High-Speed Rail and China's Electric Vehicle Adoption Miracle[†]

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Abstract

Using China's expansion of the high-speed rail system (HSR) as a quasi-natural experiment, we analyze the comprehensive vehicle registration data from 2010 to 2023 to estimate the causal impact of HSR connectivity on the adoption of electric vehicles (EVs). Implementing several identification strategies, including staggered difference-in-differences (DID), Callaway and Sant'Anna (CS) DID, and two instrumental-variable approaches, we consistently find that, by alleviating range anxiety, the expansion of HSR can account for up to one third of the increase in EV market share and EV sales in China during our sample period, with effects particularly pronounced in cities served by faster HSR lines. The results remain robust when controlling for local industrial policies, charging infrastructure growth, supply-side factors, and economic development. We also find that HSR connectivity amplifies the effectiveness of charging infrastructure and consumer purchase subsidies in promoting EV adoption.

Keywords: Electric Vehicles; High-Speed Rail; Industrial Policy

JEL Code: L52, L53, O18, Q55, R41

1 Introduction

During the past decade, countries around the world have elevated the development and adoption of electric vehicles (EVs) to a central position in their strategies to reduce greenhouse gas emissions and advance energy transition goals (Michalek et al., 2011; Holland et al., 2016, 2019; Gillingham and Stock, 2018; Gillingham, Ovaere, and Weber, 2025).[1] Surprisingly, China emerged as the global leader, miraculously achieving a market share of up to 45% for EVs among new vehicle purchases in 2024, compared to 25% in Europe and 11% in the United States.

Although subsidies and industrial policies are widely credited for China's EV success, the critical role of complementary transportation infrastructure investments is often underexplored. More specifically, range anxiety, a key factor influencing consumer decisions on EV adoption, can be mitigated either directly through improvements in battery capacity and the expansion of charging facilities, or indirectly by offering seamless alternative transportation options for long-distance travel. While most countries focus on the advancement of battery technology and the expansion of charging networks, the potential of alternative transportation infrastructure to accelerate the EV adoption remains largely overlooked.

In this paper, we empirically examine the hypothesis that the rapid expansion of China's high-speed rail (HSR) system since 2008 serve as a *complement* to EVs, providing an efficient solution for medium- to long-distance travel and addressing the range anxiety of EVs, thus accelerating the EV adoption. Reflecting this strategic complementarity, China's EV market share expanded from near zero in 2010 to around 25% (excluding hybrid vehicles) in 2023, alongside the rapid expansion of its HSR network, which exceeded 45,000 km in the same year, as shown in Panel A of Figure 1. In this study, we examine the causal relationship between China's HSR expansion and EV adoption to understand the role of transportation infrastructure in the advancement of sustainable mobility.

[Figure 1 About Here]

Recent tariffs by the United States and the European Union targeting China's EV industry reflect the intensification of competition in the global EV market.[2] Many countries criticize China's subsidies and industrial policies, but attributing her dominance in

[1]According to the International Energy Agency (2024), governments in major markets have escalated their commitments by raising EV adoption targets and investing heavily in supply chains for vehicles, batteries, and critical minerals, with combined global spending on EVs surpassing USD 400 billion in 2022.

[2]On September 13, 2024, the United States announced a 100% tariff increase on Chinese EV imports, citing the need to protect strategic domestic industries from what it perceives as unfair competition. Similarly, on October 30, 2024, the European Commission imposed a five-year anti-subsidy duty on Chinese EV imports, claiming that government support has provided Chinese manufacturers with a competitive advantage.

the EV market solely to these factors oversimplifies a complex situation. In fact, monetary incentives—such as tax credits (Beresteanu and Li, 2011; Sallee, 2011; Li et al., 2017; Jenn, Springel, and Gopal, 2018), rebates (DeShazo, Sheldon, and Carson, 2017), and price subsidies (Springel, 2021)—alongside nonmonetary drivers such as technological innovation (Forsythe et al., 2023), rising gasoline prices (Beresteanu and Li, 2011), and expanded charging infrastructure (Levinson and West, 2018), can significantly enