range. Furthermore, by incorporating a hierarchical linear model, the study reveals a synergistic effect between driving range and charging pile density.

Chapter 4 adopts a dynamic perspective to examine corporate strategies to participate in technology standardization at the regime level of technological transition in the automative industry. Using survival analysis and historical data on industry standards, it empirically tests how firms' participation in ICEV standardization influences their participation in EV standardization. Moreover, it integrates both technological and network perspectives and examines the moderating effects of technological diversification and network diversification in ICEV standardization on this relationship.

Chapter 5 investigates corporate strategic responses to market-based policies at the landscape level of technological transition in the automative industry. Adopting a quasi-natural experimental design, this study identifies changes in firm behaviors regarding the production of fuel-inefficient ICEVs before and after the implementation of the dual-credit policy. It further incorporates firm-level heterogeneity along two dimensions—product market non compliance ratio and credit market non compliance ratio.

Chapter 6 provides the concluding remarks of the dissertation. It summarizes the key findings of three studies, and discusses their theoretical, managerial, and policy implications. More importantly, the chapter also reflects on the study’s limitations and offers suggestions for future research.

Chapter 2 Literature Review

2.1 Corporate Strategies during Technological Transitions

In response to the uncertainties brought about by technological transitions, companies often need to adopt a series of strategies to maintain competitive advantages and achieve sustainable development (Christensen, 1997; Hill, 2003). The core of these strategies lies in the effective acquisition and reconfiguration of resources to adapt to the evolving dynamic environment and market demand (Tushman & Anderson, 1986; Christensen & Rosenbloom, 1995; Chaturvedi & Prescott, 2022). The strategies adopted by firms in the context of technological transitions and the underlying causes have become a key area of focus in management research. Specifically, scholars have focused on technological, inter-organizational relationship, and operational strategies. This section systematically reviews and summarizes relevant studies on these strategies.

2.1.1 Technological Strategies

During technological transitions, firm managers must decide how to allocate limited resources between the established, mature old technology and the emerging, uncertain, yet promising new technology (Sosa, 2011). In such process, some firms may adopt an active strategy towards the new technology. They may proactively invest resources to explore and embrace the new technology, aiming for technological breakthroughs and market leadership in the emerging market. In contrast, others may adopt a passive strategy. They adopt a more conservative approach to the new technology and rely on the mature traditional technology to avoid the risks associated with uncertainty (Eggers & Park, 2018). The underlying decision-making mechanisms of firms choosing between active and passive strategies towards the new technology have become a key focus in research on firms' technological strategies during technological transitions. Specifically, the factors influencing this decision can be categorized into three levels: cognitive, organizational, and environmental.

At the cognitive level, drawing on management cognition theories (Daft & Weick, 1984; Huff & Huff, 2000; Kaplan, 2011), scholars have proposed that how managers perceive and interpret technological transitions and translate their cognitions into specific actions is a critical determinant of firms' choices on technological strategies (Kiesler & Sproull, 1982; Kaplan & Tripsas, 2008; Nadkarni & Barr, 2008). Regarding the role of perception, the CEO's attention has become a central focus of research. For example, Eggers & Kaplan (2009) find that during the technological transition from copper wire to fiber-optic transmission in the telecommunications industry, the attention given by CEOs to the new technology is a key factor determining their decisions on firms' technological strategies. Similarly, Gerstner et al. (2013) uncover that CEO narcissism affects their attention to new technology during technological transitions, which in turn alters the firm's adoption strategies.

With respect to the role of interpretation, existing studies reveal several interpretative traits that affect firms' technological strategy choices. For instance, Gilbert (2006) have conducted a case study of a newspaper firm adapting to the technological shift towards digital printing in the publishing industry and discovered that whether managers interpret a technological transition as an opportunity or a threat directly impacts the level of firm investment in the new technology. Raffaelli et al.

(2019) show that the flexibility with which corporate executives interpret emerging technologies, that is, their ability to extend the boundaries of these technologies through both cognitive and emotional interpretations, can effectively reduce the inertia firms exhibit in the face of technological transitions.

At the organizational level, resources and capabilities are considered core determinants of firms' choices on technological strategies. Specifically, existing studies focus on the resources and capabilities necessary to master emerging technologies, along with the complementary assets required for their commercialization. In studies across various industries, scholars have shown that firms' accumulation of knowledge in areas of emerging technologies and their innovation capabilities significantly affect the technological strategies they adopt during technological transitions (Kaplan, 2008; Anand et al., 2010; Kapoor & Adner, 2012; Kotha et al., 2011; Eggers & Kaul, 2018). Besides, complementary resources and capabilities which often include production capabilities, distribution channels, marketing capabilities, and customer relationships also have a significant impact of corporate choices. Scholars generally agree that firms with more abundant complementary resources and capabilities for emerging technologies are more likely to adopt active technological strategies during periods of technological transitions (Mitchell, 1989; Klepper & Simons, 2000; Helfat & Lieberman, 2002; Anand et al., 2010). For example, Roy & Cohen (2017) indicate that when firms possess a large network of distributors, they are more inclined to pursue active strategies during technological transitions. This is because downstream distributors provide critical information about changes in customer demand, enabling firms to detect market dynamics early. Furthermore, Wu et al. (2014) suggest that when firms face multiple technological pathways during technological transitions, they will choose the pathway where their complementary resources and capabilities can be most effectively utilized.

Moreover, scholars also point out that the factors influencing firms' technological strategy choices during technological transitions may extend beyond the internal boundaries of the firm. Specifically, at the environmental level, the current research has shown that a firm's stakeholders like suppliers, customers, competitors, government agencies, securities analysts, and complementary firms can have a significant influence on its choices on technological strategies. For example, Benner (2010) find that securities analysts tend to offer more favorable evaluations of firms' passive technological strategies, while being comparatively more conservative when assessing active strategies. Later, Benner & Ranganathan (2012) further reveal that securities analysts' recommendations can significantly influence firms' choices on technological strategies during technological transitions. Weigelt et al. (2021) discover that the increasing number of niche participants (i.e., competitors of traditional firms) can drive traditional firms to invest in niche technologies, thus accelerating the diffusion of technological transition from niche markets to mainstream markets. Scholars have also proposed that the specific relationship forms between firms and their stakeholders can influence their technological strategy choices as well. For example, Kapoor & Lee (2013) show that the likelihood of a firm investing in new technologies is closely linked to the nature of relationship (i.e., alliance partnerships, regular business relationships, or vertical integration) it has with its complementors.

Besides, scholars have examined the interaction between these different levels of factors. For example, they suggest that managers' cognitive frameworks influence the construction and combination of organizational processes, which in turn shape the formation of firm capabilities. In turn, A firm's existing capabilities also influence how managers perceive and interpret the environment (Eggers & Kaplan, 2013). Consequently, some studies have integrated cognitive and organizational factors and investigated their combined influence on technological strategy choices during technological transitions (Tripsas & Gavetti, 2000). For instance, Kaplan (2008) note that cognitive factors, capabilities, and incentives work together to shape a firm's technological strategies in response to technological transitions. Additionally, research has focused on the interactions between other levels of factors, such as the relationship between cognitive and environmental factors (Gerstner et al., 2013) and between organizational and environmental factors (Jacobides et al., 2006). These studies emphasize the synergistic interactions among multiple factors, providing a more comprehensive perspective on firms' technological strategies during technological transitions.

2.1.2 Inter-Organizational Relationship Strategies

In the context of technological transitions, firms often adjust their inter-organizational relationships to effectively acquire and reconfigure resources (Arora & Gambardella, 1990; Pisano, 1991). Depending on the level of analysis, these inter-organizational relationships can be categorized into dyadic relationships, multi-party relationships, and network relationships. This section systematically reviews and summarizes existing research on these inter-organizational relationship strategies during technological transitions.

Regarding dyadic relationships, scholars have particularly focused on the co-opetition between incumbent firms and emerging firms. Specifically, incumbent firms are the dominant players in the existing technology market. They usually possess rich resource accumulations but may lack the knowledge and capabilities related to the new technology. On the other hand, emerging firms usually have first-mover advantages in the new technology development but lack complementary resources to commercialize these technological advantages (Ansari et al., 2016). In such cases, the relationship between incumbent and emerging firms presents a complex dynamic of both competition and cooperation. Typically, on one hand, incumbent and emerging firms may form alliances or joint ventures to integrate their resources and jointly drive the commercialization of the new technology; on the other hand, they also face fierce competition in terms of technology development and market share (Cozzolino & Rothaermel, 2018). The current research primarily explores the conditions under which these two types of firms choose to cooperate.

Some studies take the perspective of incumbents and investigate which characteristics of emerging firms they favor when considering collaborations with them. For example, Rothaermel (2002) suggests that incumbents value emerging firms' product development capabilities, size, whether the firm is publicly listed, and whether it is located within a regional technology cluster when considering potential alliance partners. Rothaermel & Boeker (2008) find that both the similarity and complementarity between incumbent firms and emerging firms significantly influence the likelihood of their collaboration. Ansari et al. (2016) propose that emerging firms can impress incumbents by presenting the future vision and potential benefits brought about by their innovations. Additionally, recent studies have increasingly focused on the perspective of emerging firms and explored under what circumstances they are willing to collaborate with the incumbents they are disrupting (Ansari & Krop, 2012). Kim et al. (2019) reveal that emerging firms carefully select partners based on the specific context when seeking cooperations with incumbents. They find that emerging firms are less likely to engage in corporate venture capital transactions with incumbents that have technological links to them. This is because such connections may exacerbate concerns about opportunistic misuse of intellectual property by incumbents. However, existing social ties between the two parties can help mitigate these concerns and increase the likelihood of collaboration.

Regarding multi-party relationships, the most discussed topic among scholars is the management of a firm's alliance portfolio during periods of technological transitions. An alliance portfolio refers to the collection of a firm's direct alliance partners (Lavie, 2007; Hoffmann, 2007). Scholars point out that during technological transitions, firms often need to adjust their alliance portfolios to adapt to environmental changes. In this process, firms must not only form new alliances with specific organizations to acquire key resources, but also reorganize their entire alliance portfolio to ensure optimal resource allocation (Lavie & Singh, 2012). For instance, Asgari et al. (2017) find that during technological transitions, firms adjust their relationships with alliance partners based on the characteristics of the resources they possess. Firms are more inclined to form new alliances with organizations that hold resources enhanced by the technological transition. At the same time, as firms establish more new alliances to acquire new resources, they are also more likely to terminate collaborations with existing partners whose resources have been weakened or unaffected by the technological transition. Moreover, Zhang et al. (2022) elucidate that, in the context of a technological transition, firms are more likely to expand their alliance portfolios internationally to acquire knowledge.

In the late 1990s, scholars have proposed a social network perspective for analysis of inter-organizational relationships (Gulati, 1998). This perspective views inter-firm cooperation not as isolated bilateral relationships, but as embedded within a broader social network. Firms' network relationships may co-evolve with technological development during periods of technological transitions. On one hand, the technological transition prompts firms to reassess whether their existing cooperation networks can address the challenges and uncertainties introduced by the new technology. On the other hand, firms' cooperative networks can also drive the generation and diffusion of technological innovations about the new technology. In recent years, scholars have increasingly emphasized that social networks are inherently dynamic and evolve over time through formation, adaptation, and dissolution (Chen et al., 2022; Jacobsen et al., 2022). However, despite the increasing interest in inter-organizational relational strategies during technological transitions, few studies have adopted the perspective of network evolution to explore the evolutionary paths and dynamic mechanisms of firms' cooperation networks in response to the external shock of technological transitions.

2.1.3 Operational Strategies

In the context of an industry's technological transition, scholars have noted that in response to the intensifying competition brought about by emerging technologies, firms may adopt or adjust their operational strategies. These strategies typically include product design, cost control, quality management, and production process optimization. However, compared to the previously discussed technological and inter-organizational relationship strategies, there has been relatively less research on operational strategies.

Scholars have found that in the early stages of an industry's technological transition, firms often adopt operational strategies to reduce costs and improve the quality of existing products, thereby enhancing their market competitiveness and alleviating the pressures brought by technological transition (Chang & Sokol, 2022). For example, Liu et al. (2023) suggest that when traditional hotels face competitive pressure from home-sharing platforms like Airbnb, they can enhance their ability to respond to challenges by analyzing user reviews to identify key areas for service quality improvement and thus further optimize service processes. Similarly, Zhang et al. (2023) find that traditional hotels can respond to the potential disruption of the sharing economy through a series of operational actions, including asset acquisitions, new projects, and facility upgrades.

In the later stages of an industry's technological transition, as firms progressively invest in emerging technologies and enter new markets, operational issues become more critical. Firms must place greater emphasis on operational efficiency and resource optimization to ensure the stable production and continued development of traditional technological products, while effectively supporting the development and market expansion of emerging technological products. For instance, Jones (2003) argues that during this stage, firms need to adopt appropriate production line management strategies to maintain their competitive advantages. Firms must plan the speed of product launches and product lifecycles carefully to balance innovation speed with cost efficiency. In platform management, firms must also pay sufficient attention to key factors such as the speed of platform introduction, the launch pace of platform-derived products, and the average lifecycle of all products under the platform. Moreover, Chevalier-Roignant et al. (2019) construct a competitive model revealing that after firms enter emerging technology markets, production flexibility becomes a crucial operational strategy for adapting to demand fluctuations.

2.2 Corporate Strategies during the Automotive Industry' Technological Transition

In recent years, in response to the growing energy shortages and environmental pollution issues, the automotive industry has been undergoing a profound technological transition, shifting from the traditional fossil fuel-based technology to the emerging electric-powered technology (Huo et al., 2013). Research on this technological transition has covered various fields, including transportation (Liao et al., 2017; Coffman et al., 2017), energy (Wu et al., 2021), environment (Tran et al., 2012), and management (Naumov et al., 2022; Guo et al., 2024).

In the research field of management, the transition from ICEVs to EVs in the automative industry provides an ideal research context for studying corporate strategies during technological transitions. This is because such process in the automotive industry encompasses the core characteristics of technological transitions. During this process, scholars can observe not only technological innovations but also the reshaping of market demand (Hardman et al., 2018), the driving force of policy environments (Harrison & Thiel, 2017; Wolinetz & Axsen, 2017), and their profound impact on corporate strategies. Moreover, the automotive industry itself, with its highly complex value chain and the intricate interactions among multiple stakeholders, makes it an ideal setting for exploring firms' diverse strategic choices (Joglekar et al., 2016).

In addition, the transition from ICEVs to EVs in the automative industry has some unique characteristics compared to technological transitions in other industries. For instance, the widespread adoption of EV technology is not primarily driven by firms' proactive efforts, but rather by external government-led initiatives (Wee, 2018). Moreover, external infrastructure, especially the construction and expansion of EV charging piles, plays a critical role in the electrification process of the automotive industry (Yu et al., 2022). At the same time, complementary innovations such as car-sharing platforms and autonomous driving systems also contribute significantly to this process (Adner & Lieberman, 2021). This characteristic contrasts with the typical technological transitions in other industries, which often rely more on internal industry resources. Overall, the emergence of EV technology is not the result of spontaneous innovation, but rather a systemic and societal innovation that depends on both technological advancements and changes in the social environment (Pinkse et al., 2014). In this section, we summarize the research on corporate strategic responses to the transition from ICEVs to EVs in the automative industry and focuses on how the unique features of this technological transition influence corporate strategies.

2.2.1 Technological Strategies

During the technological transition in the automotive industry, firms also face the trade-off between the traditional ICEV technology and the emerging EV technology. The question of whether firms adopt active or passive technological strategies in response to the new EV technology remains a key concern for scholars (Cabigiosu, 2022). Unlike the general focus on technological strategies in other technological transitions, research on the automobile industry places greater emphasis on the influence of government policies at the environmental level on firms' technological strategies.

These studies can be broadly categorized into two streams. The first stream focuses on uncovering automakers' actual behaviors in response to government policies during such technological transition. For example, Wesseling et al. (2015) find that large automakers subject to comprehensive zero-emission mandates invest significantly more in EV assets compared to their smaller counterparts. Pinkse et al. (2014) conduct a multiple-case study of European, American, and Japanese automakers and propose that automakers pursuing the emerging EV technology might follow two technological strategy paths: a private protection path and a public protection path. The public protection path refers to firms initially collaborating with public sectors, such as governments, to develop EV technologies, and later commercializing these technologies with the support of regulations and tax incentives. Bohnsack et al. (2020) also empirically observe that automakers under significant government pressure are often the first to initiate the development of EV technologies.

The second stream comprises studies that develop theoretical models to analyze firms' optimal technological strategies under various policy regimes. For example, China's dual-credit policy—which integrates Corporate Average Fuel Consumption (CAFC) credits with New Energy Vehicle (NEV) credits—has drawn considerable scholarly attention for its unique market-based mechanism that links conventional fuel-efficiency targets with the promotion of new energy vehicles through a tradable credit system (Kong et al., 2022). Under the dual-credit policy framework, some studies concentrate on automakers' optimal strategic decisions regarding R&D investments (e.g., He, 2022; He et al., 2021; Wang & Miao, 2021), while others focus on optimizing technology choices and production portfolio strategies (e.g., Lou et al., 2020; Li et al., 2020; Yu et al., 2021).

2.2.2 Inter-Organizational Relationship Strategies

Prior research on inter-organizational relationship strategies during technological transitions mainly focuses on the competition and cooperation between firms within the industry. However, the technological transition from ICEVs to EVs in the automotive industry is characterized by significant systemic and societal features. As such, research on inter-organizational relationship strategies in this context must expand beyond industry-specific relationships to include those with external organizations. Specifically, research on the inter-organizational relationship strategies of automakers during the automative industry's technological transition from ICEVs to EVs places greater emphasis on their strategic interactions with key external stakeholders, including government regulators, grid companies, charging infrastructure operators, shared mobility platforms, and data service providers.

For example, Adner & Lieberman (2021) propose that automobile manufacturers need to collaborate with complementary partners, such as shared mobility platforms or data platforms, to gain a competitive advantage in the forthcoming wave of intelligent EVs. Without such collaboration, these complementary actors may become competitors by launching their own electric vehicle products through partnerships with contract manufacturers. Yu et al. (2022) construct a game theory model for the construction of EV charging piles and analyze how the government and automobile manufacturers can achieve optimal cooperative construction plans under different construction goals and costs. Furthermore, with the innovative development of Vehicle-to-Grid (V2G) technology, EVs can achieve bidirectional energy interaction with the grid. This revolutionary technology enables EVs not only to draw power from the grid but also to return stored energy from their onboard batteries to the grid, transforming EVs into mobile energy storage units. The establishment of this bidirectional energy flow mechanism not only enhances the flexibility and stability of the grid but also provides new solutions for the large-scale adoption of renewable energy. The emergence of V2G technology and its application in smart grids have brought topics such as collaborative optimization, energy management, and value co-creation between EVs and the grid to the forefront of management research (Mak & Tang, 2024; Lauinger et al., 2024).

Besides, some studies have analyzed automakers' inter-organizational relationship strategies from the perspective of the macro business ecosystem. These studies explore the functional roles of various participants within the ecosystem and discuss how automobile manufacturers can cooperate with them effectively (Lu et al., 2014; Rong et al., 2017). These studies mainly use qualitative research methods such as in-depth interviews and case studies to systematically explore ecosystem governance strategies of automobile manufacturers in this emerging industry. Notably, scholars have emphasized the dynamic evolution characteristics of ecosystems, pointing out that their governance models need to be continuously optimized in response to technological iterations, policy adjustments, and changes in the market environment.

2.2.3 Business Model Strategies

A business model generally refers to the way a company utilizes its technology to create value (Chesbrough, 2010). Compared to technological transitions in other industries, the transition from ICEVs to EVs in the automative industry exhibits a unique characteristic of the co-evolution of technology and business models. Specifically, technological innovations in the electrification process of the auto industry are not only heavily dependent on business model innovations but also provide strong momentum for breakthrough changes in business models. Therefore, business model strategies are a critical area of research interest for scholars in the context of the transition from ICEVs to EVs in the automative industry (Kley et al., 2011; Secinaro et al., 2020).

The modular nature of EV technology, particularly the separable design of battery systems, facilitates the innovative business model known as Battery-as-a-Service (BaaS). This model allows customers to lease the battery separately from the vehicle, alleviating the two primary concerns associated with EV purchases: ownership cost and charging time anxiety. Scholars have conducted several studies investigating economic and social benefits of this emerging business model, as well as strategies for its optimization. For example, Avci et al. (2015) and Lim et al. (2015) both construct models to compare BaaS systems with traditional charging systems. They find that while the implementation of the BaaS business model could accelerate the market penetration of EVs, it might also lead to an increase in greenhouse gas emissions, as it encourages more frequent driving. Additionally, Shi & Hu (2024), conduct a game theory model and find that this business model could achieve a win-win-win situation for all parties: manufacturers can increase overall profits through the independent operation of battery assets; customers benefit from significantly reduced vehicle purchase costs; besides, the shared use of battery resources effectively reduces the overall demand for batteries, contributing to both resource conservation and environmental protection..

Furthermore, the integration of EVs with intelligent connected technologies has transformed vehicles into mobile data collection and service terminals. This facilitates data-driven business model innovations such as vehicle-sharing platforms. The optimization of vehicle-sharing platform operations based on EVs has become a key research focus among scholars. The core research topics include the spatial distribution optimization of EVs, parking resource allocation, and charging scheduling management. For example, Abouee-Mehrizi et al. (2021) develop a system optimization model to analyze the optimal strategy to use EVs in the car-sharing platform. They find that the charging speed, the number of EV charging piles, and the range of EVs are key factors which determine whether it is optimal to use EVs in the car-sharing market. Additionally, Zhang et al. (2020) explore a scenario where V2G electricity selling is integrated into the operations of car-sharing platforms. They develop a two-stage stochastic integer linear program to optimize decisions regarding the shared vehicle fleet, EV battery charging, and V2G electricity selling.

2.3 Multi-Level Perspective

It is widely agreed among scholars that technological transitions are by nature transitions of socio-technical systems (Geels, 2005a; Geels, 2010). While they encompass technological innovations, their scope extends beyond technology to include transformations in social structures, institutions, and practices. For instance, the transition from ICEVs to EVs entails not only a technological shift from combustion engines to electric drivetrains, but also the development of new charging infrastructure. Furthermore, it reflects broader cultural changes, as individuals increasingly perceive automobiles not merely as utilitarian tools, but also as sources of enjoyment, identity, and lifestyle expression.

To better understand how technological transitions emerge from the dynamic interplay between technology and society, scholars have introduced the multi-level perspective (MLP) as an analytical framework (Kemp, 1994; Kemp et al., 1998; Geels, 2002). The MLP conceptualizes socio-technical transitions as the outcome of interactions across three analytical levels: niches, regimes, and the socio-technical landscape.

Niches are protected spaces that allow radically new technologies to emerge and develop (Schot et al., 1994). Although radically new innovations often have significant potential, they typically underperform in their early stages compared to established technologies. Niches are therefore essential for technological transitions, as they provide the time and resources necessary for these technologies to mature. Niches take forms of technological niches and market niches. Technological niches refer to labs, research projects, and pilot programs where technologies can develop without immediate commercial pressures. Market niches refer to specific segments of the market where novel technologies can address the specific needs of particular user groups.

The concept of technological regimes comes from evolutionary economics (Nelson & Winter, 1982). It refers to the set of rules, routines, and institutions that guide and constrain the development, diffusion, and use of technologies within a particular sector (Rip & Kemp, 1998). These regimes contribute to the stability of the existing socio-technical systems, while simultaneously creating path dependencies that may hinder radical innovation (Geels, 2005b).

The landscape refers to the external environment in which actors operating at both the niche and regime levels are embedded. It encompasses structural trends and contextual factors such as the international landscape, governmental regulations, cultural values, and climate change that shape and constrain the conditions under which socio-technical systems evolve. It typically lies beyond the control of industry actors.

Since the introduction of the MLP, it has been widely adopted in industry-level case studies to analyze the dynamics of technological transitions across various contexts. For example, the pioneering work of Geels (2005a) applied the MLP to examine several historical cases in the transportation industry like the transition from sailing ships to steamships in the UK, from horse-drawn carriages to automobiles in the US, and from piston-engine aircraft to jetliners in the US in order to explain how technological transitions unfold. Besides, Smith (2007), Geels (2010), Verbong & Geels (2010) and other scholars have applied the MLP to examine green technological transitions. Their studies emphasize that when transitions are driven by the pursuit of cleaner or more sustainable performance rather than by price competition, a broader set of actors operating across different niches become involved. These actors interact not only through market mechanisms but also through policy interventions, social learning, and the creation of legitimacy for emerging technologies.

In recent years, researchers have started to adopt the MLP to understand the technological transition from ICEVs to EVs in the automobile industry. Berkeley et al. (2017) employed the MLP as an analytical lens to identify multi-level barriers to the European uptake of EVs and proposed corresponding policy solutions. Wu et al. (2021) adopted the MLP to depict the transition pathways toward EVs in China's automobile industry. Corradi et al. (2023) conducted a literature review to summarize driving factors for EV adoption at the niche-innovation, the socio-technical regime, and the landscape level in Europe.

Following these studies, yet differing from them in analytical focus, this thesis also adopts the MLP. However, rather than examining macro-level socio-technical transitions at the national or industry scale, it concentrates on how firms strategically respond to technological transitions. Specifically, this thesis proposes that corporate strategies during this transition are shaped by interacting factors across the niche, regime, and landscape levels , thereby linking firm-level decision-making with broader socio-technical dynamics.

Chapter 3 Study 1: Product Technical Specification Design Strategies during Technological Transitions: A Structural Demand Estimation of Electric Vehicle Driving Range

3.1 Introduction

During technological transitions, firms in the niche market can generate value from developing new technologies and thus challenge dominant competitors in the existing market (Ansari & Krop, 2012; Yu & Hang, 2010; Shao et al., 2017). However, the value creation of new technologies is fraught with uncertainty and heavily depends on customer preferences (Brockhoff, 1999; Hargadon & Douglas, 2001). New technologies are often novel and disruptive, and some of their functional characteristics may fall short compared to the existing technologies. This undoubtedly makes it harder for customers to recognize and accept their value (Ma et al., 2019). For example, while 3D printing is regarded as a 'revolutionary technology' for component manufacturing in many industries, it still struggles to meet durability requirements compared to traditional manufacturing technologies. Furthermore, the high costs and the need for specialized skills for operators pose significant challenges to its large-scale application (Bohnsack & Pinkse, 2017). Therefore, it is a crucial issue for firms in the niche market to design new technology products that customers are willing to accept compared to traditional technology products (Rindova & Petkova, 2007; Verganti, 2011; Paparoidamis et al., 2019). In other words, during technological transitions, firms that are the first to develop new technologies may not necessarily succeed. Instead, it is those that optimize product designs to align with customer needs and fully capitalize on the potential of the niche market that are most likely to emerge as the ultimate winners (Eisenman, 2013).

Driven by the urgent global need to reduce greenhouse gas emissions and thus address the climate change issue, the automotive industry is undergoing a profound technology transition from traditional internal combustion engine vehicles (ICEVs) to electric vehicles (EVs) (Pohl & Yarime, 2012). However, a major challenge during this technological transition lies in designing EVs that effectively enhance customer acceptance, particularly through the optimization of their technical specifications (Coffman et al., 2017; Yu et al., 2022). For instance, it is shown that EVs only accounted for 18% of new car sales in the UK in the first ten months of 2024, falling short of the government's 22% target. The CEO of Nissan has stated that due to the low level of customer acceptance, most automakers would face significant fines since they find it difficult to meet the 28% target set for 2025 in the UK (Financial Times, 2024). Besides, in China, despite the significant growth in EV sales in recent years, the market remains dominated by a few best-selling models. Specifically, according to the China Association of Automobile Manufacturers (CAAM), the top 10 best-selling models accounted for approximately 60% of total EV sales in 2023.

In exploring EV technical specification designs that cater to customer preferences, scholars have found that driving range is the most influential technical specification in customer decisions to purchase EVs (Coffman et al., 2017; Huang & Qian, 2018; Li et al., 2020). Typically, "range anxiety" has been recognized as a primary obstacle to EV adoption (Egbue & Long, 2012). This refers to drivers' concerns that the driving range of EVs may be insufficient to reach their destination or find a charging pile before the battery runs out (Eberle & Von Helmolt, 2010).

There are significant differences in the driving range designs across EVs from different manufacturers. For instance, in 2023, the well-known Chinese automaker Geely launched an EV model that boasts a remarkable driving range of 1,032 kilometers, making it one of the longest-range EVs in China. In contrast, subcompact EVs like the Wuling Hongguang Mini EV model have a driving range of only about 100 kilometers. In fact, merely increasing the driving range may not be the most effective strategy for enhancing the competitiveness of EVs. This is because customer purchase decisions are influenced by a range of factors, making the decision-making process highly complex. For instance, the driving range of EVs is mainly determined by battery capacity. According to the U.S. Department of Energy, each additional 1 kWh of battery capacity costs about 139 USD. Therefore, increasing the driving range of EVs can lead to a substantial rise in product costs. Thus, automobile manufacturers face an important trade-off between driving range and vehicle costs when designing EVs. Additionally, increasing the battery capacity may also significantly affect other product attributes, including vehicle size, curb weight, and maximum speed, which can strongly influence customer preferences as well. Thus, an in-depth analysis into the impact of EV driving range on customer preferences is crucial for firms in the niche market to optimize product designs.

Furthermore, the value proposition of a new technology product can be significantly shaped by the availability and quality of complementary technologies

(Adner & Kapoor, 2010, 2016a, 2016b). For instance, customer preferences for the driving range of EVs can be significantly influenced by the density of EV charging piles in markets where they are located. Specifically, in areas with a high density of EV charging piles, even a shorter driving range of EVs may not be a major concern for customers, as the availability of charging infrastructures alleviates their "range anxiety" (Bonges & Lusk, 2016). Alternatively, customers may also view the driving range of EVs and the density of EV charging piles as complementary factors that both increase their preference for EVs. Therefore, when designing the driving range of EVs to meet customer demand, automakers need to fully consider the impact of the density of EV charging piles in different markets. Thus, this study also further explores the complementary or substitution effects between the driving range of EVs at the product level and the density of EV charging piles at the market level. Specifically, we focus on two research questions in this study: *1) How does the design of the driving range of EVs affect customer preferences? 2) How does the density of EV charging piles in a market affect the relationship between the driving range design of EVs and customer preferences?*

In recent years, an increasing number of studies have focused on factors affecting customer preferences for EVs during the automotive industry's technological transition (e.g., Avci et al., 2015; Naumov et al., 2022; Zhang & Dou, 2022). They have collected preference data through surveys to analyze how customers' willingness to purchase EVs varies with different product designs (Dimitropoulos et al., 2013; Egbue & Long, 2012; Huang & Qian, 2018). Nevertheless, stated preference data may not always accurately capture actual customer purchase behaviors and could be subject to various biases (Axsen et al., 2009; Coffman et al., 2017). In addition, although some studies suggest that customer preferences for EV driving range should not be considered independent of the level of charging infrastructure in the markets where they are located (e.g., Axsen et al., 2009), empirical research examining their synergistic effects on customer preferences remains scarce.

To fill these research gaps, we collect detailed data on the sales of electric passenger vehicles in China from 2017 to 2023 and integrate them with other data from multiple sources. We construct and estimate a structural model to quantify the impact of EV driving range on customer preferences in the automotive industry. The findings indicate that customer demand for EVs is significantly elastic to driving range. Specifically, the average demand elasticity regarding driving range is 1.447.

Moreover, we find that there exists a complementary relationship between the density of EV charging piles in the markets and the driving range of EVs in shaping customer preferences. Specifically, in markets with a high level of charging pile density, the driving range elasticity of EVs is higher than that in markets with a low level of charging pile density. Through in-depth mechanism analysis, we find that the observed complementarity is primarily driven by consumers' differentiated preferences for vehicle classes under varying market conditions. In markets with well-developed charging infrastructure, consumers are able to choose medium- and large-sized EVs for intercity travel or long-distance commutes, making them more sensitive to driving range. In contrast, in areas with limited charging infrastructure, consumers are often constrained to subcompact and compact EVs, which are primarily used for short daily commutes where driving range is relatively less important.

This study offers valuable practical implications for automotive manufacturers and policy makers. By quantifying the market elasticity of EV driving range and examining the impact of the density of EV charging piles in markets on such elasticity, this study provides a foundation for them to develop optimal EV driving range design strategies tailored to different market conditions. Moreover, our mechanism analysis suggests that the density of charging infrastructure can influence the range of EV classes accessible to consumers. Accordingly, we recommend that policymakers support the expansion of charging infrastructure to enable consumers to make unrestricted choices across a diverse spectrum of EV classes.

3.2 The Related Literature

This section introduces the various literature streams relevant to this study. Specifically, our study is related to the research on product technical specification design during technological transitions, customer preferences for electric vehicles, and structural demand estimation using market-level aggregation data.

3.2.1. Product Technical Specification Design Strategies during Technological Transitions

Product design refers to a systematic problem-solving process that involves identifying issues in user needs and experiences, generating solutions through product conceptualization, development, and optimization, and determining the best solution through evaluation and refinement (March & Smith, 1995; Bayazit, 2004). It can be categorized into two types (Ravasi & Stigliani, 2012): one type focuses on technical specifications, where the design improves a product's functionality, performance, or efficiency by introducing new technologies or optimizing existing ones to meet customer demand for usability and high-tech features (Moon et al., 2015); the other focuses on product aesthetics, namely the product's appearance, form, and visual appeal to shape the brand image and emotionally resonate with customers (Micheli & Gemser, 2016).

A technological transition is essentially a process in which the design of product technical specifications continuously evolves (Abernathy & Utterback, 1978; Clark, 1985; Srinivasan et al., 2006). During technological transitions, companies in the niche market engage in intense competition over the technical specification designs of new technology products until a widely accepted dominant design is established (Eisenman, 2013). A well-considered design of technical specifications can enable new technology products to deliver a novel experience while preserving user convenience and comfort, thereby better aligning with customer needs and promoting market acceptance (Xue, 2019). In contrast, poorly designed technical specifications may hinder consumers from recognizing the functional advantages of new technologies and may lead to discomfort due to deviations from the functionality of incumbent products (Simoni et al., 2014). For example, in the case of EVs as an emerging technology, key parameters such as driving range, charging time, and energy efficiency not only influence consumers' choices between ICEVs and EVs, but also further shape their preferences among various EV models offered by different manufacturers.

3.2.2. Customer Preferences for Electric Vehicles

Since the global EV market is still in its early stages of development, market data remains relatively limited. As a result, scholars often rely on stated preference data to analyze customer preferences in this emerging market. Specifically, researchers design hypothetical scenarios to simulate customer choice behaviors when faced with EVs that have different feature combinations (Louviere, 2000). They primarily propose four kinds of factors that can significantly influence customer preferences for EVs: technological, economic, infrastructure, and policy factors (Liao et al., 2017). Among these, technological factors have received the most attention.

Concerning technological factors, the current research has primarily focused on driving range (e.g., Valeri & Danielis, 2015; Li et al., 2020), charging time (Li et al., 2018), battery warranty (Li et al., 2020), and horsepower of EVs (Achtnicht et al., 2012). Specifically, nearly all stated preference studies suggest that as the driving range of EVs increases in hypothetical scenarios, customers show a greater willingness to purchase them. The only exception is the study of Hess et al. (2012), which shows that there is no significant relationship between EV driving range and customer purchase intention. This might be attributed to the fact that the scope of the driving range hypothesized in their study is too narrow to fully capture the impact of variations in EV driving range on customer decision-making. In contrast, other technological factors, such as battery warranty and horsepower, have not shown the same level of importance as driving range in influencing customer EV purchase decisions, and their significance remains somewhat debated (Coffman et al., 2017).

Besides, regarding economic factors, scholars have suggested that both the purchase cost and the operational cost of EVs are crucial elements affecting customer purchase intentions (Glerum et al., 2014). In the early market, the relatively high purchase cost often serves as the main barrier for customers to buy EVs (Graham-Rowe et al., 2012). However, the relatively low maintenance and usage costs of EVs might boost customer willingness to purchase them instead (Valeri & Danielis, 2015). With respect to infrastructure factors, scholars mainly focus on the availability of charging facilities (e.g., Hoen & Koetse, 2014; Tanaka et al., 2014). Most of them have found that the density of charging piles plays a crucial role in shaping consumer willingness to adopt EVs. As for policy factors, scholars have focused on economic and non-economic policies. In terms of economic policies, current studies primarily focus on the impact of tax reductions and exemptions related to EV purchase and usage (e.g., Potoglou & Kanaroglou, 2007; Hoen & Koetse, 2014; Glerum et al., 2014). As for non-economic policies, the existing research has mainly concentrated on the effects of policies that allow EVs to use high-occupancy vehicle (HOV) lanes and other convenience privileges (e.g., Hackbarth & Madlener, 2013; Chorus et al., 2013).

Most studies on customer preferences for EVs have emphasized the critical role of driving range. However, as mentioned earlier, due to the lack of detailed EV market data, few empirical studies have examined actual customer demand for EV driving range. Furthermore, although scholars have suggested that the driving range of EVs and the availability of charging infrastructure jointly alleviate customers' "range anxiety"

(Shi et al., 2022), there is still a lack of empirical analysis on the interaction between these two factors in influencing customer purchase intentions.

3.2.3. Structural Demand Estimation

This study is also related to structural demand estimation research using market-level aggregation data. The estimation model was first proposed by Berry (1994) and extended by Berry et al. (1995). Grounded in utility maximization and discrete choice theory, the structural model provides a powerful approach to estimating consumer preferences for differentiated products. It integrates observed market data such as prices, product attributes, and market shares with unobserved heterogeneity in consumer tastes. The model assumes that consumers make utility-maximizing choices among a set of competing alternatives, and it uses an inversion technique to recover demand parameters consistent with observed market outcomes. This approach also addresses estimation biases arising from the endogeneity of product prices (Nevo, 2000). The structural demand estimation framework has been adopted in various fields, such as marketing (e.g., Sudhir, 2001; Narayanan et al., 2005), information systems (e.g., Dong et al., 2021), and operations management (e.g., McKie et al., 2018) in top management journals (such as *Management Science*, *Manufacturing & Service Operations Management*, *and Information Systems Research*).

In the field of operations management, scholars have employed structural demand estimation across various industries. For example, in the service industry, this method has been used to study the impact of online reviews on customer demand (e.g., Xu et al., 2021; Fang, 2022). In the transportation industry, it has been utilized to predict customer choices between different transportation options (e.g., Escobari, 2017). Notably, the automotive industry is one of the most prominent sectors where structural demand estimation is widely applied. For instance, Balachander et al. (2009) estimated the impact of scarcity strategies on customer preferences in the automotive market. Additionally, Guajardo et al. (2016) analyzed the impact of service attributes, such as warranty length and after-sales service quality, on customer demand in the U.S. automotive industry. They also explored the interaction between these service attributes and product quality, exploring how they complement or substitute each other in shaping customer preferences. Like these studies, we adopt Berry's (1994) model to estimate how customer demand responds to changes in EV driving range, as well as the interrelationship between EV driving range and charging pile density in shaping EV customer demand.

3.3 Research Context and Data Sample

The context of this study is the electric passenger vehicle (EV) market in China. In China, commercial-use electric vehicles are typically procured by government bodies or corporate entities. Their procurement decisions are shaped by institutional priorities and organizational objectives rather than individual preferences, which fall outside the scope of this study. Besides, commercial-use vehicles like public buses or fleet vehicles often operate on fixed routes, making range anxiety a less significant concern. Therefore, our analysis focuses exclusively on the sales of electric passenger vehicles.

The market in this study is defined by city and quarter. In each quarter of a city, a customer can choose from multiple EV models produced by various automobile manufacturers. Additionally, the level of EV charging infrastructure varies across markets, and customers may consider whether it can meet their daily energy replenishment needs when they make purchase decisions.

We compile data for analysis from multiple sources. First, the EV sales data in this study is obtained from a consulting firm specializing in China's automotive industry. Second, we gather data on the characteristics of EV models, including price, driving ranges, curb weight, and size, from widely recognized Chinese automotive information websites and official automotive brand websites. Third, we collect data on the level of EV charging facilities in different markets from the official industry alliance for the Chinese EV charging sector. Finally, we obtain geographical data of different markets from the National Bureau of Statistics of China and Provincial Statistical Bureau.

3.3.1 Electric Passenger Vehicle Sales Data

In this study, we use the number of newly registered compulsory traffic accident liability insurance records for each EV model[1] as a proxy for sales data. In China, all newly purchased vehicles must immediately be insured for traffic accident liability before they can complete the registration and licensing procedures. Thus, the number of newly registered compulsory traffic accident liability insurance records can reflect the actual sales of vehicles in China. This approach has also been used in previous empirical studies on vehicle sales in the Chinese automobile market (e.g., Dai & Wang,

[1] A vehicle model in this data is defined as a unique combination of "model year-automaker-brand-series-fuel type". For example, "2019-Changan Automobile-BenBen-EV" is a specific EV model in our study.

2022).

We collect quarterly sales data for EVs in all first- and second-tier cities in China from 2017 to 2023. In late 2016, China became the world's largest market for EVs. Besides, the Chinese "Automobile Industry Mid- and Long-Term Development Plan" highlighted the development of EVs as a central pillar of the country' automotive industry development strategy in 2017. Thus, we select the year of 2017 as the starting point for the sample period of our study. In China, there are 334 city-level administrative districts, which are typically divided into different tiers based on factors like population size, economic development, and political status. Among these, 19 city-level administrative districts are classified as first-tier cities, and 30 are classified as second-tier cities. The sales of EVs in these 49 first- and second-tier cities account for 69.1% of the total EV sales in China from year 2017 to 2023.

The types of vehicles considered in this study include sedans, SUVs, and MPVs, , which together constitute the majority of EV sales in China. In our original sample, there are only two sports car models and five mini van models. The available model options within these two vehicle types lack sufficient differentiation and therefore do not allow for meaningful analysis of variation in customer preferences for driving range. As such, sports cars and mini vans were excluded from the final dataset. Additionally, the vehicle sizes considered in this study include subcompact, compact, medium, and large. Since we specifically focus on battery EVs in this study, we exclude hybrid EVs, fuel cell EVs, and range-extended EVs. In total, the original sample of this study includes 102,821 observations of 503 EV models in 49 first- and second-tier cities across 28 quarters from 2017 to 2023.

3.3.2 Driving Range and Other Electric Passenger Vehicle Attribute Data

Regarding the price of EVs, we utilize the manufacturer's suggested retail price (MSRP) to measure it. Although actual transaction prices may vary due to individual dealer discounts, it is widely agreed that the MSRP is a reasonable approximation of the actual transaction price (e.g., Barwick, 2021).

The driving range of an EV refers to the maximum distance it can travel on a full charge under specific testing conditions. Initially, the New European Driving Cycle (NEDC) standard was adopted for driving range tests in China. However, the driving scenarios used in the NEDC standard primarily focus on urban and highway conditions, which do not fully reflect the actual driving environment in China. Thus, China's Ministry of Industry and Information Technology (MIIT) introduced the China Light-Duty Vehicle Test Cycle (CLTC) standard in 2021. Since then, automakers have been required to report the driving range of EVs based on the CLTC standard. Therefore, in this study, the driving range for models launched between 2017 and 2020 is based on the NEDC standard, while for models introduced between 2021 and 2023, it is based on the CLTC standard. To assess whether this treatment introduces significant bias into our analysis, we compare the driving range of the same EV models reported under both the NEDC and CLTC standards. The deviation is found to be relatively small (less than 5%).

In addition, we collect data on the size (i.e., the product of length, width, and height), curb weight, and horsepower of EVs. Since EVs are powered by electric motors rather than fuel engines, we measure horsepower as the total power of the electric motor.

The sales data in this study are collected at the model level, while the attribute data are collected at the model-trim[2] level. To match the sales data with the corresponding attribute data, we average the vehicle attributes across all trims of each model. This method has been widely adopted in previous studies on structural demand estimation in the automative market (e.g., Balachander et al., 2009; Guajardo et al., 2016). During the matching process, any observation with missing values for attributes of EVs (price, driving range, size, curb weight, or horsepower) is excluded from the analysis. Thus, the final sample in this study includes 67,648 observations of 393 EV models.

3.3.3 The Density of Charging Piles and Other Market Data

Charging piles for EVs are classified into fast-charging and slow-charging piles. Fast-charging piles use high-power direct current (DC) to charge vehicles, allowing them to replenish up to 80% of the battery in approximately 30 minutes to an hour. Thus, fast-charging piles are usually located at public high-traffic areas to support long-distance travel and provide emergency charging options for EV drivers. Differently, slow-charging piles use low-power alternating current (AC) to charge vehicles, which usually takes several hours or overnight to fully charge the vehicle. Therefore, slow-charging piles are typically installed in home garages and office parking lots, offering convenient charging solutions for daily use. Customer concerns about the driving range of EVs often stem from worries about depleting battery power during long-distance

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[2] A vehicle model-trim in this data is defined as a unique combination of "model year-automaker-brand-series-fuel type-trim". For example, "2019-Changan Automobile-BenBen-EV-EV360 Luxury Edition" is a specific EV model-trim in our study.

travel or unplanned situations. Thus, fast-charging stations are more closely related to customer demand for EV driving range than slow-charging stations. Therefore, we measured the density of charging piles by dividing the number of public fast-charging piles by the total road length in each city per quarter.

Additionally, we collect geographic information such as the annual GDP per capita and the number of households for all first- and second-tier cities from 2017 to 2023 as well.

Table 3.1 provides a summary of the measurements and descriptive statistics for all variables in this study. Furthermore, to better understand our data, we illustrate the trends in EV sales and the development of fast-charging infrastructure in China's first- and second-Tier Cities in Figure 3.1 and Figure 3.2, respectively. As shown in Figure 3.1, the number of EV models in the Chinese automative market has increased annually. Besides, the annual sales of EVs have also steadily increased, with the growth rate significantly accelerating since 2021. In Figure 3.2, we can observe that the number of public fast-charging piles has increased annually and there is a particularly sharp growth in 2023.

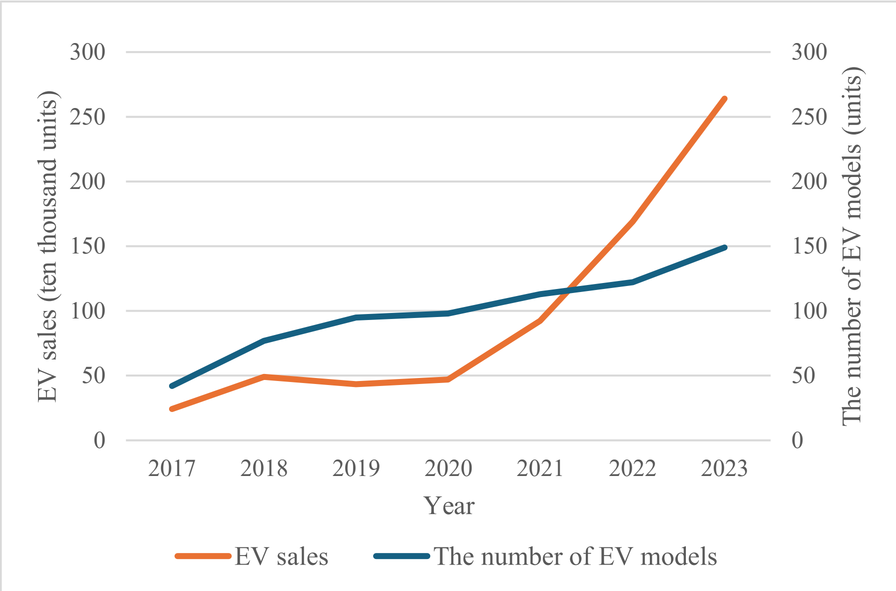

Figure 3.1 EV sales in China's first- and second-tier cities

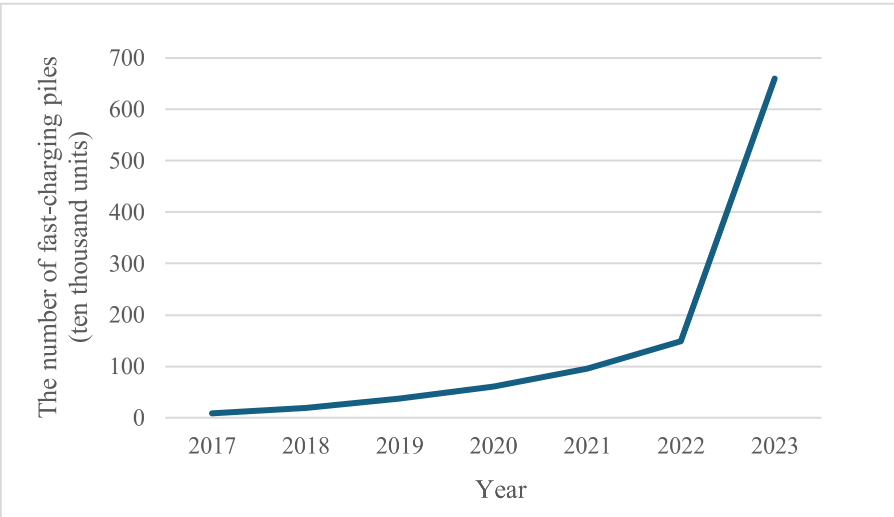

Figure 3.2 Charging infrastructure in China's first- and second-tier cities

Table 3.1 Measurements and descriptive statistics for all variables in Study 1

Variable	Measurement	Mean	SD	Min	Max
Sales (units)	The number of newly registered compulsory traffic accident liability insurance records for a specific EV model in a particular city and quarter	101.86	369.82	1	19623
Price (ten thousand yuan)	The average manufacturer's suggested retail price (MSRP) for all trims of a specific EV model	22.72	18.56	3.28	156.60
Driving range (km)	The average driving range for all trims of a specific EVmodel (NEDC driving range for models launched between 2017 and 2020 and CLTC driving range for models launched between 2021 and 2023)	439.97	132.21	100	798.75
Curb weight (kg)	The average curb weight for all trims of a specific EV model	1689.60	470.02	600	3293
Size (cubic meters)	The average product of length, width, and height for all trims of a specific EV model	12.82	2.66	3.56	20.57
Horsepower (kW)	The average total power of the electric motor for all trims of a specific EV model	154.03	111.66	15	800
Density of charging piles (units/km^2)	The ratio of the number of public fast-charging piles to the total road length in a particular city and quarter	2.46	4.75	0	158.24
GDP per capita (yuan)	The ratio of GDP to the total population in a specific city at the end of a particular year	117384.50	38466.29	31856	203489
Households (ten thousands)	The total number of households in a specific city at the end of a particular year	268.90	197.92	33	1277

3.4 Model-free Evidence

Before setting up the econometric model, we first provide model-free evidence of the relationship between EV driving range and customer demand. Specifically, Figure 3.3 illustrates the trend of market share distribution for EVs across different driving range intervals. It can be observed that the market share of EVs with a driving range of above 500 kilometers has rapidly increased in recent years, emerging as the dominant segment in the market. In contrast, EVs with a driving range of less than 200 kilometers, which once held a significant market share, have seen a continuous market share decline in recent years. Additionally, the market share of EVs with a driving range of 200 to 300 kilometers has also experienced a notable decline. Overall, we can see that there is a shift in customer demand toward high-range EV models from 2017 to 2023.

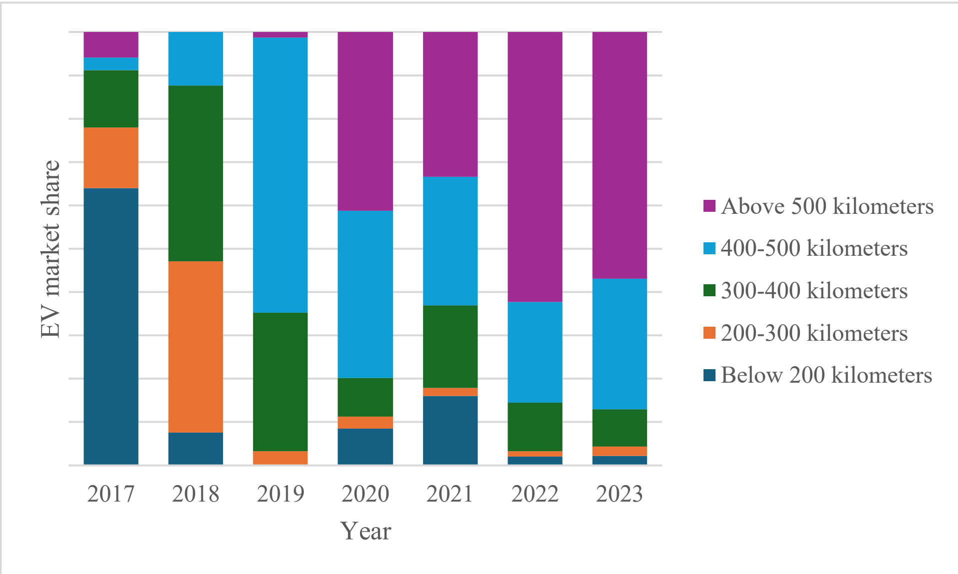

Figure 3.3 EV market share by driving range

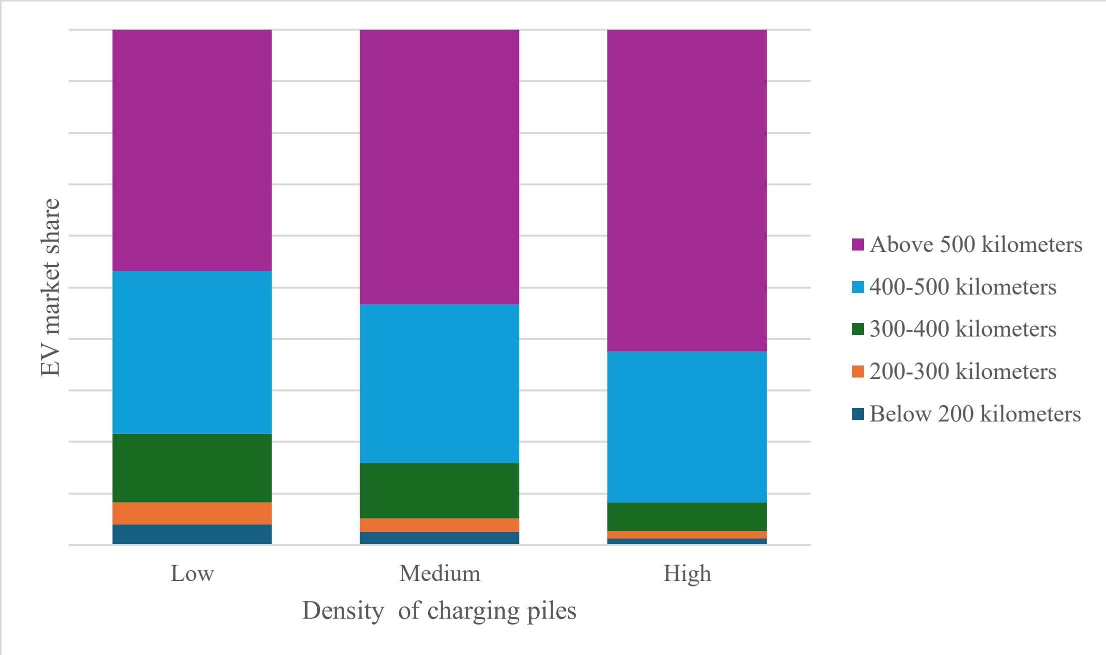

Figure 3.4 EV market share by driving range and charging pile density

Besides, we categorize first- and second-tier cities in our sample into three groups based on the density of charging piles in the year of 2023: low (with an average of 0.72 fast-charging piles per kilometer of road length), medium (with an average of 2.12 fast-charging piles per kilometer of road length), and high (with an average of 14.99 fast-charging piles per kilometer of road length). In Figure 3.4, we compare the market share of EVs across different driving range intervals in three market groups. It is shown that, in cities with a higher level of charging pile density, high-range EV models, particularly those with a driving range of over 500 kilometers, have a larger market share. This suggests that the density of charging piles in the market may strengthen the positive effect of EV driving range on customer demand.

3.5 Econometric Model

3.5.1 Demand Model Formulation

We apply Berry's (1994) model, which derives the demand function by aggregating individual utility functions. Specifically, the customer i's utility function for purchasing EV model j in city m in quarter t can be expressed as:

$$u_{ijmt} = \lambda_i Range_{jt} + x'_{jt}\beta_i - \alpha_i p_{jt} + \xi_{jt} + \varepsilon_{ijmt} \tag{3.1}$$

where x_{jt} represents the observed vehicle attribute vector (e.g., size and curb weight) of EV model j in quarter t, $Range_{jt}$ is the driving range and p_{jt} is the price of model j in quarter t, ξ_{jt} represents other product attributes (e.g., interior and service characteristics) that are not observed for researchers but are perceivable by consumers. ε_{ijmt} is the idiosyncratic shock, which is assumed to follow a Type I extreme value distribution.

In Berry's (1994) model, the key to integrating market data for estimating customer preferences lies in constructing the average utility function for all consumers. The coefficient β_i for the vehicle attribute x^k_{jt} at the individual level can be decomposed into a common effect for all consumers (β) and an individual heterogeneity (σ). Thus, the impact of the vehicle attribute x^k_{jt} on customer i's utility can be expressed as $(\beta_k + \sigma_k v_{ik})x^k_{jt}$, where β_k and σ_k are the parameters to be estimated, and v_{ik} is the individual-level disturbance term following a standard normal distribution. We use the same approach to decompose the price coefficient α_i and the coefficient λ_i for $Range_{jt}$. Thus, the individual consumers' utility function can be partitioned into three parts: the average utility function, the individual heterogeneity function, and the individual error term. Thus, the utility function for individual customers is:

$$u_{ijmt} = \delta_{jt} + \mu_{ijmt} + \varepsilon_{ijmt} \tag{3.2}$$

where δ_{jt} is the average utility for EV model j in quarter t that:

$$\delta_{jt} = \lambda Range_{jt} + x_{jt}'\beta - \alpha p_{jt} + \xi_{jt} \tag{3.3}$$

And μ_{ijmt} is the individual heterogeneity effect of customer i in city m in quarter t. If we assume that d_{jt} is an indicator variable for vehicle attributes that exhibit heterogeneity in customer preferences, μ_{ijmt} can be expressed as:

$$\mu_{ijmt} = \sum_{m=1}^{M} \sigma_m d_{jt}^m \zeta_{im} \tag{3.4}$$

3.5.2 Main Effects Model

According to Berry (1994) and Berry et al. (1995), consumer purchasing behaviors follow the utility maximization principle. It means that customer i will choose EV model j in city m in quarter t if and only if $u_{ijmt} \geq u_{ikmt}$, k=0,1,2,…,J. Here, J represents the total number of EV models available, and k=0 is the outside good. In this study, the outside good refers to the situation where customer i in city m in quarter t chooses not to purchase any of the EV models observed in the sample. The average utility and individual heterogeneity for the outside good are assumed to be zero. Thus, if customer i chooses the outside good in city m in quarter t, the utility is expressed as $u_{i0mt} = \varepsilon_{i0mt}$.

If we define $v_{ijmt} = \mu_{ijmt} + \varepsilon_{ijmt}$, then the market share for EV model j in city m in quarter t is the probability that v_{imt} falls within the region

$A_j(\delta) = \{v_{imt} \setminus \delta_{jt} + v_{ijmt} > \delta_{kt} + v_{ikmt},\ \forall k \neq j\}$. If we assume that v_{imt} follows a distribution with a density function of $f(\cdot)$, then the market share s_{jmt} is given by:

$$s_{jmt} = \int_{A_j(\delta)} f(v)dv \tag{3.5}$$

Thus, estimating customer preferences based on the market share of products relies on the assumption about the distribution of v_{imt}. If we assume that differences in individual customer preferences only reflect in the individual error term ε_{ijmt}, then the market share of EV model j in city m in quarter t is:

$$s_{jmt} = \frac{\exp(\delta_{jt})}{\sum_{k=1}^{J} \exp(\delta_{kt})} \tag{3.6}$$

Furthermore, as mentioned earlier, the average utility of the outside option is typically defined as 0. Based on this, we derive the relationship function between market share, average utility, and parameters to be estimated as follows:

$$\ln(s_{jmt}) - \ln(s_{0mt}) = \delta_{jt} = \lambda Range_{jt} + x'_{jt}\beta - \alpha p_{jt} + \xi_{jt} \tag{3.7}$$

Equation (3.7) represents our main model to estimate the impact of driving range on customer demand for EVs. We use the total sales of all EV models (hybrid EVs, fuel cell EVs, and range-extended EVs are included) as the measure of market size. With respect to market share, we measure it by calculating the ratio of the sales of a particular EV model in city m in quarter t to its corresponding market size. Additionally, we measure the market share of the outside good by calculating the ratio of the difference between the total market size and the total sales of EV models observed in the sample to the corresponding market size.

3.5.3 Model with Interactions

This study not only focuses on the impact of EV driving range on customer demand but also further explores how the density of charging piles in different markets influences such relationship. In such situation, the customer utility function for purchasing EV model j in city m in quarter t can be expressed as:

$$\begin{gathered} u_{ijmt} = x'_{jt}\beta_i + y'_{mt}\gamma_i + \\ \lambda_i^1 Range_{jt} + \lambda_i^2 Charging_{mt} + \lambda_i^3 Range_{jt} \times Charging_{mt} \\ -\alpha_i p_{jt} + \xi_{jt} + \omega_{mt} + \varepsilon_{ijmt} \end{gathered} \tag{3.8}$$

where x_{jt} represents the observed vehicle attribute vector (e.g., size and curb weight) of EV model j in quarter t, while y_{mt} denotes the observed market attribute vector for city m in quarter t(e.g., GDP per capita and the number of households). The interaction term between the driving range of EV model j in quarter t ($Range_{jt}$) and the density of charging piles for city m in quarter t ($Charging_{mt}$) is also included in the equation. Additionally, ξ_{jt} and ω_{mt} denote the vectors of vehicle and market attributes which are unobservable to researchers but observable to customers, respectively. ε_{ijmt} is the individual idiosyncratic shock.

By using the inversion method of Berry (1994) discussed in subsection 3.5.2, which maps the observed product market share back to its mean utility, we derive the model with interactions used in this study to estimate how the density of charging piles influences customer preferences for EV driving range as:

$$\begin{gathered} \ln(s_{jmt}) - \ln(s_{0mt}) = \delta_{jmt} \\ = x'_{jt}\beta + y'_{mt}\gamma + \lambda(Range_{jt}, Charging_{mt}, Range_{jt} \times Charging_{mt}) - \alpha p_{jt} + \omega_{mt} + \xi_{jt} \end{gathered} \tag{3.9}$$

In this equation, the variables are structured across multiple levels. Specifically, consumer purchasing behaviors are nested within different markets where multiple EV models exist. Within the same market nest, interdependence may arise among customer preferences for EV driving range, as they are collectively influenced by the density of charging stations. This highlights the hierarchical nature of decision-making in the EV market. Moreover, $Range_{jt} \times Charging_{mt}$ is a cross-level interaction term, where the driving range ($Range_{jt}$) is a vehicle-level variable, and $Charging_{mt}$ is a market-level variable. To address this multi-level estimation issue, this study adopts the hierarchical linear model (HLM) approach (Hofmann, 1997). The approach allows for capturing both within-market variation (i.e., the impact of driving range on customer demand within the same market in this study) and between-market variation (i.e., the impact across different markets in this study) (Snijders & Bosker, 2011). Using this method, we can precisely estimate the independent contributions of attributes at different hierarchical levels within the nested structure. Furthermore, the method allows us to estimate the coefficient for the cross-level interaction, revealing how the higher-level variable (i.e., the density of charging piles in this study) moderates the effect of the lower-level variable (i.e., EV driving range) on customer demand.

3.5.4 Identification and Instruments

In structural demand estimation models, product attributes are typically treated as exogenous because they are determined during the product design stage and are not directly influenced by consumer choices or other market factors. However, product prices are often regarded as endogenous variables. This is because firms can easily adjust prices based on the fluctuations in market demand (Berry et al., 1995). To address the potential price endogeneity, we adopt the two-stage least squares (2SLS) method in this study. Specifically, we construct instrumental variables (IVs) for the price of a specific EV model by calculating the sum of the attributes of (i) other EV models within the same market and (ii) other EV models within the same class and market. This approach is a widely adopted practice in structural demand estimation research (e.g., Ghose & Han, 2014; Guajardo et al., 2016; Grigolon et al., 2018; Dong et al., 2021). The validity of this series of IVs lies in the fact that while the attributes of other vehicle models do not directly affect customer utility for a given vehicle model, they can influence firms' pricing strategies through the mechanism of market competition (Berry, 1994).

3.6 Results

3.6.1 Main Effects Model Results

In estimating the main effects model in Equation (3.7), we include control variables such as vehicle size, curb weight, and horsepower. Additionally, class dummy variables are included to account for differences across vehicle classes. Furthermore, we include year dummies and city dummies to account for variations across different markets. Table 3.2 reports the results from both ordinary least squares (OLS) and two-stage least squares (2SLS) estimations.

In the first stage of the 2SLS model, the F-statistic for the instrumental variables was 83.82, far exceeding the critical threshold of 10, indicating that the selected instruments exhibit strong explanatory power for the endogenous variables (Staiger & Stock, 1997). Furthermore, we run the under-identification test of our instruments in the second state. The Anderson Canonical Correlation LM statistics yield a value of 680.24 $(p < 0.001)$, allowing us to strongly reject the null hypothesis that the instruments are under-identified. Thus, we conclude that our instruments are valid to address the endogeneity issue.

In Table 3.2, the coefficients for price in both the OLS and 2SLS models are significantly negative. Consistent with previous research, after addressing the endogeneity of product prices, we find that customers exhibit greater sensitivity to price, with the absolute value of the coefficient increasing from 0.025 to 0.035 (Berry et al., 1995; Guajardo et al., 2016). Moreover, the results show that the horsepower of the EV has a significant positive impact on customer demand. Regarding the primary focus of this study, driving range, both the OLS and 2SLS models consistently demonstrate a significant positive impact on customer demand (the coefficients are 0.003 and 0.004, respectively).

Table 3.2 Main model results of Study 1

	OLS		2SLS	
	Coefficient	SD	Coefficient	SD
Price	-0.025***	(0.001)	-0.035***	(0.008)
Driving range	0.004***	(0.000)	0.003***	(0.000)
Size	0.033***	(0.009)	0.011	(0.020)
Curb weight	-0.001***	(0.000)	-0.000	(0.000)
Horsepower	0.003***	(0.000)	0.004***	(0.000)
Constant	-3.716***	(0.086)	-3.859***	(0.110)
Class dummies	Included		Included	
Year dummies	Included		Included	
City dummies	Included		Included	
Observations	67648		65409	
R^2	0.253		0.252	

Notes: 1) The dependent variable is $\ln(s_{jmt}) - \ln(s_{0mt})$ in Equation (3.7); 2) * p<0.05, ** p<0.01, *** p<0.001; 3) The vehicle classes include subcompact sedan, subcompact SUV, compact sedan, compact MPV, compact SUV, medium sedan, medium SUV, large sedan, large MPV, and large SUV; 4) The number of observations in the 2SLS model is smaller than that in the OLS model since some EV models do not have other models within the same market and same class to construct their instrumental variables.

3.6.2 Model with Interactions Results

In the model with interactions, in addition to product-level control variables, we also include two market-level controls: GDP per capita and the number of households. Since we employ the hierarchical linear model (HLM), which inherently accounts for both within-market and between-market variations in the coefficients when estimating our model with interactions, we do not include city or year fixed effects. We only include class dummies of EVs in this model.

In the first stage of the 2SLS, the F-statistic for the instrumental variables is 96.14, significantly surpassing the critical threshold of 10, thereby demonstrating the strength of our instruments. Furthermore, in the second stage, the results of the under-identification test indicate that the Anderson Canonical Correlation LM statistic is 760.45, providing strong evidence that our instruments are not under-identified.

To further understand the composition of variance in the HLM model, we follow the approaches of Snijders & Bosker (2011) and Hox et al. (2017) to calculate the variance partition coefficient (VPC). The VPC measures the proportion of total variance at the lower level (product level in this study) that is attributable to the higher level (market level in this study). In our model, a higher VPC indicates that between-market variances have a larger influence on consumers' product-level choices (Wani et al., 2021). The result shows that the VPC in the model with interactions is 0.581, meaning that 58.1% of the variance in customer preferences for EVs comes from systematic differences between markets.

Table 3.3 reports the detailed results of the model with interactions in this study. The results show that, after controlling for between-market variances, the driving range still has a significant positive impact on customer demand for EVs in both the OLS and 2SLS models. Additionally, the coefficient of the cross-level interaction term is significantly positive, indicating a complementary relationship between market charging pile density and EV driving range in influencing customer demand.

Table 3.3 Model with interactions results of Study 1

	OLS		2SLS	
	Coefficient	SD	Coefficient	SD
Product-level variables				
Price	-0.026***	(0.001)	-0.063***	(0.006)
Driving range	0.003***	(0.000)	0.002***	(0.000)
Size	0.041***	(0.009)	-0.046**	(0.018)
Curb weight	-0.001***	(0.000)	0.001**	(0.000)
Horsepower	0.003***	(0.000)	0.006***	(0.000)
Market-level variables				
Charging pile density	-0.024***	(0.005)	-0.024***	(0.005)
GDP per capita	-4.69e-06***	(1.08e-06)	- 4.27e-06***	(1.06e-06)
Households	-0.001***	(0.000)	-0.001***	(0.000)
Cross-level interaction				
Driving range × Charging pile density	3.11e-05***	(7.39e-06)	3.42e-05***	(7.65e-06)
Constant	-2.819***	(0.157)	-3.100***	(0.158)
Class dummies	Included		Included	
Observations	67648		65409	
Between-group variance in random intercept	3.543	(0.226)	3.490	(0.243)
Between-group variance in random slope	3.05e-06	(3.20e-07)	3.34e-06	(3.81e-07)
Within-group variance	2.866	(0.016)	2.927	(0.017)

Notes: 1) The dependent variable is $\ln(s_{jmt}) - \ln(s_{0mt})$ in Equation (3.9); 2) * p<0.05, ** p<0.01, *** p<0.001

3.6.3 Additional Analyses

We also conduct a series of additional analyses based on the coefficients obtained from the regression models in Tables 3.2 and 3.3. First, we quantify the price change that corresponds to a given change in the driving range in terms of its impact on the mean utility of purchasing an EV. The results indicate that the median consumer willingness to pay for each additional kilometer of driving range is approximately 857 RMB, which accounts for about 0.5% of the median price of an EV. This suggests that consumers are willing to pay an additional cost equivalent to 0.5% of the vehicle price for every extra kilometer of driving range.

Furthermore, we also calculate the market elasticity of the driving range of EVs. We take the partial derivative of Equation (3.7) with respect to the driving range as:

$$\frac{\frac{\partial s_{jmt}}{\partial Range_{jt}}}{s_{jmt}} - \frac{\frac{\partial s_{0mt}}{\partial Range_{0t}}}{s_{0mt}} = \lambda \tag{3.10}$$

By substituting the market share function of EV model j in city m in quarter t $s_{jmt} = \frac{\exp(\delta_{jt})}{\sum_{k=1}^{J}\exp(\delta_{kt})}$ and the marginal effect function of driving range on the mean utility $\frac{\partial \delta_{jt}}{\partial Range_{jt}} = \lambda$ into Equation (3.10), we derive the formula for calculating the driving range elasticity of EV model j in city m in quarter t, as shown in Equation (3.11).

$$\frac{\partial s_{jmt}}{\partial Range_{jt}} \frac{Range_{jt}}{s_{jmt}} = \lambda Range_{jt}(1 - s_{jmt}) \tag{3.11}$$

Using the estimated coefficient values from Table 3.2 and the formula in Equation (3.11), we compute the average driving range elasticity of all EVs to be 1.447.

Additionally, we calculate the average market elasticities of EV driving range across different vehicle classes, with detailed results presented in Table 3.4.

As shown in Table 3.4, larger EVs seem to exhibit higher driving range elasticity. For the same vehicle type, such as sedans, consumers purchasing larger models (the driving range elasticity is 2.103) tend to be more sensitive to the driving range than those purchasing subcompact (the driving range elasticity is 0.917) and compact models (the driving range elasticity is 1.401). This may be attributed to the fact that the usage needs for larger vehicles often involve long-distance travel, where driving range becomes a more significant factor in decision-making.

Table 3.4 Driving range elasticities by vehicle classes

Vehicle class	Driving range elasticity
Subcompact sedan	0.917
Subcompact SUV	1.244
Compact sedan	1.401
Compact MPV	1.281
Compact SUV	1.589
Medium sedan	1.822
Medium SUV	1.756
Large sedan	2.103
Large MPV	1.424
Large SUV	1.942

Furthermore, to examine how market charging pile density impacts customer demand for the driving range of EVs, this study categorizes markets into two groups: high-charging-pile-density and low-charging-pile-density markets (the density of charging piles is above and below the median density, respectively). We then calculate the average driving range elasticity in each market group. The results show that the average driving range elasticity in low-charging-pile-density markets is 1.313, while that in high-charging pile-density markets is 1.581, which is approximately 20% higher than that in low-charging-pile-density markets. This further confirms the complementary relationship between market charging pile density and EV driving range in influencing customer demand.

We also investigate the potential mechanisms underlying such complementarity. Building on the previous analysis, we observe significant differences in the driving range elasticities across various vehicle classes. Therefore, it is reasonable to hypothesize that this complementarity may be driven by variations in the sales distribution of EV classes between high- and low-charging-pile-density markets. To explore this further, we summarize the total sales of different EV classes in these two types of markets in Table 3.5.

Table 3.5 EV sales distribution by vehicle class and market groups

Vehicle class	Sales in low-charging-pile-density markets	Sales in high-charging-pile-density markets	Difference in sales percentage (%)
Subcompact Sedan	820,789	757,874	-3.98%
	(51.99%)	(48.01%)	
Subcompact SUV	205,667	166,567	-10.50%
	(55.25%)	(44.75%)	
Compact Sedan	534,006	875,584	+24.24%
	(37.88%)	(62.12%)	
Compact MPV	15,909	14,634	-4.18%
	(52.09%)	(47.91%)	
Compact SUV	212,335	754,971	+56.10%
	(21.95%)	(78.05%)	
Medium Sedan	210,014	502,256	+41.02%
	(29.49%)	(70.51%)	
Medium SUV	157,782	945,006	+71.38%
	(14.31%)	(85.69%)	
Large Sedan	81,862	371,067	+63.86%
	(18.07%)	(81.93%)	
Large MPV	13,586	25,733	+30.90%
	(34.55%)	(65.45%)	
Large SUV	50,512	174,651	+55.14%
	(22.43%)	(77.57%)	

Notes: Sales percentage for a particular vehicle class within the market group are in parentheses.

From Table 3.5, it can be observed that as the size category of EV models increases from subcompact to large, their sales percentage in high-charging-pile-density markets shows a significant upward trend. Specifically, the sales of subcompact EVs are roughly the same in both high- and low-charging-pile-density markets. However, for medium and large EVs, the sales percentage in high-charging-pile-density markets can be up to four times that in low-charging-pile-density markets.

Therefore, we infer that the impact of market charging pile density on EV driving range elasticity is likely mediated by its effect on customer preferences for vehicle classes. Specifically, we argue that in low-charging-pile-density markets, customer choices of EV classes are limited by the lack of adequate charging infrastructure, prompting consumers to opt for subcompact and compact EVs that are better suited for fixed routes and short-distance travel where a smaller driving range is sufficient. As a result, consumers in these markets are less sensitive to EV driving range, as their focus is more on other factors such as affordability and convenience rather than the range itself.

In contrast, in high-charging-pile-density markets, the more abundant charging infrastructure significantly broadens consumers' options when purchasing EVs, allowing them to comfortably choose medium- and large-sized EVs for long-distance travel and extended commutes. Since these larger vehicles typically require a greater driving range, consumers in these markets are more attuned to variations in driving range. As a result, the driving range elasticity of EVs in high-charging-pile-density markets is significantly higher than that in low-charging-pile-density markets.

3.6.4 Robustness Checks

To test the robustness of the results, we conduct four robustness checks. Table 3.6 presents the main results of these checks. Due to space constraints, only the results from the model with interactions using the 2SLS estimation method are reported.

First, regarding the measurement of driving range, since EVs released in different periods have adopted different standards, we include an indicator variable for the NEDC standard in all models to control for any potential impacts arising from the different measurement standards. The results demonstrate that the key estimates related to driving range and charging pile density in our study remain consistent.

Second, the model results may be affected by extreme data values. For example, the charging pile density in Shenzhen is much higher than that in other cities, exceeding three times that of the city with the second-highest charging pile density. Thus, we exclude all observations from Shenzhen in our model. The results are in line with those in Table 3.3, further verifying the robustness of the findings.

Third, we employ an alternative measure of charging pile density. Specifically, we use the ratio of the number of public fast-charging piles to land area as a substitute for the ratio of public fast-charging piles to total road length. The results remain unchanged, demonstrating the robustness of our results.

Fourth, beyond charging pile density, other market characteristics, such as GDP per capita and the number of households, may also moderate the relationship between EV driving range and customer demand. To further assess the robustness and reliability of our results, we incorporate interaction terms between EV driving range and GDP per capita, as well as between driving range and the number of households, into the model with interactions to account for such potential moderating effects. The results show that after including these cross-level interaction terms, the core findings of the model with interactions remain consistent.

Table 3.6 Robustness check results of Study 1

	(1)		(2)		(3)		(4)	
	Coefficient	SD	Coefficient	SD	Coefficient	SD	Coefficient	SD
Product-level variables								
Price	-0.005	(0.008)	-0.063***	(0.006)	-0.063***	(0.006)	-0.062***	(0.006)
Driving range	0.002***	(0.000)	0.002***	(0.000)	0.002***	(0.000)	0.002***	(0.000)
Size	0.120***	(0.021)	-0.042*	(0.018)	-0.039*	(0.018)	-0.041*	(0.017)
Curb weight	-0.002***	(0.000)	0.001*	(0.000)	0.001*	(0.000)	0.001*	(0.000)
Horsepower	0.002**	(0.001)	0.006***	(0.000)	0.006***	(0.000)	0.006***	(0.000)
Market-level variables								
Charging pile density	-0.027***	(0.005)	-0.241***	(0.024)	-0.024***	(0.002)	-0.021***	(0.005)
GDP per capita	-2.61e-06*	(0.000)	-2.19e-06*	(1.09e-06)	-2.28e-06*	(1.02e-06)	-6.98e-06***	(1.05e-06)
Households	-0.001**	(0.000)	-0.001***	(0.000)	-0.001***	(0.000)	-0.001***	(0.000)
Cross-level interaction								
Driving range × Charging pile density	3.96e-05***	(7.93e-06)	4.39e-04***	(3.79e-05)	3.92e-05***	(3.06e-06)	3.4e-05***	(6.28e-06)

Notes: 1) The dependent variable is $\ln(s_{jmt})-\ln(s_{0mt})$ in Equation (3.9); 2) * p<0.05, ** p<0.01, *** p<0.001

3.7 Concluding Remarks

At the niche level of technological transitions, the design of technical specifications plays a critical role in determining whether new technology products can penetrate the mainstream market. However, limited consumer information compared to established technologies makes it challenging for firms to accurately identify true consumer preferences. Traditional management research has typically relied on stated preference data to investigate consumer preferences for new technology products. Yet, such data may not fully reflect real-world purchasing behavior (Liao et al., 2017).

To address this limitation, in the context of the automotive industry's transition from ICEVs to EVs, we adopt a novel dataset on the Chinese EV market compiled from multiple sources. Using a structural demand estimation model, we estimate market elasticities for EV driving range and examine how charging pile density shapes the relationship between driving range and consumer demand.

Our results show that the estimated average driving range elasticity is 1.447, indicating that a 1% increase in driving range leads to a 1.447% increase in EV sales. Additionally, we find a complementary relationship between charging pile density and EV driving range in shaping market demand. Consumers in high-charging-pile-density markets demonstrate greater sensitivity to EV driving range improvements than those in low-charging-pile-density markets. Specifically, a 1% increase in driving range leads to a 1.581% increase in EV sales in high-charging-pile-density markets, whereas the corresponding increase in low-charging-pile-density markets is only 1.313%.

Besides, by quantifying the average driving range elasticity across different EV classes, we further propose that the observed complementarity between charging pile density and EV driving range is driven by the influence of charging infrastructure availability on consumers' choice of vehicle classes and their intended commuting purposes.

Our findings provide important managerial implications for automakers. First, the empirical estimates of EV driving range elasticities provide automakers with a data-driven basis for decision-making. Managers can integrate these elasticity parameters with battery cost information to determine optimal range configurations tailored to specific market segments. Second, the identified positive moderating effect of charging pile density on consumer preferences for driving range offers practical guidance for differentiated product design strategies. Specifically, in markets with a higher level of charging pile density, consumers exhibit greater sensitivity to changes in driving range, suggesting that extending driving range of EVs can significantly improve product competitiveness. In contrast, in markets with a lower level of charging density, consumer sensitivity is relatively weaker, and manufacturers may prioritize cost control and price competitiveness while ensuring a basic level of driving range.

Moreover, our findings also provide the mechanism analysis of the complementary relationship between charging pile density and EV driving range reveals that in markets with insufficient charging infrastructure, consumers' purchasing choices are significantly constrained, primarily limited to micro and compact EV models with shorter ranges. This finding highlights a structural linkage between charging infrastructure development and product diversity in the EV market. Accordingly, we recommend that policymakers incorporate charging infrastructure coverage into performance evaluation criteria for urban NEV (New Energy Vehicle) promotion policies. By advancing infrastructure deployment, such measures can help foster more balanced and inclusive growth of the EV market.

Chapter 4 Study 2: Decision Dynamics of Manufacturing Firms' Participation in Technology Standardization during Technological Transitions

4.1 Introduction

During technological transitions, the standardization of emerging technologies is of critical importance. Standardization refers to the process of reaching a consensus on formal technical specifications for technologies (Wen et al., 2020). For emerging technologies that lie outside the incumbent regime, standardization not only fosters their continuous innovation but also accelerates their acceptance and diffusion (Blind et al., 2023; Nylund et al., 2022; Foucart & Li, 2021; Grillo et al., 2024). For example, during the technological transition from traditional internal combustion engine vehicles (ICEVs) to electric vehicles (EVs) in the automotive industry, Carlos Tavares, CEO of global automaker Stellantis, pointed out that the lack of unified EV standards is a major barrier to accelerating the transition (Financial Times, 2024). He emphasized that the absence of clear EV standards creates technological uncertainty, making it difficult for firms to allocate resources effectively, which hinders large-scale EV production.

While in the early stages of human technology use, technology standards emerged spontaneously with minimal involvements of organizations, today, the process of technology standardization is more dependent on strategic collaboration among various organizations (Blind & Mangelsdorf, 2016). During technological transitions, firms can gain competitive advantages by actively participating in emerging technology standardization, ensuring that standards align with their technological strengths. For instance, in the 1990s, Qualcomm pushed its proprietary CDMA technology to become the global 3G standard, defeating the GSM-dominated European Telecom Alliance and securing a core position in the global mobile communication industry. On the other hand, participating in technology standardization may incur significant costs and divert attention from existing technologies (Brem & Nylund, 2024b). For example, companies like Apple and Intel were deeply involved in wireless communication technology standardization at different stages, leading to a temporary diversion of R&D resources from existing products. Thus, in the context of technological transitions, the decision to whether engage in emerging technology standardization or not has become a crucial strategic issue (Chen et al., 2017).

In recent years, there has been growing academic interest in studying firms' decisions to participate in technology standardization (Narayanan & Chen, 2012; Fiedler et al., 2023; Schott & Schaefer, 2023; Blind et al., 2023; Grillo et al., 2024). The existing literature suggests that certain firm characteristics, such as technological capabilities (Zhang et al., 2024), organizational structures (Blind & Mangelsdorf, 2016), and innovation behaviors (Blind et al., 2022), influence firms' participation in technology standardization. However, these studies usually take a static view, overlooking the impact of firms' past behaviors on their current decisions. Therefore, to fill such research gap, this study aims to investigate the dynamic evolution of firm decisions on participation in technological standardization. Technological transitions provide an ideal context for studying the evolution of firm strategies (Hill & Rothaermel, 2003; Romanelli & Tushman, 1994), as they disrupt existing industry structures and competition, forcing firms to adapt their strategies to cope with such transitions (Eggers & Francis Park, 2018). Thus, we focus on this research context to explore how firms' decisions on participation in technological standardization evolve and propose our first research question as follows:

RQ1: *How does a firm's participation in incumbent technology standardization influence its subsequent participation in emerging technology standardization during technological transitions?*

We further argue that the impact of a firm's participation in incumbent technology standardization on its subsequent involvement in emerging technology standardization during technological transitions depends not only on the extent of its participation, but also on the manner in which it participates. Previous research has pointed out that diversification or specialization is a key characteristic of important strategic decisions such as innovation activities, alliances, and transactions (Ramanujam & Varadarajan, 1989; Lee et al., 2017; Wen et al., 2021). Diversification typically refers to the extent of dispersion of members in a group on a specific attribute (Harrison & Klein, 2007). A diversification strategy can provide firms with diverse resources, information, and capabilities (Baum et al., 2000), but it may also increase managerial complexity and costs (Goerzen & Beamish, 2005; Duysters & Lokshin, 2011). Therefore, the strategic issue of whether to pursue a diversified or specialized approach in key operational activities has always been a topic of interest among scholars (Hitt et al., 2006; Wan et al., 2011). However, despite the importance of technology standardization as a strategic decision, there is little research on its impact in terms of the degree of diversification. To fill this gap, this study further explores how the degree of diversification in incumbent technology standardization moderates the impact of participation in incumbent technology standardization on firms' subsequent participation in emerging technology standardization.

Standard-setting during technological transitions is inherently multifaceted, as firms' strategic decisions are shaped by both technological imperatives and network dynamics. Specifically, on one hand, participation in technology standardization reflects firms' strategic commitment to particular technological trajectories (Sosa, 2011; Eggers & Park, 2018). On the other hand, recent studies emphasize that standardization processes increasingly function as collaborative arenas through which firms gain access to knowledge, influence, and legitimacy via interorganizational network ties (Bar & Leiponen, 2014; Blind & Mangelsdorf, 2013; Wen et al., 2020). As such, participation in technology standardization also constitutes a form of network-building activity. Therefore, to capture the dual strategic logics that underpin manufacturing firms' participation in technology standardization during technological transitions, this study adopts both technology and network perspectives (Blind & Mangelsdorf, 2016). Accordingly, we simultaneously examine how the degrees of technological and network diversification in firms' participation in incumbent technology standardization affect their subsequent participation in emerging technology standardization. Therefore, we propose our second research question as follows:

RQ2: *How do the levels of technological and network diversification in firms' participation in incumbent technology standardization moderate the effect of their participation in incumbent technology standardization on their participation in emerging technology standardization during a technological transition?*

To address the above research questions, this study utilizes longitudinal data from 217 automotive manufacturers and 466 automotive technology standards from 2000 to 2023. The study employs survival analysis models to test our hypotheses. The results indicate that during technological transitions, the extent of a firm's participation in incumbent technology standardization is positively related with its participation in emerging technology standardization. Besides, we also find that the degree of technological diversification in a firm's participation in incumbent technology standardization can weaken such positive effect.

The contributions of this study are as follows: First, unlike previous studies that examine the impact of a company's current characteristics on its participation in technology standardization from a static perspective, our research adopts a dynamic view, revealing how a company's participation in technology standardization evolves during a technological transition. Second, this study challenges traditional theories of firm inertia in technological transitions suggesting that that companies deeply embedded in incumbent technologies are resistant to emerging technologies during technological transitions. By incorporating both technology and network perspectives, we find that a company's participation in incumbent technology standardization enables it to accumulate resources from alliance networks. These accumulated resources outweigh the effect of technology inertia, ultimately facilitating the company's participation in emerging technology standardization during technological transitions. Third, this study broadens the research on corporate diversification by moving beyond the traditional focus on the direct impact of diversification on firm performance. It highlights the role of diversification in dynamic decision-making processes, showing that a company's technological diversification in incumbent technology standardization may contribute to its inertia in participating in emerging technology standardization during technological transitions.

4.2 Literature Review and Hypotheses

4.2.1. Firm Participation in Technology Standardization

Technology standards refer to a set of specifications or guidelines designed to ensure that the materials, processes, personnel, or services involved in a technology can guarantee its intended use (Baron & Spulber, 2018). The establishment of a technology standard can reduce the number of different solutions to the same technical problem, thus avoiding ineffectiveness when facing multiple options (Wiegmann et al., 2017). Therefore, standards can play a critical role in determining the success of a technology and often play a key role in driving technological transitions in the industry (Featherston et al., 2016; Grillo et al., 2024). Technology standards can be divided into de facto standards and de jure standards, depending on how they are developed. De facto standards are dominant designs which emerge naturally through technological competition and widespread use, while de jure standards are established through formal inter-organizational cooperation procedures (Brem et al., 2016). Compared to de facto standards, de jure standards are more legitimate and of higher quality (Leiponen, 2008). More importantly, during an industry's technological transition, when emerging technologies are still in their early stages and various technological solutions exist, it is difficult to establish a universally accepted dominant design (Teece, 1986). Consequently, in such transitional phases, de jure standards play a more important role than de facto standards. Thus, this study specifically focuses on de jure technology standardization. For the sake of simplicity, we will henceforth refer to de jure technology standardization as technology standardization.

Firms play a central role in the process of technology standardization. However, research on the factors driving firms' participation in this process has only started to gain momentum in recent years (Blind & Mangelsdorf, 2016). On one hand, existing studies highlight that participating in technology standardization has become an important approach for firms to gain and sustain competitive advantages (Blind et al., 2023). On the other hand, due to the public good nature of technology standards, the benefits derived from participation in technology standardization are difficult for any single firm to fully capture (Swann, 2000). Besides, firms often need to make significant resource investments and bear opportunity costs to participate in the standardization process. As such, academic consensus holds that firm participation in technology standardization is not a random act, but a strategic decision influenced by firm characteristics (Blind et al., 2021).

Empirical studies have shown that a firm's inclination to participate in technology standardization is significantly related to its organizational characteristics, such as firm size, R&D intensity, and innovation performance (Wakke et al., 2015; Blind & Mangelsdorf, 2016; Blind et al., 2021; Zhang et al., 2024). These studies generally propose that firms with higher innovation performance, abundant resources, and strong technology capabilities are more likely to actively engage in standardization efforts. However, most of these studies are based on a static perspective, focusing on the impact of factors such as resource endowments at a specific point in time. Nevertheless, this static perspective fails to reveal the dynamic evolution of firms' participation in technology standardization and does not explain the potential path dependence characteristics of their strategies in such process. To address this research gap, we explores the dynamics of firms' participation in technology standardization and systematically examinines the impact of firms' past participation in incumbent technology standardization on their subsequent emerging standardization decisions during technological transitions.

4.2.2. The Dynamics of Firms' Participation in Technology Standardization

The dynamics of firms' decision-making during technological transitions is a key focus in the management literature (Helfat, 2003). For example, scholars have explored how firms reallocate capabilities and resources between incumbent and emerging technologies during technological transitions (e.g., Rosenbloom, 2000; Lavie, 2006), as well as how organizational relationships are restructured to adapt to emerging technologies (e.g., Lavie & Singh, 2012; Asgari et al., 2017; Cozzolino & Rothaermel, 2018). Participation in technology standardization involves resource allocation and the establishment of inter-organizational relationships, so this study posits that a firm's participation in incumbent technology standardization will influence its subsequent decision-making in emerging technology standardization.

From a technology perspective, participation in technology standardization helps firms secure a more favorable market position for their technologies. By shaping the development of industry standards, firms can facilitate the broad adoption of their technologies, thereby expanding their market share (Besen & Farrell, 1994). Differently, from a network perspective, technology standardization is a process of collaboration between different organizations, during which firms can expand their network, collect information, and gain knowledge (Blind & Mangelsdorf, 2016). Therefore, we adopt both two perspectives to investigate firms' decisions dynamics regarding participation in technology standardization during technological transitions.

Specifically, from a technology perspective, we argue that the higher a firm's level of participation in incumbent technology standardization, the more inertia it may exhibit in emerging technology standardization. This is because the greater a firm's participation in incumbent technology standardization, the stronger its dominance in the incumbent technology market, and the higher its resistance to the development of emerging technologies to protect its existing technological advantages and competitiveness (Brem & Nylund, 2024a). Additionally, firms' participation in technology standardization is a resource-dependent activity (Wang et al., 2023). The process of standardization requires firms to invest substantial human, financial, and technological resources to drive the development and promotion of the standards. Therefore, a high level of participation in incumbent technology standardization indicates that a firm has already invested significant resources in the incumbent technology development path. This could result in resource rigidity (Gilbert, 2005; Brem & Nylund, 2024b), making the firm more dependent on the incumbent technology trajectory. Since emerging technologies are still in their early stages and often do not perform as well as mature incumbent technologies, firms tend to consolidate their existing technological advantages rather than divert resources to less mature emerging technologies (Christensen & Bower, 1996).

Thus, we propose our first competing hypothesis:

H1a: *The higher the level of a firm's participation in incumbent technology standardization, the lower the likelihood that the firm participates in emerging technology standardization.*

However, from a network perspective, we argue that the higher a firm's participation in incumbent technology standardization, the more likely it is to engage in emerging technology standardization. This is because technology standardization is conducted in the form of strategic alliances (Nambisan, 2013). Greater participation in incumbent technology standardization indicates that a firm is more deeply embedded in inter-organizational networks formed through these alliances.

In management and organizational research, inter-organizational networks have been widely recognized as a critical topic of interest (Gulati et al., 2000). Scholars have noted that a firm's resources not only come from internal accumulation but also largely from the inter-organizational networks it is embedded in (Lavie, 2007). These networks provide firms with reliable, novel, and timely information (Burt, 1992), while also enabling the sharing of resources and capabilities among organizations (Uzzi, 1996). In the context of technological transitions, access to knowledge and resources is crucial for firms to successfully adapt to emerging technologies (Eggers & Park, 2018). Therefore, firms with a higher level of participation in incumbent technology standardization are more likely to leverage the knowledge and resources within their alliance networks, thereby enhancing their abilities to actively engage in emerging technology standardization.

Furthermore, firms with a higher degree of participation in technology standardization tend to gain greater influence and authority within the inter-organizational networks that shape industry-wide standardization (Wen et al., 2020). Despite transitions in the technological environment, the positions firms have established within the industry's technology standardization network through their participation in incumbent technology standardization continue to exert influence, ensuring their sustained impact on emerging technology standardization.

Therefore, we propose our second competing hypothesis:

H1b: *The higher the level of a firm's participation in incumbent technology standardization, the higher the likelihood that the firm participates in emerging technology standardization.*

4.2.3. The Role of Diversification in the Incumbent technology standardization

The early concept of diversification typically referred to a firm's engagement in multiple product markets or business sectors to spread risk and increase revenue sources (Ansoff, 1957; Martin & Sayrak, 2003). Recently, the concept of diversification has evolved beyond a firm's product and business scope to encompass technological diversification (Miller, 2006), international diversification (Hitt et al., 2006), relational network diversification (Lee et al., 2017) and others. Most of the research on diversification focuses on its impact on firm performance (Lee et al., 2017; Schommer et al., 2019; Ahuja & Novelli, 2017). Some scholars argue that diversification strategies enable firms to mitigate risks and enhance overall corporate stability (Markides & Williamson, 1994). However, other scholars suggest that diversification may lead to increased management complexity, thereby raising managerial costs and impacting firm performance negatively (Goerzen & Beamish, 2005).

Technological Diversification. Technological diversification refers to the degree of variance in a firm's technological base (Gambardella & Torrisi, 1998). The role of technological diversification in firm performance has been widely studied in recent years (Garcia-Vega, 2006; Huang & Chen, 2010). Scholars generally agree that technological diversification enhances a firm's innovation efficiency because it provides opportunities to explore various technologies and combine knowledge from different fields to generate more innovative ideas (Suzuki & Kodama, 2004).

From a technology perspective, when the level of a firm's participation in incumbent technology standardization remains constant, a higher degree of technological diversification indicates involvement in a wider range of incumbent technology categories, reflecting the firm's expertise across multiple technological domains in the incumbent technology trajectory. This diversified knowledge advantage enables firms to foster the ongoing development of the incumbent technology by integrating existing knowledge, thereby unlocking its full potential.

In the context of technological transition, investing in emerging technologies is a high-risk strategy, as the success rate of innovations that rely on entirely new and relatively unfamiliar knowledge tends to be low (Fleming, 2001). Therefore, when firms' innovation in the incumbent technology path is underperformed, they are more likely to shift to the emerging technology path in search of competitive opportunities (Eggers & Kaul, 2018). In contrast, if a firm still has significant potential for innovative growth in the incumbent technology path, it may prefer to continue investing in the incumbent technology path to solidify its market position. As previously discussed, a higher level of technological diversification in the incumbent technology trajectory provides firms with more innovation opportunities. Therefore, we argue that greater technological diversification in incumbent technology standardization strengthens a firm's reliance on the incumbent technology path, diminishing its enthusiasm for participating in emerging technology standardization. Thus, we posit the following hypothesis:

H2a: *When a firm's degree of technological diversification in incumbent technology standardization is higher, its participation in incumbent technology standardization will be less likely to promote (or more likely to hinder) its participation in emerging technology standardization.*

Network Diversification. Network diversification refers to the diversity of partners within the inter-organizational network that a firm is embedded in (Goerzen & Beamish, 2005). Inter-organizational networks are essential for firms to acquire resources and information; however, the efficiency of this acquisition largely depends on the characteristics of the network structure (Phelps, 2010; Kumar et al., 2022).

From a network perspective, trust and reciprocity among network members significantly influence network efficiency since they reduce opportunistic behaviors in collaborations, facilitating smoother and more efficient resource and information transfer (Dyer & Singh, 1998). Prior research has shown that as the degree of network diversification increases, the differences in backgrounds and goals between network members make it more difficult to build trust and reciprocity within the network (Jiang et al., 2010). Besides, network diversification often leads to differences in interests and priorities, increasing the costs and difficulties of cooperation. Therefore, when the network diversification of strategic alliances formed through incumbent technology standardization in which firms participate is high, the efficiency of acquiring resources and information from these networks may be lower. Thus, the likelihood of leveraging resources acquired from networks formed in incumbent technology standardization to participate in emerging technology standardization decreases.

Furthermore, in highly diversified networks, the influence within the network a firm gains through participation in incumbent technology standardization may become diluted. Diversity in backgrounds, goals, and priorities of network members often leads to conflicts of interest, which can dilute the firm's influence and reduce its ability to coordinate efforts effectively. In turn, the firm's capacity to exert control or shape decisions within the network is weakened, making it harder to leverage the accumulated influence in incumbent technology standardization networks on shaping emerging technology standardization.

Therefore, we propose the following hypothesis:

H2b: *When a firm's degree of network diversification in incumbent technology standardization is higher, its participation in incumbent technology standardization will be less likely to promote (or more likely to hinder) its participation in emerging technology standardization.*

The conceptual model for this study is shown in Figure 4.1.

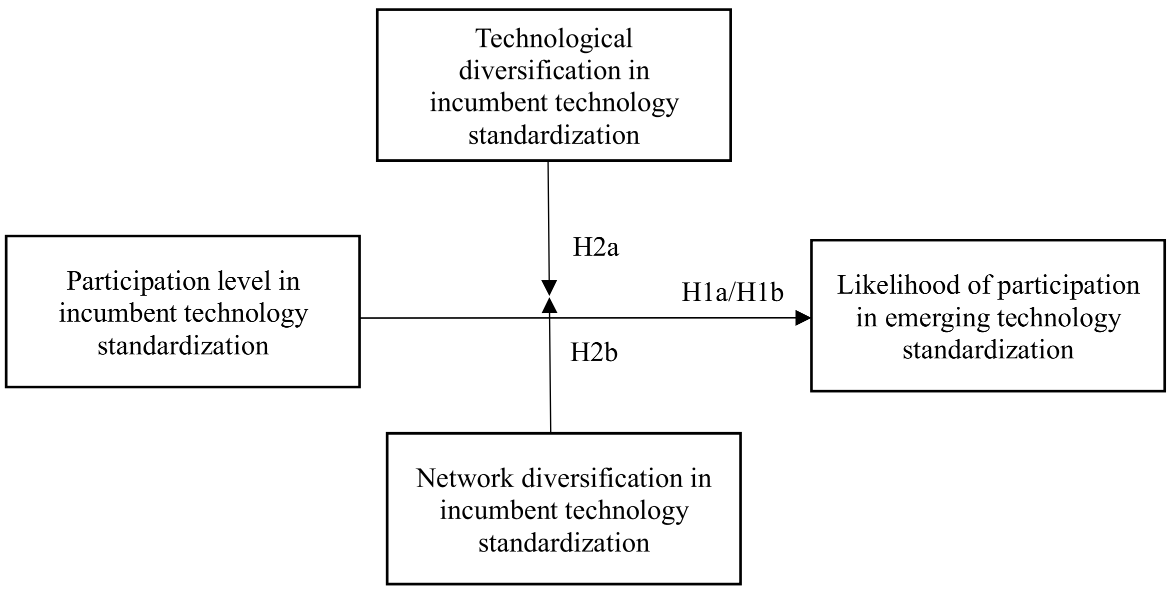

Figure 4.1. Conceptual model of Study 2

4.3 Methodology

4.3.1. Research Context

This study aims to explore the dynamics of firms' participation in emerging and incumbent technology standardization during technological transitions. To address our research questions, we focus on the technological transition from traditional internal combustion engine vehicles (ICEVs) to electric vehicles (EVs) in the Chinese automotive industry. The reasons for selecting this research context are as follows: First, automotive technology is highly complex and involves numerous different components. Therefore, compared to other industries, the demand for standardization in the automotive sector is more crucial to ensure the compatibility of various parts (Baum et al., 2000). Second, the transition from ICEVs to EVs in the automative industry represents one of the most important and rapidly developing technological transition nowadays (Bergek et al., 2013). It is shown that the sales of EVs in 2023 increased by 3.5 million units compared to 2022, marking a 35% year-on-year growth. This figure is more than six times that of 2018 (International Energy Agency, 2024). During this technological transition, automobile manufacturers must make strategic decisions on whether to invest resources in ICEV or EV technologies. Third, China is one of the most influential countries driving the technological transition from ICEVs to EVs in the global automotive industry (Wen et al., 2021). As early as the "10th Five-Year Plan" between 2001 and 2005, China began actively promoting the research and development of EV technologies. Today, China stands as the world's largest producer and a technological leader in the EV industry (Xiong et al., 2022). Therefore, we believe that the Chinese automotive industry between 2000 and 2023 provides an ideal empirical context for studying how firms make complex decisions regarding their participation in emerging and incumbent technology standardization during a technological transition.

4.3.2. Data and Sample

To conduct this study, we collected data from multiple sources. First, we collected data on national standards in the Chinese automotive industry from the National Standard Information Public Service Platform, which is operated by the Standardization Administration of China (SAC). This platform publishes all official national standards in China. Previous studies on technology standardization, such as Zhang et al. (2024) and Hu & Liu (2022), have also used data from this platform.

Specifically, we identified automotive national standards using the Chinese Classification for Standard (CCS) codes. The CCS system includes 24 main categories and 1,606 subcategories of standards, with classification codes comprising a letter and two digits, representing the main category and subcategory of the standards (SAC, 2021). We selected all standards between 2000 and 2023 that fell within the CCS code range of T00 to T49[3] and extracted their key information such as titles, publication dates, scope, and drafting units. After an initial search, we identified 738 automotive national standards. We then carefully reviewed these standards and excluded those related to other fields (e.g., motorcycles). This results in a final sample of 711 standards with 1,136 different drafting units.

Among all the drafting units, this study focused on automotive manufacturing companies (National Economic Industry Code C36[4]). First, we obtained organizational-level data on these companies from the National Enterprise Credit Information Publicity System and the Incopat Global Patent Database. The National Enterprise Credit

[3] The CCS codes from T00 to T09, T10 to T19, T20 to T29, T30 to T34, T35 to T39, and T40 to T49 represents standards related to comprehensive vehicles, automotive engines, vehicle chassis and bodies, general automotive electronics, electrical equipment and instruments, and other automotive standards, respectively.

[4] This study utilizes the latest GB/T4754-2017 National Economic Industry Classification Standard published in 2017.

Information Publicity System, operated by the State Administration for Market Regulation, is the official platform for disclosing information on all registered enterprises in China. The Incopat Global Patent Database has been widely used in prior studies (e.g., Han et al., 2024; Wang et al., 2023) to retrieve detailed patent information, including applicant names, application years, and citation counts. Finally, data on the institutional environment of the companies was collected from the China Provincial Technological Index Report, which has been used in prior empirical studies on Chinese enterprises (e.g., Zhao et al., 2019; Xie & Zhu, 2021).

After excluding firms with missing information, the final sample includes 217 automotive manufacturing companies and the 466 automotive standards they drafted. The sample profile is presented in Table 4.1.

Table 4.1. Sample profile of Study 2

Panel A: The distribution of publication years for the sampled standards.		
Publication year	Frequency	Percentage (%)
2003	1	0.21
2005	2	0.43
2006	10	2.15
2007	2	0.43
2008	9	1.93
2009	12	2.58
2010	2	0.43
2011	24	5.15
2012	33	7.08
2013	13	2.79
2014	10	2.15
2015	31	6.65
2016	23	4.94
2017	53	11.37
2018	16	3.43
2019	27	5.79
2020	36	7.73
2021	58	12.45

2022	47	10.09
2023	57	12.23
Total	466	100

Panel B: The industry subsegment distribution for the sampled firms.		
Industry segment	Frequency	Percentage (%)
Automobile manufacturing	65	29.95
Automobile engine manufacturing	2	0.92
Modified automobile manufacturing	8	3.69
Low-speed vehicle manufacturing	1	0.46
EV manufacturing	1	0.46
Automobile body and trailer manufacturing	12	5.53
Automobile parts and accessories manufacturing	118	54.38
Others	10	4.61
Total	217	100
Panel C: The distribution of launch year for the sampled firms.		
Launch year		
<2000	87	40.09
2000-2005	63	29.03
2005-2010	36	16.59
2010-2015	15	6.91
⩾2015	16	7.37
Total	217	100

4.3.3. Measures

Dependent variable. The dependent variable in this study is *participation in emerging technology standardization* (NTS), which reflects whether and when automobile manufacturing firms participate in drafting emerging technology standards (specifically, EV technology standards in this study). It is a firm-year event dummy variable. Typically, if a firm participates in drafting at least one EV technology standard in a given year, this variable is coded as 1.

In this study, automotive technology standards are classified into emerging technology (EV) and incumbent technology (ICEV) standards, based on their scope of application. Specifically, each national automotive technology standard document indicates the scope of vehicle types it applies to at its beginning. We collected this information and defined those standards that apply exclusively to EVs (including battery EVs, hybrid EVs, and fuel cell EVs) as emerging technology standards. The remaining automotive technology standards are classified as incumbent technology (ICEVs) standards. According to this classification, among the 466 automotive technology standards in the sample, 101 are identified as emerging technology standards, while 365 are identified as incumbent technology standards. Table 4.2 presents the classification of technology standards in this study.

Table 4.2. The yearly distribution of incumbent and emerging technology standards

Publication year	Frequency of incumbent technology standards	Percentage of incumbent technology standards (%)	Frequency of emerging technology standards	Percentage of emerging technology standards (%)
2003	1	100	0	0
2005	2	100	0	0
2006	10	100	0	0
2007	2	100	0	0
2008	9	100	0	0
2009	10	83.33	2	16.67
2010	2	100	0	0
2011	24	100	0	0
2012	33	100	0	0
2013	11	84.62	2	15.38
2014	10	100	0	0
2015	13	41.94	18	58.06
2016	17	73.91	6	26.09
2017	39	73.58	14	26.42
2018	11	68.75	5	31.25
2019	23	85.19	4	14.81
2020	28	77.78	8	22.22
2021	39	67.24	19	32.76
2022	38	80.85	9	19.15
2023	43	75.44	14	24.56
Total	365		101	

Independent variable. The independent variable of interest in this study is *extent of participation in incumbent technology standardization* (OTS). This is measured by the number of ICEV standards a firm has drafted during the observation period.

Moderating variables. The moderating variables in this study are *technological diversification in incumbent technology standardization* (TD) and *network diversification in incumbent technology standardization* (ND). Regarding diversification, following the approach used by Jiang et al. (2010), we adopt the Blau Index of Variability to measure it. The formula for the Blau Index (Blau, 1977) is as follows:

$$D = 1 - \sum p_i^2$$

where p represents the proportion of elements belonging to a particular category, and i indicates different categories.

This index is widely used in the literature to measure the level of group diversification (e.g., Harrison & Klein, 2007; King et al., 2011), with values ranging from 0 to 1, where 0 indicates a completely homogeneous group, and 1 indicates a completely heterogeneous group.

For *technological diversification in incumbent technology standardization* (TD), this study uses the China Classification Standard (CCS) codes to differentiate the various technology categories involved in the ICEV technology standardization. Specifically, when calculating the Blau Index, p_i represents the proportion of ICEV standards a firm has drafted within a specific CCS code category relative to the total number of ICEV standards it has drafted during the observation period.

For *network diversification in incumbent technology standardization* (ND), this study follows the approach of Goerzen & Beamish (2005) and adopts the proportion of unique connections in the network to measure it. Specifically, p_i in the Blau Index here is calculated as the proportion of a specific unique connection (i.e., a partnership) within the inter-organizational network formed by the firm through its participation in ICEV standardization during the observation period.

Control Variables. To ensure the robustness of the results, several control variables that may influence a firm's participation in technology standardization are included in our model. First, compared to small and medium-sized enterprises, large enterprises may have more resources and experiences in technology standardization (Blind et al., 2021). Therefore, our study controls for *firm size* (Size), using the natural logarithm of the number of employees as a proxy. Second, we include *firm age* (Age) as another organizational-level control variable to account for the impact of organizational experience on a firm's decisions on technology standardization during technological transitions in the industry. Additionally, prior research has indicated that a firm's ownership type can affect its strategic goals, which in turn influences decisions related to technology standardization (Zhang et al., 2024). Therefore, this study uses two dummy variables for ownership type: state-owned enterprises (SOEs) and joint ventures (JVs). For the *SOE* (SOE) variable, firms owned by the Chinese government are coded as 1, and others as 0. For the *JV* (JV) variable, firms jointly funded by two or more independent companies or entities are coded as 1, while those solely funded by a single company or entity are coded as 0. Furthermore, participation in technology standardization is closely linked to a firm's innovation activities. Indeed, some of prior research has treated participation in technology standardization as an extension of firms' innovation activities (Blind, 2006; Organization for Economic Cooperation and Development, 2018). To control for the effect of a firm's innovation activities of the emerging technology on its participation in emerging technology standardization, this study includes the *stock of emerging technology patents* (Patent) as a control variable.

It is measured by the natural logarithm of the number of EV patents filed by a firm during the observation period. Following prior research (Yuan & Li, 2021), patents related to the EV technology are identified using the International Patent Classification (IPC) codes B60L-011*, B60L-003*, B60L-015*, B60K-001*, B60W-010/08, B60W-010/24, and B60W-010/26. We also review the patents carefully and filter out those unrelated to the EV technology. Finally, a firm's institutional environment can influence the value it derives from technology behaviors, such as participating in emerging technology standardization (Blind et al., 2017; Vedula, 2018). Therefore, this study controls for *institutional development* (ID), measured by the technology index of the province where the firm's headquarters is located. This index is developed by the National Economic Research Institute, and it measures the regional progress of technological development. A higher technology index for a province indicates a more developed institutional environment.

In addition, the standardization process typically lasts 24 to 36 months (Wen et al., 2020), implying that decisions regarding participation in standardization are generally made 2 to 3 years in advance. Therefore, considering this time lag effect, this study applies a 2-year lag to the time-varying control variables in the model to more accurately reflect the true decision-making conditions when firms decide to participate in technology standardization.

4.3.4. Empirical Model

Since we focus on the factors influencing firms' decisions to participate in emerging technology standardization during industry technological transitions, we employ survival analysis to estimate both the main and moderating effects. Survival analysis is widely used to analyze the likelihood of an event occurring over time (Cox, 1972). Unlike logistic regression models, survival analysis models simultaneously consider both the occurrence of an event and its timing. Therefore, this study utilizes survival analysis to estimate whether and when automobile manufacturing firms engage in emerging technology standardization (Allison, 1984). Additionally, another advantage of survival models is that they are less susceptible to bias from right-censored data (Hosmer et al., 1999). In this study, some automobile manufacturing firms had not participated in any emerging technology standardization by the end of the observation period. This right-censoring characteristic of the data makes survival analysis particularly well-suited for the research context of this study.

Specifically, we use the proportional hazard model for survival analysis in this study. While the hazard function of the proportional hazard model has a fully parameterized regression structure, it does not require specifying the functional form of survival time, making it a semi-parametric model (Hosmer et al., 1999). Specifically, the hazard function in the proportional hazard model is the product of the baseline hazard function and the exponential function of the covariates, as shown in the following formula:

$$h(t, x, \beta) = h_0(t)e^{x\beta}$$

where $h_0(t)$ represents the baseline hazard function, x is the vector of covariates, and β is the vector of regression coefficients. Specifically, this study adopts the Anderson-Gill (AG) version of the proportional hazard model (Andersen & Gill, 1982). Unlike the standard Cox model proposed by David Cox in 1972, which is only suitable for events that occur once, the AG model can handle the occurrence of repeated events (Therneau & Grambsch, 2000). In the AG model, repeated events are treated as independent, and after each event occurs, the subject re-enters into the risk set. In the context of this study, automobile manufacturing firms may participate in emerging technology standardization multiple times over different years. Therefore, to comprehensively reflect automobile manufacturers' participations in emerging technology standardization, the AG proportional hazard model is a more appropriate approach.

4.4 Results

4.4.1. Main Results

Table 4.3 presents the descriptive statistics and correlation matrix results for all variables in this research. The variance inflation factor (VIF) values for all variables in our research model range from 1.11 to 2.17, which are well below the threshold of 10 (Mason & Perreault, 1991). Therefore, we can conclude that multicollinearity is not a major concern in this study.

Table 4.3. Descriptive statistics and correlation matrix of Study 2

	Min	Max	Mean	S.D.	1	2	3	4	5	6	7	8	9	10
1 NTS	0	1	0.49	0.50	1.00									
2 OTS	1	83	11.67	16.09	**0.46**	1.00								
3 TD	0	0.89	0.39	0.35	**0.54**	**0.64**	1.00							
4 ND	0	0.99	0.93	0.10	**0.34**	**0.32**	**0.46**	1.00						
5 Size	0	4.81	3.11	0.92	**0.49**	**0.41**	**0.48**	**0.26**	1.00					
6 Age	1	68	19.56	10.06	-0.03	**0.21**	**0.13**	-0.07	0.03	1.00				
7 SOE	0	1	0.09	0.29	**0.18**	**0.30**	**0.22**	0.08	0.07	**0.22**	1.00			
8 JV	0	1	0.17	0.38	**0.14**	0.10	**0.17**	0.06	**0.32**	-0.02	**-0.15**	1.00		
9 Patent	0	5.99	1.23	1.63	**0.51**	**0.52**	**0.51**	**0.27**	**0.52**	0.08	**0.24**	0.01	1.00	
10 ID	6.12	12.39	10.01	1.43	**-0.32**	**-0.19**	**-0.24**	**-0.14**	**-0.35**	-0.01	**-0.31**	0.00	**-0.32**	1.00

Notes: Bolded values indicate significance at the 0.05 p-value level.

Table 4.4 reports the results of the AG proportional hazards model. In Model 1, we included control variables such as Size, Age, and Patent to account for potential factors that may influence a firm's participation in emerging technology standardization. In Model 2, we introduced the independent variable OTS to test the main effect in our research model. Model 3 incorporates the first interaction term between OTS and TD, as proposed in Hypothesis 2. Model 4 tests the interaction between OTS and ND. Model 5 presents the results of the full model.

In Models 1 to 5, the coefficient of Patent is significantly positive. This echoes previous studies like Blind & Mangelsdorf (2016) and Blind et al. (2021) on the role of innovation activities in promoting a firm's participation in industry technology standardization. In Model 2, the relationship between OTS and NTS is significantly positive (β=0.022, p<0.01). Furthermore, we calculated the hazard ratio (HR) for OTS. The results show that for each unit increase in the degree of participation in incumbent technology standardization, the likelihood of a firm participating in emerging technology standardization increases by 2.2%. Therefore, we conclude that Hypothesis 1b is supported, while Hypothesis 1a is rejected. In other words, the result of this study aligns more with the network perspective rather than the technology perspective, suggesting that firms acquire the resources and capabilities from incumbent technology standardization alliance networks, which in turn facilitates their active participation in emerging technology standardization.

In Model 3, the coefficient of the interaction term between OTS and TD is significantly negative (β=-0.086, p<0.01). However, in Model 4, the interaction term between OTS and ND is not significant (β=-1.137, p>0.1). Thus, Hypothesis 2a is supported, while Hypothesis 2b is rejected. Specifically, TD significantly reduces the positive effect of OTS on NTS, while the effect of ND is not significant. To better illustrate the impact of TD on the relationship between OTS and NTS, Figure 4.1 depicts how the relationship between OTS and the hazard ratio for NTS varies at high and low levels (i.e., one standard deviation above and below the mean) of TD. As shown in Figure 4.1, when the level of TD is low, OTS significantly increases the hazard ratio for NTS. However, when the level of TD is low is high, this relationship flattens.

Table 4.4. AG proportional hazards model results of Study 2

	Dependent variable: NTS				
	Model 1	Model 2	Model 3	Model 4	Model 5
Size	0.694**	0.600*	0.437	0.481	0.418
	(0.299)	(0.307)	(0.295)	(0.296)	(0.303)
Age	-0.008	-0.014	-0.016	-0.009	-0.013
	(0.019)	(0.023)	(0.021)	(0.020)	(0.020)
SOE	0.464	0.270	0.220	0.196	0.219
	(0.346)	(0.298)	(0.277)	(0.253)	(0.263)
JV	0.164	0.084	-0.023	0.039	-0.013
	(0.300)	(0.261)	(0.263)	(0.254)	(0.260)
Patent	0.392***	0.304**	0.229**	0.259***	0.224**
	(0.083)	(0.106)	(0.105)	(0.099)	(0.101)
ID	-0.132	-0.113	-0.122	-0.118	-0.123
	(0.085)	(0.084)	(0.085)	(0.080)	(0.085)
OTS		**0.022*****	0.048***	0.079*	0.046
		(0.007)	(0.015)	(0.046)	(0.053)
TD			0.886*		0.627
			(0.498)		(0.520)
ND				-1.031	4.050
				(9.046)	(10.618)
OTS×TD			**-0.086*****		-0.059*
			(0.031)		(0.034)
OTS×ND				**-1.137**	-0.181
				(0.787)	(1.023)
Log likelihood	-838.357	-829.862	-814.872	-815.991	-811.728
Number of observations	373	373	373	373	373
Number of events	181	181	181	181	181

Notes: 1) *p<0.1, ** p<0.05, *** p<0.01; 2) The numbers in parentheses represent the standard errors of the corresponding coefficients or constants; 3) The regression coefficients of the variables of interest are bolded.

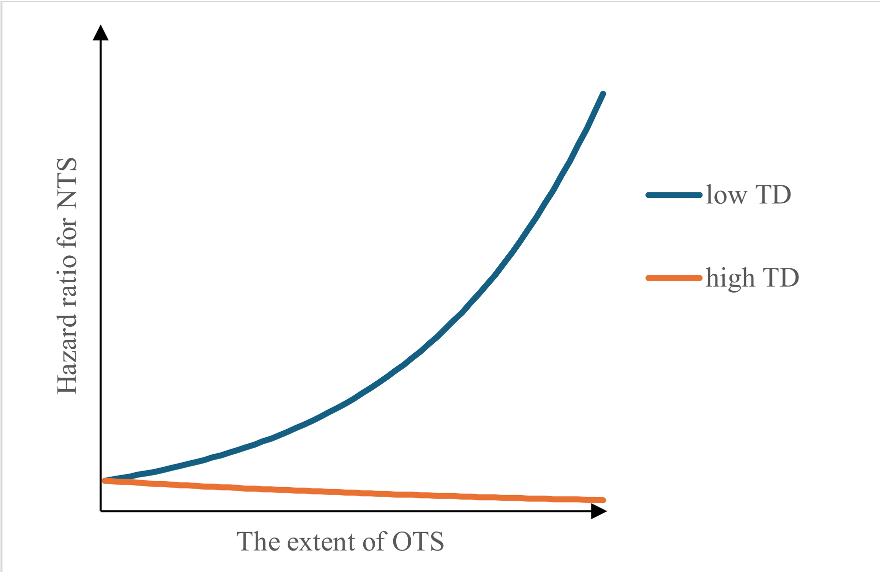

Figure 4.2. Moderation effects of TD on the relationship between OTS and NTS

4.4.2. Robustness Check

We conducted several additional tests to verify the robustness of our findings. First, we adopted an alternative measure for our dependent variable. Specifically, we replaced the binary indicator of whether a firm participates in emerging technology standardization during the observation period with the actual number of emerging technology standards it contributes to. Since the survival model is not suitable for situations where multiple events occur simultaneously, namely when the dependent variable is a count variable, we opted for negative binomial model to test our hypotheses. The results of this robustness test are presented in Table 4.5. We can find that OTS is positively related with NTS and the coefficient for the interaction of OTS and TD is significantly negative. Thus, the robustness of our results has been demonstrated.

Table 4.5. Study 2 Results for alternative measure of the dependent variable

	Dependent variable： NTS		
	Model 1	Model 2	Model 3
Size	0.267***	0.233***	0.261***
	(0.082)	(0.083)	(0.090)
Age	-0.009	-0.012	-0.025
	(0.013)	(0.013)	(0.015)
SOE	0.566	0.475	1.054
	(0.525)	(0.523)	(0.717)
JV	-0.219	-0.291	-0.104
	(0.358)	(0.367)	(0.397)
Patent	0.177**	0.254***	0.161*
	(0.086)	(0.085)	(0.090)
ID	0.242***	0.193**	0.002
	(0.079)	(0.086)	(0.097)
OTS	**0.934*****	1.364***	-5.212**
	(0.113)	(0.212)	(2.471)
TD		3.086***	
		(0.545)	
ND			14.64***
			(2.896)
OTS×TD		**-1.543*****	
		(0.285)	
OTS×ND			**8.146****
			(3.733)
Constant	-7.080***	-7.205***	-12.65***
	(1.014)	(1.090)	(3.493)
N	4258	4258	4258
AIC	1312.139	1269.335	1188.41
BIC	1375.705	1345.613	1264.689

Notes: 1) The results are derived using negative binomial regression models; 2) p<0.1, ** p<0.05, *** p<0.01; 3) The numbers in parentheses represent the standard errors of the corresponding coefficients or constants; 4) The regression coefficients of the variables of interest are bolded.

Second, we also adopted alternative measurement approaches for the moderating variables TD and ND. Specifically, following previous research like Bu et al. (2024) and Van De Vrande (2013), we replaced the Blau index with the entropy measure to calculate diversification. The calculation formula of the entropy measure is as follows:

$$D = \sum_{i} p_i \times \ln\left(\frac{1}{p_i}\right)$$

where p represents the proportion of elements belonging to a particular category, and i indicates different categories. $\ln\left(\frac{1}{p_i}\right)$ is the assigned weight for the proportion in each category. Table 4.7 presents the results for alternative measurement methods for the moderating variables. We find that the results of the moderating effects remain consistent and robust.

Table 4.6. Study 2 Results for alternative measurement approaches for the moderating variables

	Dependent variable：NTS	
	Model 1	Model 2
OTS	0.043*** (0.014)	0.044 (0.027)
TD	0.417** (0.197)	
ND		0.454 (0.292)
OTS×TD	**-0.030***** (0.010)	
OTS×ND		**-0.024*** (0.014)
Control variables	Included	Included
Log likelihood	-817.151	-812.951
Number of observations	373	373
Number of events	181	181

Notes: 1) p<0.1, ** p<0.05, *** p<0.01; 2) The numbers in parentheses represent the standard errors of the corresponding coefficients or constants; 3) The regression coefficients of the variables of interest are bolded.

4.5 Discussion and Conclusions

4.5.1. Theoretical Contributions

This study makes several important theoretical contributions. First, it advances the literature on technology standardization by uncovering the dynamics of firm decision-making on participation in technology standardization during technological transitions. Specifically, we find that a firm's level of participation in incumbent technology standardization positively impacts its propensity to participate in emerging technology standardization. The determinants of firm participation in technology standardization have only recently become a focal point of research (Blind & Mangelsdorf, 2016; Blind et al., 2021; Zhang et al., 2024). Nevertheless, while scholars have emphasized decision dynamics when faced with external upheavals like technology transitions (Thietart, 2016; Vuori & Tushman, 2024), there is little research investigating the role of such dynamics as a determinant of firm decisions regarding whether to participate in technology standardization or not. Thus, our study highlights a new research direction by adopting a dynamic perspective and investigating how firms adjust their strategies on participation in technology standardization in response to external upheavals in the technology landscape.

Second, this study contributes to the literature on corporate behaviors during technological transitions by challenging the traditional assumption that firms deeply embedded in incumbent technologies are inherently resistant to emerging technologies. We find that firms with significant investment in incumbent technology standardization are not necessarily hindered in transitioning to emerging technologies; instead, such investment may facilitate their participation in emerging technology standardization. Recently, scholars have increasingly called for more research on the phenomenon where incumbents proactively respond to emerging technologies during technological transitions, rather than being slow to adapt to changes (Eggers & Francis Park, 2018; Eggers & Kaul, 2018; Kuhlmann et al., 2022). This study responds to this call by moving beyond the traditional notion of firm inertia and emphasizing the heterogeneity in how firms' behaviors in the incumbent technology trajectory influence their actions in the emerging technology trajectory.

Last but not least, we find that technological diversification in incumbent technology standardization can diminish the positive impact of a firm's participation in incumbent technology standardization on its subsequent participation in emerging technology standardization. Prior research on technological diversification has primarily focused on its relationship with corporate innovation performance (Lin et al., 2006; Garcia-Vega, 2006; Huang & Chen, 2010). Scholars generally agree that technological diversification allows firms to expand their knowledge base, thereby fostering new ideas and innovative solutions and improving their innovation performance. However, departing from existing studies, this research uncovers a potential downside of technological diversification that firms deeply engaged in multiple domains within the incumbent technology trajectory may develop inertia, reducing their responsiveness to technological transitions. Therefore, this study expands the scope of research on technological diversification by offering a novel theoretical perspective that explores how diversification strategies influence firms' future technological decisions, rather than focusing solely on their current performance effects.

4.5.2. Managerial Implications

This study also offers several practical insights for business managers. First, our findings indicate the strategic importance of firm participation in technology standardization. Specifically, in the context of technological transitions, participation in technology standardization not only strengthens a firm's competitive position in existing markets but also allows it to accumulate critical experience and resources for future engagement in emerging technology standardization. This, in turn, enhances the firm's adaptability during technological transitions. Therefore, we recommend that managers should encourage their companies to actively participate in technology standardization.

Second, we reveal that technological diversification within incumbent technology standardization may weaken the promoting effect of a firm's participation in incumbent technology standardization on its subsequent participation in emerging technology standardization. This highlights the need for managers to carefully consider the inertia that technological diversification might introduce during technological transitions. Specifically, firms pursuing diversification within the incumbent technology trajectory should optimize their resource allocation, ensuring that while engaging in incumbent technology standardization, adequate resources are also dedicated to the research, development, and standardization of emerging technologies. This strategy helps mitigate the risks of path dependence and prevents a decline in responsiveness to emerging technological transitions.

Chapter 5 Study 3: Market-based Deployment Policies and Corporate Technology Choice and Production Strategies during Technological Transitions: Empirical Evidence from China's Dual-Credit Policy

5.1. Introduction

Given the significant economic and social implications of technological transitions, governments around the world have frequently sought to accelerate such processes through the implementation of various deployment policies (Peters et al., 2012; Schmidt et al., 2016; Zhou et al., 2025). Early forms of these deployment policies were primarily government-based, involving stringent regulations on incumbent technologies and financial incentives for emerging ones (Yu et al., 2020; Wang, 2022). For instance, in the context of the automotive industry's transition from internal combustion engine vehicles (ICEVs) to electric vehicles (EVs), the Chinese government has gradually implemented stricter fuel consumption standards on ICEVs in four stages since 2004 (Wang, 2019). These regulations set clear thresholds for fuel economy of ICEVs, with non-compliant firms facing severe penalties such as fines and restrictions on production licensing. Additionally, in 2009, China introduced EV purchase subsidies in 13 pilot cities. Based on the success of these pilot programs, the subsidy policy was quickly scaled nationwide (Yu et al., 2020; Wang, 2022).

However, such government-based deployment policies have notable limitations. They often fail to provide firms with sufficient flexibility for adaptation (Kroes et al., 2012). Majumdar and Marcus (2001) argue that rigid regulations may be less effective than more flexible approaches. Hu et al. (2021) further suggest that overly stringent mandates may unintentionally increase the likelihood of corporate non-compliance, especially when firms struggle to meet the prescribed standards due to limited resources and capabilities, and when regulatory monitoring is inadequate. Besides, although fiscal incentives such as subsidies and tax credits can effectively promote the adoption of emerging technologies, their heavy reliance on public funding raises concerns about long-term policy sustainability (Li et al., 2018; Li et al., 2020).

Accordingly, scholars and policymakers have increasingly shifted their attention from government-based deployment policies to market-based deployment policies, which provide firms with greater flexibility to adapt in the context of technological transitions (Jiang et al., 2023). Such policies leverage market signals like pricing mechanisms and market competition rather than direct government regulations or subsidies to incentivize firms to adopt new technologies. A representative example is California's Zero Emission Vehicle (ZEV) mandate, one of the most influential market-based policies driving the U.S. automotive sector's transition from ICEVs to EVs (Collantes & Sperling, 2008). The ZEV mandate uses a tradable credit system requiring automakers to produce a minimum proportion of ZEVs. Manufacturers that fail to meet this threshold are required to purchase credits from compliant firms, thereby establishing a trading market for ZEV compliance.

In the context of technological transitions, corporate technology choice and production strategies under different constraints represent a classic topic in operations management research (Heim & Peng, 2022). Early studies have primarily concentrated on constraints such as demand uncertainties, production costs, and capacity limitations (Crew & Kleindorfer, 1976; Cohen & Halperin, 1986). In recent years, however, the proliferation of deployment policies aimed at accelerating technological transitions has drawn growing scholarly attention to the impact of policy-induced constraints on firm decision-makings (Drake et al., 2016). In particular, the role of market-based deployment policies has emerged as a central focus of recent academic research, largely due to their inherent uncertainties and flexibilities (Aldy & Stavins, 2012). For instance, scholars have conducted several theoretical models and simulation analyses to estimate the efficiency of the cap-and-trade policy, a representative market-based deployment instrument for facilitating green technological transitions (Villoria-Sáez et al., 2016; Schmalensee & Stavins, 2017; Ji et al., 2023). However, the findings from these studies are mixed. Some scholars argue that such market-based mechanism can effectively promote the technological transition by simultaneously providing incentives for green technologies while imposing penalties on polluting alternatives (Gong & Zhou, 2013; Fan et al., 2023). Others, however, suggest that firms may exploit the flexibility of these policies to continue producing polluting products, particularly due to uncertainties associated with market dynamics (Schmalensee & Stavins, 2017; Blyth et al., 2007). Given these conflicting conclusions, scholars have called for more empirical research that directly investigates how market-based deployment policies influence firms' technology choice and production decisions in real-world settings (Bai & Ru, 2024). However, empirical evidence on this issue remains limited.

To address this research gap, this study examines the implementation of the Measures for the Parallel Administration of the Average Fuel Consumption and New Energy Vehicle Credits of Passenger Vehicle Enterprises in China, commonly referred to as the dual-credit policy. This policy integrates two distinct credit systems: the Corporate Average Fuel Consumption (CAFC) credit system, which imposes fuel efficiency standards on ICEVs, and the New Energy Vehicle (NEV) credit system, which requires automakers to meet a minimum production quota of EVs. Manufacturers are obligated to comply with both credit requirements. A defining characteristic of the dual-credit policy is its market-based design, which allows firms to trade surplus credits to compensate for any deficits. This setting exemplifies a circumstance where regulators utilize a market-based framework designed to induce technological transitions through firm-level compliance incentives. For regulators, this policy is designed to encourage firms to gradually phase out fuel-inefficient ICEV models and develop EV models. However, automakers heavily embedded in fuel-inefficient ICEV technologies may find it more cost-effective to purchase credits rather than undertake costly technological upgrades to achieve compliance. In light of the misalignment between the objectives of automakers and regulators under the dual-credit policy, the effectiveness of this market-based mechanism in reducing the production of fuel-inefficient ICEVs remains uncertain. Therefore, we propose our first research questions as follows:

RQ1: *Can the market-based mechanism of the dual-credit policy effectively reduce the production of fuel-inefficient internal combustion engine vehicles (ICEVs)?*

Moreover, scholars have aruged that firm-specific characteristics like the production ratio between ICEVs and EVs may significantly influence how automakers respond to the dual-credit policy in their technology choice and production decisions (e.g., Lou et al., 2020). Therefore, to further investigate the mechanism through which the dual-credit policy influences automakers' technology choice and production strategies, this study also examines firm-level heterogeneity along two specific dimensions: product market noncompliance ratio and credit market noncompliance ratio. Thus, we propose our second research questions as follows:

RQ2: *How do firm-specific characteristics (i.e., product market noncompliance ratio and credit market noncompliance ratio) moderate the influence of the dual-credit policy's market-based mechanism on firms' technology choice and production decisions?*

To address these research questions, the study uses a dataset comprising 15,927 observations on production volumes and vehicle attributes of 1452 ICEV model years, covering the period from January 2017 to December 2018, a 24-month window that spans the implementation of the dual-credit policy. To estimate the causal effect of the policy, the study adopts a quasi-natural experimental difference-in-discontinuities (DiDC) design proposed by Grembi et al. (2016). This approach enables the identification of the dual-credit policy's effect by disentangling it from confounding factors, such as the pre-existing fuel consumption regulation GB27999-2014.

After verifying the validity of the DiDC design, the study estimates the average treatment effect of the dual-credit policy by comparing discontinuities in production volumes before and after the implementation of the dual-credit policy across treatment and control groups. The results indicate that the policy has, somewhat counterintuitively, increased the production of fuel-inefficient ICEVs. Moreover, both automakers' product market noncompliance ratio and credit market noncompliance ratio significantly amplify this unintended effect.

To our knowledge, this study is the first to provide empirical evidence of the backfire effect of a market-based deployment policy in practice, and to demonstrate how firms' non-compliance levels across both product and credit markets can systematically reinforce such unintended policy outcomes. The findings offer several managerial and policy implications. For firm managers, our results suggest that they need to remain cautious about the potential technological inertia that market-based deployment policies may induce. While such policies offer flexibility to adapt during technological transitions, it is essential that firms actively utilize this window of opportunity to develop new technologies in order to avoid falling behind. For policymakers, our study suggests that they must carefully calibrate pricing mechanisms and enforce regulatory oversight when implementing market-based deployment policies, in order to avoid potential backfire effects. Furthermore, differentiated strategies should be designed based on firms' varying levels of compliance, enabling more targeted guidance and support to ensure that policy objectives are met across the spectrum of firm capabilities.

5.2. The Related Literature

5.2.1. Corporate Technology Choice and Production Strategies

This study is first relevant to the existing literature on corporate technology choice and production decisions. In the context of technological transitions, firms often face choices between competing technologies, and such decisions are shaped by a range of factors. Scholars have broadly classified these influencing factors into three categories: economic, cognitive, and social (Gilbert, 2005; Tripsas, 2009).

Economic factors were the primary focus of early analytical research. By constructing theoretical models, scholars have investigated optimal corporate technology choice and production decisions under different economic conditions. For instance, Crew and Kleindorfer (1976) conducted a seminal work on optimal production and pricing decisions of competiting technologies under price-driven and stochastics technology demand. Their study incorporated variations in investment and variable costs associated with different technologies. Building on this foundation, subsequent studies have relaxed the assumptions of the original models to investigate optimal decision-making under more complex conditions, such as supply-side uncertainty (Chao, 1983) and supply intermittency (Hu et al., 2015). Furthermore, with the rapid development of research on sustainable operations in recent years, scholars have increasingly focused on firms' choices between sustainable and non-sustainable technologies. In this context, the role of economic factors like pollution abatement costs, energy consumption costs, and other sustainability-related expenditures has received growing attention (Krass et al., 2013; Wang et al., 2013; Drake et al., 2016).

In addition, empirical studies have challenged the traditional assumption of fully rational decision-makers by introducing a cognitive perspective to identify the cognitive factors that might influence firms' technology choice and production decisions. These studies reveal that decision-makers' attention allocation, cognitive biases, risk preferences, and perceptions of technological value significantly affect corporate behaviors in this regard (Danneels, 2003; Kaplan & Tripsas, 2008). For example, Eggers and Kaplan (2009) found that in the midst of technological transitions, a firm's choice between old and new technologies is largely determined by the CEO's level of attention to the emerging technology. Besides, Gilbert (2006) argued that whether top managers interpret the emerging technology as a threat or an opportunity also significantly influences their technology adoption decisions.

Last, from a social perspective, scholars have identified various social actors that may influence firms' technology choice and production decisions during technological transitions. For instance, Weigelt et al. (2021) found that prosumers who act as both producers and consumers can significantly influence corporate decisions by shaping market demand. Additionally, security analysts play an important role in shaping firms' technology choices by providing investment guidance in capital markets (Benner, 2007; Benner, 2010). Among these social actors, scholars have identified government policy as playing a particularly critical role (Belis-Bergouignan et al., 2004; Safarzyńska & Van Den Bergh, 2010). They emphasize that policy support is a key catalyst for technological transitions, especially for technologies with significant externalities in areas like environmental protection and energy security (Kemp, 1997).

Under the influence of government policy, firms must consider not only conventional cost factors but also policy-induced compliance costs in their technology choice and production decisions. To capture these dynamics, scholars have developed theoretical models to examine firms' technology choice and production strategies under various policy instruments, such as government subsidies (Chemama et al., 2019; Raz & Ovchinnikov, 2015) and tax policies (Krass et al., 2013). However, the relationship between policy design and firms' strategic responses remains insufficiently understood, particularly as policy instruments have become increasingly complex and adaptive in recent years. There is a recent call for more research on firm decision-making regarding technology choice and production strategies under new policy instruments like market-based deployment policies (Wiener, 2004; Joglekar et al., 2016; Helper et al., 2021).

5.2.2. Market-based Deployment Policies

This study is also closely related to the literature on the role of market-based deployment policies in technological transitions. Market-based policy instruments refer to policy mechanisms that guide specific behaviors by leveraging market signals rather than direct administrative mandates (Stavins, 2003). In the context of technological transitions, unlike traditional command-and-control deployment regulations that impose uniform technological requirements and thus equalize the degree of technological change across firms, market-based deployment policies equalize the associated costs of such changes (Tietenberg, 1995). As a result, such market-based policies allow firms the flexibility to determine the scale and timing of their technological investments based on individual capabilities and market conditions.

The existing research on the role of market-based deployment policies during technological transitions encompasses two levels of analysis: the macro level, which focuses on industry-wide responses, and the micro level, which examines firm-level behaviors. At the macro level, scholars are primarily concerned with the overall effectiveness of these policies within an industry, particularly their impact on the market penetration of emerging technologies during periods of technological transitions (e.g., Wang et al., 2018; Li et al., 2019; Wu et al., 2022). Besides, for the increasingly widespread use of market-based deployment policies in promoting green technological transitions like the cap-and-trade program, researchers have focused on the environmental outcomes of these policies, such as their effectiveness in reducing carbon emissions (Napolitano et al., 2007; Kroes et al., 2012; Bai & Ru, 2024; Zhao et al., 2019; He et al., 2020). At the micro level, scholars have employed theoretical models to investigate how market-based deployment policies influence firms' strategic decision-making during technological transitions. These studies typically explore how such policies affect firm behaviors in areas such as production planning, R&D investment, and pricing strategies (e.g., Li et al., 2018; Yu et al., 2021; Ding & Zhu, 2023).

In the automotive industry's technological transition from ICEVs to EVs, the dual-credit policy has recently attracted significant scholarly attention as a representative example of a market-based deployment policy (Wang et al., 2017). At the macro level, existing studies have primarily focused on evaluating its impact on EV sales, overall industry profits, fuel consumption, and greenhouse gas emissions within the automotive sector (He et al., 2020; Wu et al., 2022). In addition, some researchers have examined the effectiveness of the dual-credit policy in comparison with other deployment instruments, such as NEV subsidies and the Corporate Average Fuel Consumption CAFC regulations on ICEVs (Li et al., 2018; Ou et al., 2018). At the micro level, researchers have explored how the dual-credit policy affects automakers' production mix and R&D decisions (He et al., 2021; Li et al., 2020; Ding & Zhu, 2023). Although these studies provide valuable insights, they primarily rely on game-theoretic models and simulation-based approaches to predict the potential effects of the dual-credit policy.

However, its actual impact in empirical settings remains something of a black box.

5.3. Empirical Setting

In China, the dual-credit policy was issued in September 2017 and put into effect in April 2018 (Ministry of Industry and Information Technology, MIIT, 2017). It is a parallel management regulation of both the Corporate Average Fuel Consumption (CAFC) credits and the New Energy Vehicle (NEV) credits.

The CAFC credit system requires automakers to comply with fuel efficiency standard for their ICEVs[5]. Specifically, the standard referred to here is GB27999-2014, which was officially announced in December 2014 and came into effect in January 2016 (MIIT, 2014). This standard establishes the evaluation method and target for the fuel consumption of ICEV models, as well as the calculation method of the average fuel consumption for ICEV models produced by each automaker. The evaluation method draws primarily on the New European Driving Cycle (NEDC) laboratory test. And the fuel consumption target of a ICEV model is determined based on its curb weight (shown in Table 3.1).

Table 5.1. Standards for fuel consumption of ICEVs in the CAFC credit system

Curb weight (CW/kg)	Fuel consumption target (L/km)
CW ≤ 750	4.3
750 < CW ≤ 865	4.3
865 < CW ≤ 980	4.3
980 < CW ≤ 1090	4.5
1090 < CW ≤ 1205	4.7
1205 < CW ≤ 1320	4.9
1320 < CW ≤ 1430	5.1

5 Under the dual-credit policy, ICEVs refer to those powered by fossil fuels like gasoline, diesel, gaseous fuels, or alcohol-ether fuels. Notably, non-plug-in hybrid electric passenger vehicles are also classified as ICEVs.

1430 < CW ≤ 1540	5.3
1540 < CW ≤ 1660	5.5
1660 < CW ≤ 1770	5.7
1770 < CW ≤ 1880	5.9
1880 < CW ≤ 2000	6.2
2000 < CW ≤ 2110	6.4
2110 < CW ≤ 2280	6.6
2280 < CW ≤ 2510	7.0
2510 < CW	7.3

The calculation of an automaker's CAFC credits is based on its average fuel consumption relative to the target. If a company's average fuel consumption exceeds the target, it incurs a credit deficit, whereas consumption below the target results in surplus credits. Specifically, the CAFC credits of an automaker i in year t earned are determined using the following formula:

$$Credit_{CAFC,it} = (\sum_{k=1}^{K_{it}} v_{kt} \times FC_{target,kt}) \times e_t - (\sum_{k=1}^{K_{it}} v_{kt} \times FC_{actual,kt}) \qquad (5.1)$$

where, K_{it} is the total number of ICEV models an automaker i produces in year t, v_{kt} is the production volume of a ICEV model k in year t. $FC_{target,kt}$ and $FC_{actual,kt}$ are target fuel consumption and actual fuel consumption of a ICEV model k in year t, respectively. e_t is a multiplier to the final-year CAFC target in year t. This multiplier decreases over time, gradually tightening the target for fuel efficiency (134% in 2016, 128% in 2017, 120% in 2018, 110% in 2019, and 100% in or after 2020).

Before the implementation of the dual-credit policy, automakers were required to continuously reduce the CAFC of their ICEV models through technological advancements in order to comply with the GB27999-2014 standard. Failure to meet this standard resulted in several penalties, including public disclosure of non-compliance, suspension of new product approvals, restrictions on expanding production capacity, and increased scrutiny during customs clearance, import inspections, and other regulatory processes (MIIT, 2014).

The dual-credit policy introduced the NEV credit system alongside the CAFC credit system, providing automakers with additional flexibility. Specifically, the NEV credit system requires manufacturers to ensure that a specific percentage of their passenger cars produced are EVs. Manufacturers earn NEV credits based on the type and performance of the electric passenger vehicles (EPVs)[6] they produce, with higher credits awarded for vehicles with longer electric ranges and better energy efficiency. The NEV credits of an automaker i in year t are calculated as follows:

$$Credit_{NEV,it} = \sum_{m=1}^{M_{it}} credit_{mt} \times v_{mt} - (\sum_{k=1}^{K_{it}} v_{kt}) \times r_t \tag{5.2}$$

where, M_{it} is the total number of EPV models an automaker i produces in year t, v_{mt} is the production volume of an EPV model m in year t, $(\sum_{k=1}^{K_{it}} v_{kt})$ is the total production volume of ICEV models an automaker produces in year t. r_t is the required minimum production ratio of EPVs regulated by the government in year t. It was set at zero in 2018, and was subsequently established at 10%, 12%, 14%, 16%, and 18% for the years 2019, 2020, 2021, 2022, and 2023, respectively.

Moreover, the dual-credit policy provides a mechanism of credit trading. Specifically, automakers who exceed their NEV or CAFC targets can sell their excess

[6] Under the dual-credit policy, electric passenger vehicles are those powered by electricity, including plug-in hybrid, battery, and fuel cell electric passenger vehicles.

credits to those who fail to meet the required levels. This trading mechanism allows firms to offset their deficits in one category (either NEV or CAFC) by purchasing credits from others, facilitating compliance without necessarily changing their production strategies. However, the NEV credits are non-transferable once purchased, and firms are prohibited from trading CAFC credits directly. The trading of NEV credits is allowed between non-affiliated firms, but it cannot be resold once acquired. Besides, while CAFC credits cannot be bought or sold directly in the market, they can be transferred between affiliated or shareholder companies.

To further understand the empirical context of our study, Figure 5.1 summarizes the evolution of the dual-credit policy during our sample period, specifically the development trajectory of regulations on fuel-inefficient ICEV models. The figure indicates that ICEV models were initially subject to the standard GB27999-2014 alone. Later, the introduction of the dual-credit policy provided an additional market-based mechanism for automakers to flexibly adapt to the technology transition from ICEVs to EVs in the passenger vehicle market. Therefore, to investigate the impact of market-based policy instruments on corporate technology choice and production strategies during technological transitions, we should eliminate the confounding effect of the CAFC credit system that has been in effect since the announcement of the standard GB27999-2014 in December 2014. In the following methodology section, we will discuss this issue in more detail.

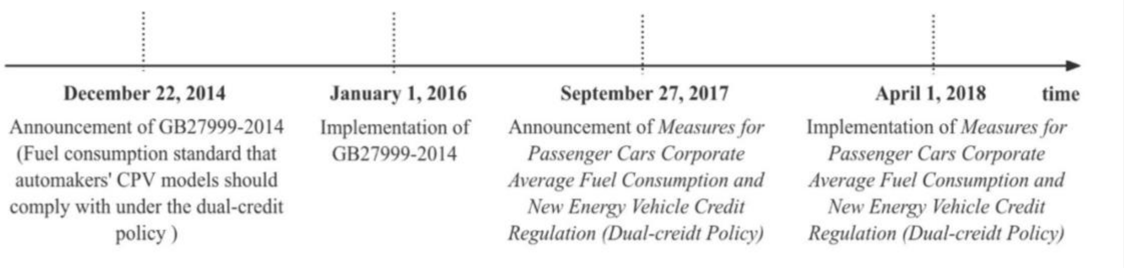

Figure 5.1. The evolution of the dual-credit policy

5.4. Data and Model-free Evidence

5.4.1. Data and Sample

We collected data from different sources for analysis. We acquired data on the production of ICEVs in China from a research firm specializing in China's automotive industry. Besides, we gathered data on vehicle attributes such as fuel consumption, size, and curb weight from widely recognized Chinese automotive information websites like *AutoHome* and official automotive brand websites. Last, we obtained information on the dual-credit policy and related policies from the Chinese Ministry of Industry and Information Technology (MIIT) and other Chinese government agencies.

The core data set of our study is monthly production data of all ICEV models in China. Our original data covers 28823 observations of 1964 ICEV models between January 2017 and December 2018, a 24-month time window around the implementation of the dual-credit policy[7]. A ICEV model refers to a unique combination of "automaker-brand-series-displacement". For example, "Volkswagen-Audi-A3-1.8L" represents a specific ICEV model. Since automakers usually release updates for their models including adjustments in aesthetic design, technological configurations, and performance parameters annually, empirical analyses of the automobile market should be conducted at the model year level (e.g., 2017-Volkswagen-Audi-A3-1.8L is a specific model year) (Guajardo et al., 2016; Sun et al., 2021). However, the production data used in this study do not differentiate between various model years of the same vehicle model within a given calendar year. When multiple model years of a particular vehicle are available in the market, consumers typically prefer the latest version. Accordingly, this study attributes the production volume of an ICEV model in a given

[7] We also use a shorter time window as robustness check for our empirical analysis.

calendar year to its latest model year. For example, the production of the Volkswagen-Audi-A3-1.8L in 2017 is considered to correspond to that of the 2017-Volkswagen-Audi-A3-1.8L.

Besides, as discussed earlier in Subsection 5.4.1, under the dual-credit policy, the fuel consumption of ICEV models is required to comply with the standard of GB27999-2014 , which was implemented in 2016. To isolate the impact of the dual-credit policy on automakers' behaviors and eliminate the confounding effects of earlier fuel consumption standards[8], we focus exclusively on ICEV model years registered in 2016 or later. Moreover, this sample reduction helps ensure that the majority of ICEV model years in our sample are situated within comparable stages of the product life cycle. This helps reduce potential biases arising from product life cycle effects. This elimination reduces our data to 19581 monthly observations of 1792 ICEV model years.

We further enriched the dataset by matching production data with fuel consumption information and other model year-specific attributes of ICEVs. Regarding fuel consumption, we used values measured under the New European Driving Cycle (NEDC) laboratory test condition, which serves as the standard testing procedure under the dual-credit policy. Additionally, we collected data on various model year attributes, including automaker type (domestic, foreign, or joint venture), vehicle type (sedan, SUV, or MPV), price, size (calculated as the product of length, width, and height), and curb weight. Specifically, for the price of ICEV model years, we used the manufacturer's suggested retail price (MSRP). While actual transaction prices of vehicles may vary due to dealer-specific discounts, the MSRP is widely regarded as a reasonable proxy for the final transaction price.

[8] Before GB27999-2014, there was standard GB27999-2011 for the fuel consumption of ICEVs produced in China.

Attribute data of ICEV model years are available at the model year-trim level. For example, "2017-FAW-Volkswagen-Audi-A3-1.8L-Sportback 35 TFSI Progressive" is a specific model year-trim in the attribute data set. To align these two data sets, following prior studies like Balachander et al. (2009) and Guajardo et al. (2016), we aggregated trim-level attributes to the model level by calculating the average values of all trims under a specific ICEV model year[9]. After matching and excluding ICEV model years with variables of missing values, our final sample consists of 15927 observations of 1452 model years from 121 automakers. Figure 5.2 displays the data processing procedure in this study.

[9] We also use other aggregation approaches like calculating the median value as robustness checks.

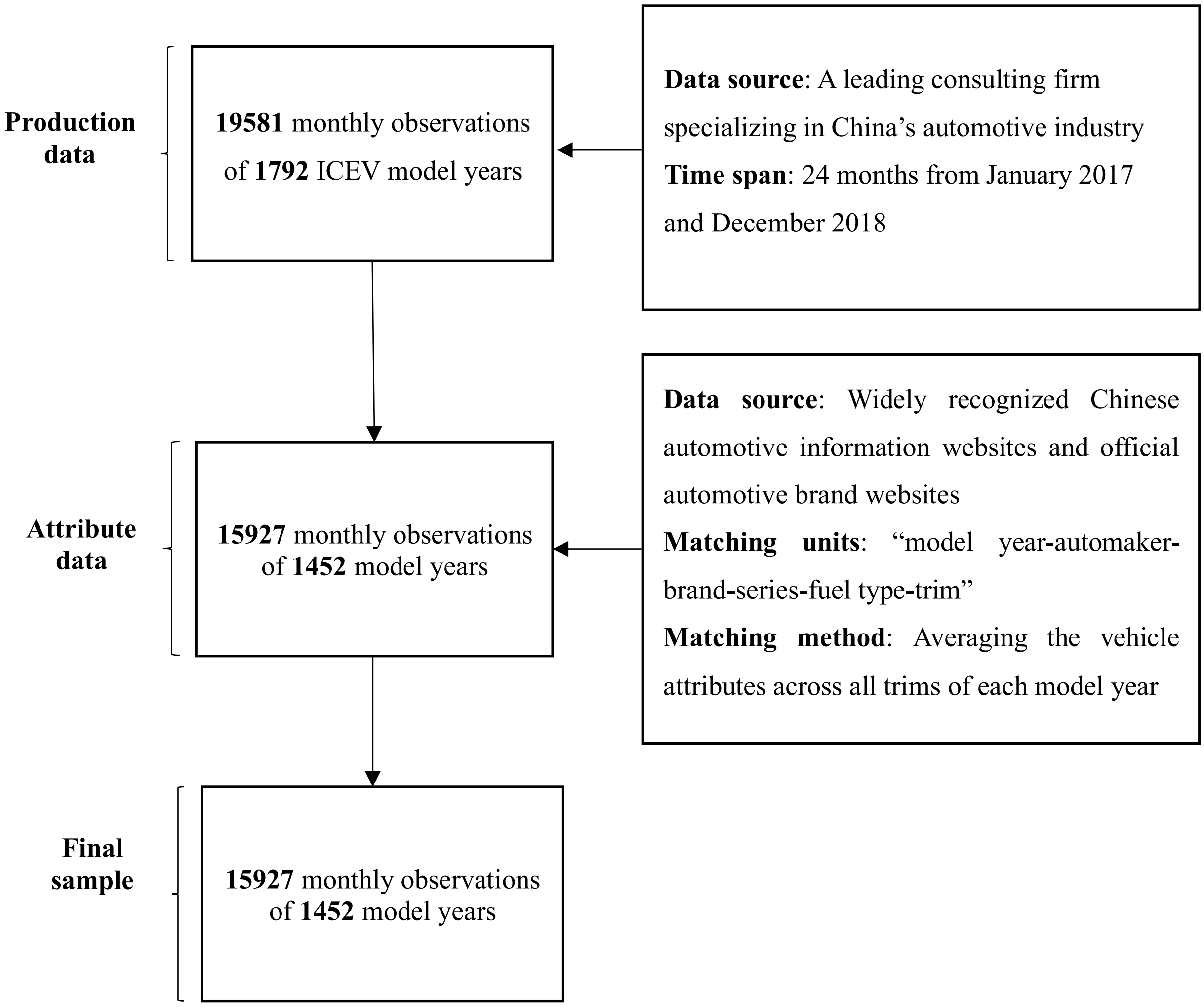

Figure 5.2. Data processing flow in Study 3

5.4.2. Model-free Evidence

Before setting up the econometric model, we first provide model-free evidence by plotting the production trend of ICEV model years with excessive fuel consumption over time. The patterns in Figure 5.3 reveal a significant increase in production of fuel-inefficient ICEV model years following the announcement of the dual-credit policy in September 2017. Furthermore, a comparison of the same months in 2017 and 2018 reveals that ICEV model years with excessive fuel consumption experienced higher production volume in 2018.

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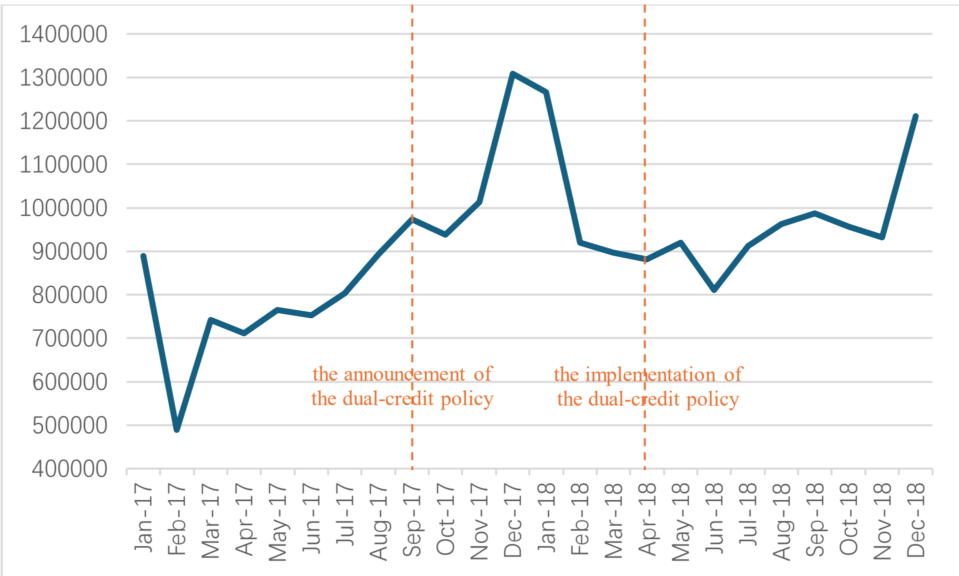

Figure 5.3. Monthly production volume of ICEV model years with excessive fuel consumption

5.5. Difference-in-discontinuities Design

5.5.1. Difference-in-discontinuities Overview

Difference-in-discontinuities (DiDC) design, introduced by Grembi et al. (2016), is a quasi-experimental econometric method that combines elements of traditional difference-in-difference (DID) and regression discontinuity designs (RDD). It allows researchers to examine both temporal and discontinuity variations in the variables of interest for causal inference simultaneously (Eggers et al., 2018; Tramontin Shinoki et al., 2024). Since its introduction, it has been increasing applied in economics studies, especially in evaluating the effects of policies and legislations in different contexts like crime (e.g., Chicoine, 2017), social welfare (e.g., Hazan et al., 2019), labor market (e.g., Bennedsen et al., 2022), and political economics (e.g., Lassébie, 2020). Nevertheless, there is little research in the business management field adopting this design to enhance the robustness of causal inference.

Researchers have identified appealing features of DiDC design compared with standard DID and RDD in some settings (Tramontin Shinoki et al., 2024). Specifically, standard RDD applies in situations where individuals receive a treatment based on whether a continuous variable crosses a predefined threshold. It operates on the assumption that individuals just below the threshold serve as valid counterfactuals for those just above the threshold (Lee & Lemieux, 2010). However, when multiple confounding treatments exist at the threshold, RDD estimates may become biased. DiDC addresses this issue by leveraging the temporal variation in these confounding treatments (Grembi et al., 2016). In addition, unlike standard RDD, which focuses on observations near the threshold, DiDC incorporates a broader range of sample data, allowing for more accurate and robust estimation of treatment effects. Moreover, the DID design relies on the strict parallel trends assumption, which posits that, in the absence of treatment, the difference in outcomes between the control and treatment groups would have remained constant over time. In contrast, DiDC relaxes the parallel trends assumption by allowing for systematic differences between treatment and control groups, thus providing greater flexibility in identifying causal effects.

5.5.2. Difference-in-discontinuities Design in Our Study

Model Setup

There are two challenges in testing the impact of the dual-credit policy on the production of fuel-inefficient ICEV model years in the automotive industry. First, we cannot adopt a standard RDD design because there are confounding policy effects on ICEV model years that change sharply at the threshold of fuel consumption target. Specifically, as previously discussed, ICEV model years with excessive fuel consumption in the treatment group were penalized under the GB27999-2014 standard prior to the implementation of the dual-credit policy. Following the dual-credit policy's introduction, however, these models were subject not only to potential penalties under the existing standard but also to additional impacts imposed by the credit market trading mechanism. Therefore, upon the implementation of the dual-credit policy, both the penalties stipulated under the GB27999-2014 standard and the market-based incentives introduced by the policy exhibit discontinuous changes at the fuel consumption threshold. Besides, we cannot apply a standard difference-in-difference (DID) design since ICEV model years with and without excessive fuel consumption may not satisfy the parallel trends assumption. For instance, ICEVs with high and low fuel consumption may follow distinct product life cycles. Consequently, at the time of the dual-credit policy implementation, these vehicles may be at different stages of their respective cycles, potentially introducing bias into the DID estimation due to cycle-related effects. As discussed in the Subsection 5.5.1, the DiDC design can overcome the limits of these approaches. This is because, aside from exceeding or falling below the threshold, vehicle models located near the fuel consumption target are highly comparable in terms of product characteristics like product cycles.

We define FC_{it} as the fuel consumption of a specific ICEV model year i at time

t. The first treatment applied to ICEV model years corresponds to the implementation of the GB27999-2014 standard in 2016. We denote this treatment indicator as S_{it}, where S_{it} equals to 1 if FC_{it} exceeds the fuel consumption target FC_{target} and equals to 0 if it is below the target, based on the GB27999-2014 standard. The second treatment is the implementation of the dual-credit policy since April 2018. We define this treatment as D_{it}, where D_{it} equals to 1 if $\mathrm{FC}_{it} > FC_{target}$ and $t \geq t_0$, where t_0 is the implementation time of the dual-credit policy. Therefore, the two treatment indicators in our setting are described as follows:

$$
\begin{aligned}
S_{it} &= \begin{cases} 1 & \text{if } \mathrm{FC}_{it} > FC_{target} \\ 0 & \text{otherwise} \end{cases} \\
D_{it} &= \begin{cases} 1 & \text{if } \mathrm{FC}_{it} > FC_{target} \text{ and } t \geq t_0 \\ 0 & \text{otherwise} \end{cases}
\end{aligned}
\tag{5.3}
$$

We define the production volume of a specific ICEV model year i at time t as $Y_{it}(S_{it}, D_{it})$. Therefore, the standard RD estimate at the threshold FC_{target} before the implementation of the dual-credit policy can be written as $\tau_{RD\_before} = \tilde{Y}(1,0)^{+} - \tilde{Y}(0,0)^{-}$, while that after the policy implementation can be expressed as $\tau_{RD\_after} = Y(1,1)^{+} - Y(0,0)^{-}$, where,

$$
\tilde{Y}^{+} \equiv \lim_{FC_{it} \to FC_{target}^{+}} E[Y_{it} | FC_{it} = FC_{target}, t < t_0] \quad \tilde{Y}^{-} \equiv \lim_{FC_{it} \to FC_{target}^{-}} E[Y_{it} | FC_{it} = FC_{target}, t < t_0]
$$

$$
Y^{+} \equiv \lim_{FC_{it} \to FC_{target}^{+}} E[Y_{it} | FC_{it} = FC_{target}, t \geq t_0] Y^{-} \equiv \lim_{FC_{it} \to FC_{target}^{-}} E[Y_{it} | FC_{it} = FC_{target}, t \geq t_0].
$$

The DiDC estimate τ_{DiDC} can be represented as follows:

$$
\tau_{DiDC} \equiv \left[Y(1,1)^{+} - Y(0,0)^{-} \right] - \left[\tilde{Y}(1,0)^{+} - \tilde{Y}(0,0)^{-} \right] \tag{5.4}
$$

According to Grembi et al. (2016), when two requirements are satisfied, we have

$\tau_{DiDC} = Y(1,1) - Y(0,0) - Y(1,0) + Y(0,0) = Y(1,1) - Y(1,0)$, which is the actual dual-credit policy effect on the production of ICEV models with excessive fuel consumption we focus on in this study.

The first requirement is that the assignment variable (i.e., fuel consumption of ICEV model years in our study) cannot be manipulated to fall above or below the threshold (i.e., fuel consumption target for ICEV model years in our study) when the treatment is assigned (i.e., the implementation of the dual-credit policy in our study). This is similar to the standard assumption in RD design, which identifies the absence of manipulation. In our setting, automakers typically update the designs of their ICEV models on an annual basis. Since the period between the announcement and the implementation of the dual-credit policy is only seven months, it is unlikely that automakers would have enough time to manipulate the fuel consumption of their ICEV model years once they are aware of the policy. In addition, in Subsection 5.6.1, following prior research like Eggers et al. (2018) and Tramontin Shinoki et al. (2024), we adopt two tests to check whether there is manipulative sorting empirically.

The second assumption is that the effect of the confounding treatment (i.e., the implementation of the standard GB27999-2014 for the fuel consumption of ICEV model years in our study) does not vary with time. This is similar to the standard parallel trends assumption in DID design, but it only needs to be satisfied within a small range around the threshold. Regarding this assumption, we also conduct a parallel trends test on the discontinuity of the production volume of ICEV models around the fuel consumption target.

Model Estimation

The DiDC estimator is computed based on the four boundary points, where the outcome variable Y_{it} is regressed on the assignment variable FC_{it}. Specifically, following the standard RD design (Lee & Lemieux, 2010), we select the sample in a small neighborhood around the threshold ($1-h \le \frac{FC_{it}}{FC_{target}} \le 1+h$, where we set h as 0.2, we also use different bandwidths ranging from 0.1 to 0.5 as robustness checks in our study) and apply a local linear regression on either side of FC_{target} both before and after the dual-credit policy implementation. After that, we calculate the difference between the production volume discontinuity before and after t_0. Our estimation model can be written as follows:

$$\begin{aligned} Y_{it} &= \alpha_0 + \alpha_1 FC_{it}^{*} + \mathrm{D}_i(\gamma_0 + \gamma_1 FC_{it}^{*}) \\ &+ T_t\left[(\beta_0 + \beta_1 FC_{it}^{*} + \mathrm{D}_i(\delta_0 + \delta_1 FC_{it}^{*})\right] + \eta X_{it} + \zeta_{it} \end{aligned} \tag{5.5}$$

where $FC_{it}^{*} = FC_{it} - FC_{target}$ is the normalized fuel consumption of ICEV models, D_i and T_t are indicators for excessive fuel consumption and the period after the implementation of the dual-credit policy, X_{it} is a vector of control variables (e.g., price, size, weight). Since DiDC is a quasi-natural experiment, we only include a small number of control variables. δ_0 is the DiDC estimator we focus on and identifies the impact of the dual-credit policy on the production volume of excessive fuel consumption ICEV models.

5.6. Results

5.6.1. DiDC Design Validity Tests

Since we select a bandwidth of 0.2 around the threshold (i.e., the fuel consumption target) for our regression discontinuity (RD) sample, we drop ICEV model years of which the absolute relative distance between their actual fuel consumption and the target fuel consumption (i.e., $\frac{FC_{it} - FC_{target}}{FC_{target}}$) is larger than 0.2. This results in a sample of 12897 observations of 1163 ICEV model years. Among them, 375 ICEV model years belong to the control group that their fuel consumption is lower than the target, while 785 of them belong to the treatment group with excessive fuel consumption. Table 5.2 provides the descriptive statistics for vehicle attributes of ICEV model years in the control group and in the treatment group.

Table 5.2. Descriptive statistics for vehicle attributes in control and treatment group

Panel A: ICEV model years with compliant fuel consumption (control group)				
	Mean	S.D.	Min	Max
Price	14.42	13.01	3.78	127.3
Curb weight	1410.62	239.84	880	2296
Size	12.54	1.42	6.95	19.36
Domestic automaker	0.21	0.41	0	1
Joint venture automaker	0.63	0.48	0	1
Panel B: ICEV model years with excessive fuel consumption (treatment group)				
	Mean	S.D.	Min	Max
Price	14.17	13.81	3.78	198.8
Curb weight	1528.97	277.03	898	2587
Size	13.62	1.74	8.40	20.12
Domestic automaker	0.46	0.50	0	1
Joint venture automaker	0.38	0.49	0	1

Before testing the impact of the dual-credit policy on production volumes of ICEV model years, we first provide empirical evidence on the two assumptions of our DiDC design as discussed before.

Regarding the assumption that there is no manipulative sorting of fuel consumption for ICEV model years before and after the implementation of the dual-credit policy, we first adopt the density test proposed by McCrary (2008). Specifically, if there is no discontinuity in the difference between the densities of the assignment variable before and after the treatment at the threshold, we can conclude that the assumption of no manipulation holds. In Figure 5.4, we plot scatter points along with first-order polynomial fits to depict the distribution of the difference in fuel consumption densities between the pre-treatment and post-treatment periods for ICEV model years around the target. The results show that this difference remains continuous at the target.

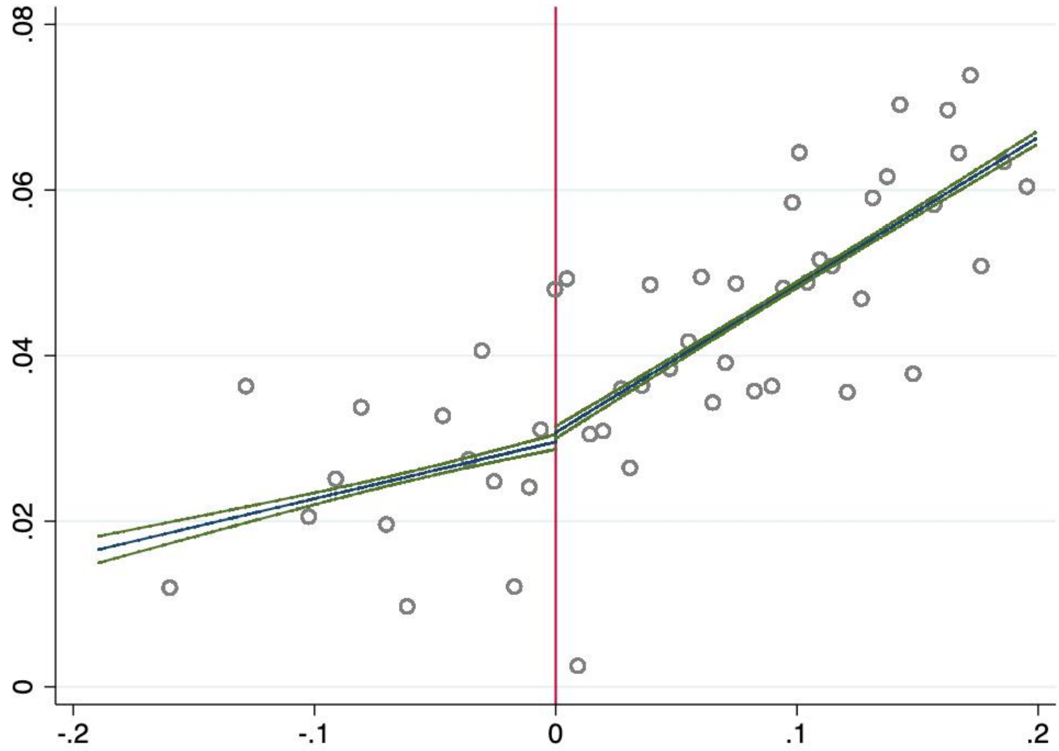

Figure 5.4. Density test for fuel consumption of ICEV model years

Notes: The x-axis represents the relative distance between an ICEV model year's fuel consumption and the target under the standard GB27999-2014, the y-axis represents the difference in fuel consumption densities of ICEV models before and after the dual-credit policy; The central line is a spline first-order polynomial fit in difference in fuel consumption densities, the lateral lines represent the 95% confidence interval.

Moreover, we adopt the approach of Lee (2008) and Lee & Lemieux (2010) and show the distribution of baseline covariates (i.e., size of ICEV models) with respect to the assignment variable (i.e., fuel consumption) around its target in Figure 5.5 as well. According to Lee (2008) and Lee & Lemieux (2010), if there is no manipulative sorting of ICEV models into treatment and control groups, the baseline covariates for them with fuel consumption around the target should not have significant differences.

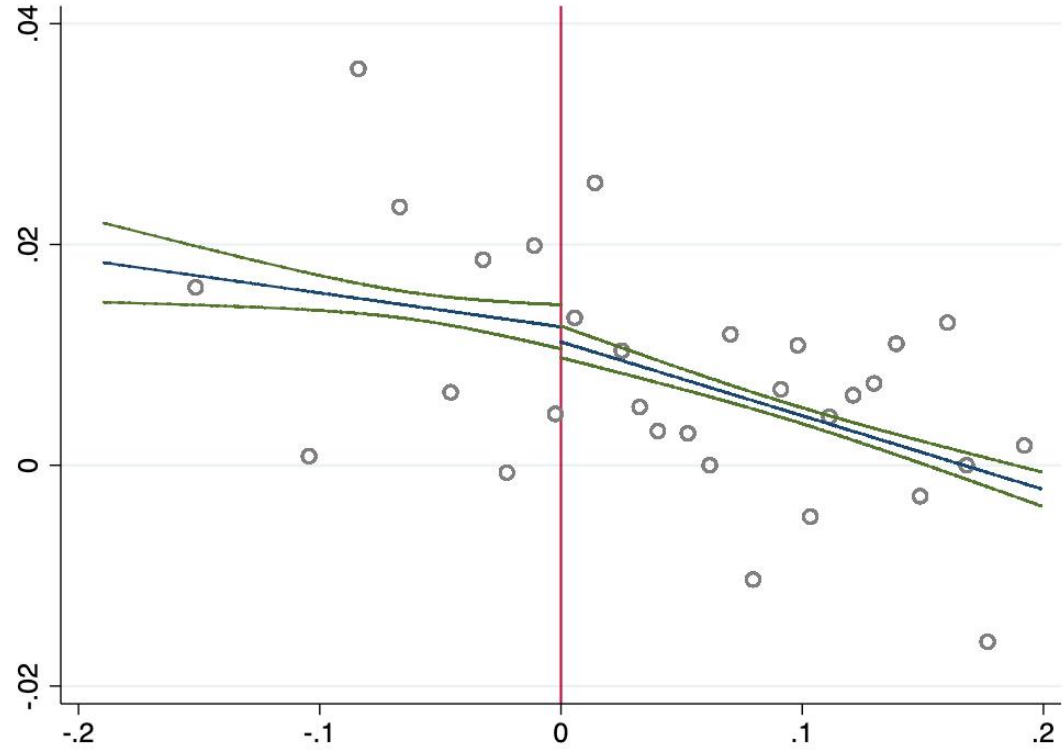

Figure 5.5. Density test for size of ICEV model years

Notes: The x-axis represents the relative distance between an ICEV model year's fuel consumption and the target under the standard GB27999-2014, the y-axis represents the difference in size densities of ICEV models before and after the dual-credit policy; The central line is a spline first-order polynomial fit in difference in size densities, the lateral lines represent the 95% confidence interval.

With respect to the second assumption that the effect of the confounding policy does not vary with time, we adopt a falsification test during the period before the implementation of the dual-credit policy. Specifically, we assume that the dual-credit policy was implemented in May 2017 before its official announcement, and perform a DiDC estimation to determine whether a significant discontinuity exists in the differences in the production volume of ICEV model years around the fuel consumption target between the pre-treatment and post-treatment periods. For this analysis, we define the pre-treatment period as January 2017 to April 2017 and the post-treatment period as May 2017 to August 2017. The results are presented in Table 5.3. From this table, we can observe that the treatment effect is not statistically significant, suggesting that the production volume of fuel-inefficient ICEV models did not change notably at time points before the announcement of the dual-credit policy. Thus, we can conclude that the DiDC design in our study is valid.

Table 5.3. Falsification test before the implementation of the dual-credit policy

	Dependent variable: the logarithm of the production volume of ICEV model years	
	Model 1	Model 2
Treatment effect considered, $T_t \times D_i$	**-0.286** (0.367)	**-0.380** (0.353)
Excessive fuel consumption, D_i	1.101^{***} (0.147)	0.943^{***} (0.137)
Normalized fuel consumption, FC_{it}^*	-24.46^{***} (4.693)	-13.22^{***} (4.596)
Normalized fuel consumption × Treatment effect considered, $FC_{it}^* \times T_t \times D_i$	-13.02 (15.52)	-16.36 (15.13)
Normalized fuel consumption × Excessive fuel consumption, $FC_{it}^* \times D_i$	-0.697 (6.341)	-13.66^{**} (6.048)
Post-treatment period, T_t	0.365 (0.271)	0.448^{*} (0.266)
Normalized fuel consumption × Post-treatment period, $FC_{it}^* \times T_t$	18.49 (12.11)	21.42^{*} (11.90)
Curb weight		-0.002^{***} (0.000)
Size		0.382^{***} (0.052)
Price		0.009^{*} (0.004)
ICEV class fixed effects	Included	Included
Automaker type fixed effects	Included	Included
Constant	5.997^{***} (0.107)	3.774^{***} (0.363)
Observations	4084	4084
R^2	0.0173	0.1243

Notes: 1) * p<0.05, ** p<0.01, *** p<0.001; 2) The numbers in parentheses represent the t values of the corresponding coefficients or constants; 3) The sample size is the number of observations within the optimal bandwidth around the cutoff, where the bandwidth is selected automatically using the Calonico-Cattaneo-Titiunik

(CCT) method based on the minimum mean squared error (MSE) criterion; 4) ICEV classes include sedans, SUVs, and MPVs; 5) Automaker types include domestic automakers, foreign automakers, and joint ventures.

5.6.2. Empirical Results

After validating the assumptions of the DiDC design, we explore the causal relationship of interest in this subsection. First, we illustrate the descriptive distribution of changes in ICEV production volumes around the fuel consumption target before and after the implementation of the dual-credit policy in Figure 5.6. It is observed that there is a clear discontinuity at the threshold. Specifically, the change in production volume for ICEV model years with excessive fuel consumption is significantly greater after the policy implementation compared to the change for those with compliant fuel consumption. This result suggests that the implementation of the dual-credit policy may incentivize the production of fuel-inefficient ICEVs.

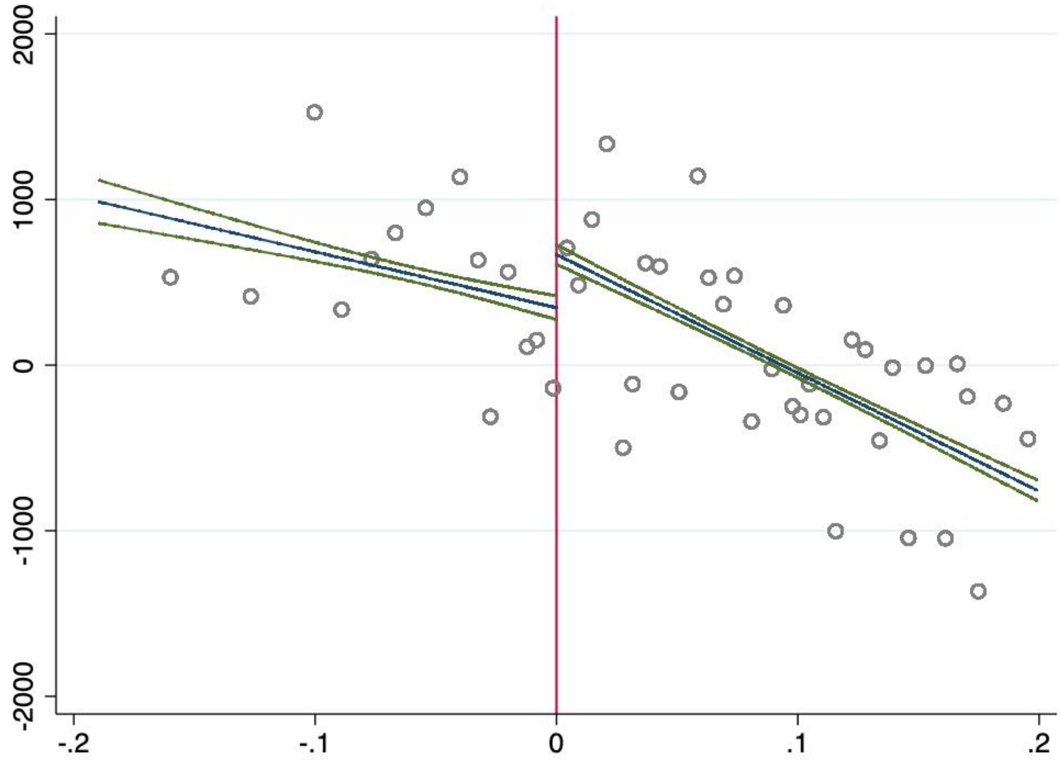

Figure 5.6. Graphical evidence of the impact of the dual-credit policy

Notes: The x-axis represents the relative distance between an ICEV model year's fuel consumption and the target under the standard GB27999-2014, the y-axis represents the difference in production volunes of ICEV model years before and after the dual-credit policy; The central line is a spline first-order polynomial fit in production volume differences of ICEV model years, the lateral lines represent the 95% confidence interval.

Next, we estimate the impact of the dual-credit policy using Equation (5.5), with the results reported in Table 5.4. Column (1) presents the baseline specification based on Equation (5.5), while Column (2) includes a set of baseline covariates, such as vehicle price, size, and curb weight. The results in Column (1) indicate that the estimated treatment effect is significantly positive ($\beta = 0.666$, $p < 0.05$). In Model 2, after incorporating the control variables, the coefficient remains significantly positive ($\beta = 0.841$, $p < 0.01$). These findings suggest that the implementation of the dual-credit policy encouraged automakers to produce more excessive fuel consumption ICEVs.

Table 5.4. The DiDC estimation of the impact of the dual-credit policy

	Dependent variable: the logarithm of the production volume of ICEV model years	
	Model 1	Model 2
Treatment effect considered, $T_t \times D_i$	**0.666**** (0.312)	**0.841***** (0.298)
Excessive fuel consumption, D_i	0.395 (0.265)	0.0746 (0.261)
Normalized fuel consumption, FC_{it}^{*}	20.67** (9.587)	31.80** (9.781)
Normalized fuel consumption × Treatment effect considered, $FC_{it}^{*} \times T_t \times D_i$	31.63** (13.95)	25.69* (13.49)
Normalized fuel consumption × Excessive fuel consumption, $FC_{it}^{*} \times D_i$	-40.02*** (11.81)	-46.74*** (11.54)
Post-treatment period, T_t	-0.642*** (0.235)	-0.699*** (0.231)
Normalized fuel consumption × Post-treatment period, $FC_{it}^{*} \times T_t$	-40.10*** (11.05)	-39.99*** (11.04)
Curb weight		-0.002*** (0.000)
Size		0.399*** (0.053)
Price		0.008* (0.004)
ICEV class fixed effects	Included	Included
Automaker type fixed effects	Included	Included
Constant	6.709*** (0.202)	4.247*** (0.413)
Observations	3897	3897
R^2	0.0177	0.1319

Notes: 1) * p<0.05, ** p<0.01, *** p<0.001; 2) The numbers in parentheses represent the t values of the corresponding coefficients or constants; 3) The sample size is the number of observations within the optimal bandwidth around the cutoff, where the bandwidth is selected automatically using the Calonico-Cattaneo-Titiunik (CCT) method based on the minimum mean squared error (MSE) criterion; 4) ICEV classes include sedans, SUVs, and MPVs; 5) Automaker types include domestic automakers, foreign automakers, and joint ventures.

To analyze firm-level heterogeneity in the impact of the dual-credit policy on automakers' ICEV technology choice and production decisions, this study introduces two moderating variables: the product market noncompliance ratio (PNR) and the credit market noncompliance ratio (CNR). Specifically, PNR is calculated as the ratio of the difference between the monthly production volumes of excessive and compliant fuel consumption ICEVs to the production volume of excessive fuel consumption ICEVs. CNR is defined as the ratio of the absolute value of the average negative fuel consumption credits generated by excessive fuel consumption ICEVs to the difference between the average credits generated by compliant ICEVs and the absolute value of those generated by excessive ICEVs.

To assess the moderating effects of these two variables, we extend the DiDC estimation model specified in Equation (5.5) by incorporating interaction terms between the treatment indicator and PNR and CNR, yielding the adjusted specifications in Equations (5.6) and (5.7). The estimation results of Equations (5.6) and (5.7) are reported in Columns (1) and (2) of Table 5.5, respectively.

$$\begin{aligned} Y_{it} &= \alpha_0 + \alpha_1 FC_{it}^{*} + \mathrm{D}_i(\gamma_0 + \gamma_1 FC_{it}^{*}) \\ &+ T_t\left[(\beta_0 + \beta_1 FC_{it}^{*} + \mathrm{D}_i(\delta_0 + \delta_1 FC_{it}^{*})\right] + \\ &\mathrm{PNR}_{it}(\varepsilon_0 + \varepsilon_1 T_t \mathrm{D}_i) + \eta X_{it} + \zeta_{it} \end{aligned} \tag{5.6}$$

$$\begin{aligned} Y_{it} &= \alpha_0 + \alpha_1 FC_{it}^{*} + \mathrm{D}_i(\gamma_0 + \gamma_1 FC_{it}^{*}) \\ &+ T_t\left[(\beta_0 + \beta_1 FC_{it}^{*} + \mathrm{D}_i(\delta_0 + \delta_1 FC_{it}^{*})\right] + \\ &\mathrm{CNR}_{it}(\varepsilon_0 + \varepsilon_1 T_t \mathrm{D}_i) + \eta X_{it} + \zeta_{it} \end{aligned} \tag{5.7}$$

In Table 5.5, the coefficient of the interaction term between the treatment effect and PNR is significantly positive in Model 1 ($\beta = 0.020$, $p < 0.01$). In Model 2, the interaction term between the treatment effect and CNR is also significantly positive ($\beta = 0.017$, $p < 0.01$). These results provide empirical support that automakers' noncompliance ratio in both the product and credit markets significantly enhance the incentivizing effect of the dual-credit policy on their production of excessive fuel consumption ICEVs.

Table 5.5. Firm heterogeneity in the impact of the dual-credit policy

	Dependent variable: the logarithm of the production volume of ICEV model years	
	Model 1	Model 2
Treatment effect considered, $T_t \times D_i$	0.733** (0.302)	0.748** (0.302)
PNR_{it}	-0.006 (0.006)	
Treatment effect considered $\times$ PNR_{it}, $T_t \times D_i \times \mathrm{PNR}_{it}$	**0.020***** **(0.006)**	
CNR_{it}		-0.001 (0.003)
Treatment effect considered $\times$ CNR_{it}, $T_t \times D_i \times \mathrm{CNR}_{it}$		**0.017***** **(0.004)**
Excessive fuel consumption, D_i	0.132 (0.264)	0.118 (0.264)
Normalized fuel consumption, FC_{it}^*	21.31** (9.649)	21.45** (9.671)
Normalized fuel consumption $\times$ Treatment effect considered, $FC_{it}^* \times T_t \times D_i$	24.22* (13.41)	24.03* (13.43)
Normalized fuel consumption $\times$ Excessive fuel consumption, $FC_{it}^* \times D_i$	-39.24*** (11.43)	-39.28*** (11.45)
Post-treatment period, T_t	-0.667*** (0.235)	-0.672*** (0.236)
Normalized fuel consumption $\times$ Post-treatment period, $FC_{it}^* \times T_t$	-31.67*** (10.92)	-31.83*** (10.94)
Curb weight	-0.002***	-0.002***

	(0.000)	(0.000)
Size	0.392***	0.394***
	(0.053)	(0.053)
Price	0.012***	0.012***
	(0.004)	(0.004)
ICEV class fixed effects	Included	Included
Automaker type fixed effects	Included	Included
Constant	4.114***	4.120***
	(0.421)	(0.413)
Observations	3771	3771
R^2	0.1441	0.1429

Notes: 1) * p<0.05, ** p<0.01, *** p<0.001; 2) The numbers in parentheses represent the t values of the corresponding coefficients or constants; 3) The sample size is the number of observations within the optimal bandwidth around the cutoff, where the bandwidth is selected automatically using the Calonico-Cattaneo-Titiunik (CCT) method based on the minimum mean squared error (MSE) criterion; 4) ICEV classes include sedans, SUVs, and MPVs; 5) Automaker types include domestic automakers, foreign automakers, and joint ventures.

5.7. Conclusions and Discussions

This study examines Chinese automakers' technology choices and production decisions regarding ICEVs in the context of the dual-credit policy. To empirically assess the policy's impact, we employ a difference-in-discontinuities (DiDC) design as a quasi-natural experimental approach. The results from our baseline model provide robust causal evidence that the implementation of the dual-credit policy has unintentionally incentivized the production of ICEVs with excessive fuel consumption. This finding is consistent with prior theoretical research suggesting that market-based deployment policies, when applied in the presence of distorted market signals, may produce unintended outcomes that diverge from their original policy objectives.

For example, Betz and Sato (2006) observe that in the first phase of the EU Emissions Trading System (EU ETS), the free allocation of carbon allowances across industries undermines the effectiveness of the market mechanism. Similarly, Kill et al. (2010) argue that overly generous emissions caps lead to a surplus of carbon credits, thus driving down carbon prices and weakening firms' incentives to invest in emission-reduction technologies. Similar concerns have also been raised in theoretical analyses of the dual-credit policy. For instance, Chen et al. (2025), using an agent-based modeling (ABM) approach, demonstrate that an imbalance in market power between NEV manufacturers and conventional ICEV manufacturers can lead to lower-than-expected credit prices. As a result, the policy fails in up to 70% of the simulated scenarios.

Second, the moderating effect results show that the dual-credit policy has an even stronger impact on promoting the production of excessive fuel consumption ICEVs among automakers with higher product market or credit market noncompliance ratios. This finding is consistent with two widely recognized drivers of corporate noncompliance identified in the literature, namely, the tendency to cater to consumer preferences and the desire to avoid excessive compliance costs.

Specifically, from the demand-side perspective, previous studies suggest that when firms are forced to balance regulatory compliance and profitability, they often prioritize consumer preferences such as price and performance even at the expense of compliance (Bennett et al., 2013). In this study, a higher product market noncompliance ratio reflects stronger market performance of excessive fuel consumption ICEV model years within an automaker's product portfolio. Accordingly, the compliance flexibility introduced by the dual-credit policy incentivizes these firms to further expand the production of such fuel inefficient models.

From the supply-side perspective, firms with limited technological capabilities or insufficient R&D capacity often face high costs in upgrading fuel efficiency of ICEVs (Hausberger, 2011). Our findings show that firms with a higher level of credit market noncompliance ratio are more likely to respond to the dual-credit policy by producing more noncompliant ICEVs and offsetting their deficits through NEV credit purchases, rather than engaging in costly technological upgrades.

This study offers critical practical implications for corporate managers. Our findings show that market-based deployment policies implemented under weak regulatory enforcement and distorted price signals might lead to increased production of outdated technologies. Thus, we suggest that corporate managers should be fully aware of the strategic risks embedded in such compliance flexibility of market-based deployment policies. Specifically, compliance arbitrage should not be regarded as a viable long-term solution for sustainable development. Instead, firms should seize the current policy window to initiate forward-looking technological upgrades to build sustained competitive advantages in the future market.

Besides, this study also offers important implications for policy makers. Our main results indicate that, in the design and implementation of market-based deployment policies, the absence of effective price regulation mechanisms and strict regulatory oversight can lead to backfire effects. To address this issue, policymakers should consider two key areas of improvement in the design of market-based deployment instruments. First, the mechanism for determining credit prices should be optimized. A more efficient credit trading system should be established to prevent abnormal price fluctuations or persistently low credit prices, thereby enhancing the signaling and incentive functions of credit pricing. Second, regulatory oversight mechanisms should be reinforced. A more comprehensive system is needed to enhance data verification in critical areas such as credit accounting, product technical specifications, and corporate compliance practices. Enhanced transparency and scrutiny can help prevent firms from manipulating data that undermine the policy's intended effects.

Our moderating effect results suggest that such backfire effects of market-based deployment policies are more pronounced among firms disadvantaged in technological transitions, whether in the product market or the credit market. This underscores the need for targeted regulation and differentiated policy support for firms in the design and implementation of market-based deployment policies. Specifically, policymakers should account for technological performance and market performance of different firms. Such tailored support can guide lagging firms to participate more effectively in the technological transitions.

Chapter 6 Conclusions

6.1 Summary of Study Findings

Grounded in the multi-level perspective (MLP), in the context of the transition from ICEVs to EVs in China's automative industry, this thesis explores corporate strategies under factors in different levels of technological transitions. The major findings and conclusions drawn from this thesis are as follows:

(1) Major findings and conclusions of Study 1

At the niche level, Study 1 employs a structural demand estimation model to systematically quantify the impact of driving range on EV market demand. Besides, it examines how the availability of charging infrastructure shapes customer preference for EV driving range. The results show that the average EV driving range elasticity is 1.447, indicating a high level of consumer sensitivity to changes in this technical specification. Furthermore, the analysis uncovers a counterintuitive complementarity between EV driving range and charging pile density in determining market demand. To further uncover the underlying mechanism of this complementary effect, our supplementary analyses indicate that charging pile density indirectly shapes driving range elasticity by influencing customer preferences for different vehicle classes (i.e., subcompact, compact, medium, and large).

(2) Major findings and conclusions of Study 2

At the regime level of technological transitions, Study 2 investigates how firms' participation in incumbent technology standardization affects their subsequent participation in emerging technology standardization. It further explores how this relationship is moderated by the extent of firms' technological and network diversification within incumbent standardization activities. Analyzing longitudinal data from 217 automotive manufacturers and 466 automotive technology standards from 2000 to 2023, we find that a high level of participation in incumbent technology standardization faciliates rather than hinders participation in emerging technology standardization. Besides, we find that this positive effect is negatively moderated by the degree of technological diversification within incumbent technology standardization, whereas network diversification does not exhibit a significant moderating effect.

(3) Major findings and conclusions of Study 3

At the landscape level, Study 3 investigates automakers' technology choice and production strategies in response to the dual-credit policy, which is a representative market-based deployment instrument introduced by the government during technological transitions. Based on a quasi-natural experimental Difference-in-Discontinuities (DiDC) approach, this study shows that the dual-credit policy has reinforced the production of fuel-inefficient ICEVs. Besides, further firm-level heterogeneity analysis reveals that this effect is more pronounced among firms with higher product market or credit market noncompliance ratios.

6.2 Research Implications

6.2.1 Theoretical Implications

The theoretical implications of the three studies are briefly summarized as follows:

Study 1 advances the literature on technology design during technological transitions by moving beyond the traditional reliance on stated preference data. It introduces an innovative structural demand estimation approach based on real market data. This method not only strengthens the external validity of the findings but also offers a more practical and generalizable empirical tool for future research on consumer preferences regarding the design of emerging technologies. In addition, this study also examines product technical specification during technological transitons in the context of a broader technological ecosystem, with particular attention to the role of complementary products. While the ecosystem perspective has been widely recognized as a framework for understanding firm strategies during technological transitions since Teece (1986), most prior research has concentrated on technology selection and licensing decisions. In contrast, limited research has applied the ecosystem perspective to product technical specification designs. This study addresses this gap by firstly providing empirical evidence on how the attributes of complementary products influence consumer preferences for key technical specifications of focal products. In doing so, it advances the integration of ecosystem theory and technology design, offering a novel perspective for cross-disciplinary research in these fields.

Study 2 extends prior research on technology standardization by moving beyond its prevailing static perspective and highlighting the path-dependent nature of firm participation. Specifically, it shows that participation in incumbent technology standardization does not necessarily lead to technological inertia during technological transitions. Instead, such participation can strengthen firms' capacity to participate in emerging technology standardization by facilitating the accumulation of critical resources through standardization networks. It enriches our understanding of how firms dynamically adapt to technological transitions. Furthermore, this study uncovers a negative moderating effect of technological diversification within incumbent technology standardization in such path-dependence effect. This finding challenges the dominant view of diversification as an inherently positive asset and extends our understanding of its long-term strategic implications by highlighting the potential for strategic inertia arising from diversified technology standardization paths.

Study 3 contributes to the growing literature on corporate strategies under market-based deployment policies during technological transitions. While existing research has largely relied on theoretical modeling and numerical simulations, empirical evidence based on firms' actual behaviors remains limited. There is still ongoing debate about the effectiveness of such policies in driving firms' technological renewal. Contributing to this debate, our study is the first to offer empirical evidence on the incentive effects of market-based deployment policies on corporaote technology choice and production decisions in real-world contexts. Besides, this study innovatively incorporates firm heterogeneity into the analysis of market-based deployment policy effects. Our findings suggest that differences in firms' resource endowments and market structures play a critical role in shaping their policy responses. This sheds light on future research accounting for the systematic heterogeneity across firms when evaluating the effects of market-based policies.

6.2.2 Managerial Implications

The managerial insights of the three studies are briefly summarized as follows:

In Study 1, our estimated driving range elasticities offer a data-driven foundation for firms to make informed EV design decisions. This study enables EV automakers to integrate range responsiveness with battery cost considerations to optimize model configurations across market segments. The moderating role of charging pile density further suggests that automakers should tailor their product design strategies to local charging infrastructure conditions. Specifically, in cities with a higher level of charging pile density, automakers should prioritize launching mid- to large-sized EV models with superior range performance to fully capture market potential. In contrast, in markets where charging infrastructure remains underdeveloped, excessively extending driving range is unlikely to generate cost-effective outcomes.

Study 2 underscores the strategic value of technology standardization as a key mechanism for firms to navigate technological transitions. Specifically, we suggest that managers should encourage active firm participation in standardization activities since they can acquire critical resources to adapt to technological transitions from strandardization networks. Moreover, firm managers should remain cautious of the inertia that technological diversification within incumbent technology standardization may generate during technological transitions. While diversification can enhance firms' competitiveness within existing technological trajectories, it may also lock firms into established paths and reduce their responsiveness to emerging technological trajectories. Therefore, when pursuing diversified development within incumbent technologies, managers should simultaneously reserve sufficient exploratory capacity for the research, development, and standardization of emerging technologies.

Study 3 highlights the strategic importance for corporate managers to recognize the potential risks embedded in the compliance flexibility of market-based deployment policies during technological transitions. Managers should avoid relying on short-term compliance arbitrage strategies, as such practices may undermine long-term competitiveness and sustainable growth. Instead, firms should proactively leverage the current flexible market-based policy environment to pursue forward-looking technological upgrades and capability development. Besides, for policy makers, we suggest that they should enhance the design of market-based deployment instruments by improving the efficiency of credit pricing mechanisms and strengthening regulatory oversight. Furthermore, policymakers should provide differentiated regulatory and policy support to technologically lagging firms, as they are more susceptible to the backfire effects of market-based deployment policies.

6.3 Limitations and Future Research Directions

The limitations of this thesis that pave the way for future research are summarized as follows:

First, while this thesis adopts the MLP and comprehensively incorporates factors from all three levels to examine their influences on corporate strategies during technological transitions, the scope of factors within each level remains limited. For analytical clarity and data availability, only the most representative factors were selected. Future research could include additional dimensions like managerial cognitions (Kiesler & Sproull, 1982; Kaplan & Tripsas, 2008; Nadkarni & Barr, 2008). For instance, in the context of Study 2, firms' cognitive perceptions of emerging technologies could significantly affect their participation in emerging technology standardization.

Second, the analysis focuses on the technological transition in China's automative industry, which may constrain the generalizability of the findings. China's automative industry provides a valuable context for examining corporate strategies during technological transitions, given its representative market scale and strong policy support. However, differences exist across countries in terms of institutional settings, consumer preferences, infrastructure development, and technological evolution paths. Therefore, future research could extend this framework to other countries or regions to verify and enrich the findings of this thesis.

Third, due to data availability, although this thesis identifies and provides preliminary evidence for the mechanisms through which customer preferences and policy factors influence firms' strategic responses during technological transitions, the analyses are not sufficiently comprehensive. For instance, in Study 1, another potential mechanism underlying the relationship between driving range and charging pile density lies in the availability of alternative business models such as battery swapping. When the density of charging infrastructure is low, consumers may mitigate range anxiety by adopting battery-swapping services. This substitution effect reduces consumers' dependence on driving range as a key decision criterion, thereby weakening the sensitivity of their vehicle choice to range performance. Investigating the impact of charging pile density on the sales of EV models with battery swapping could provide fresh insights.

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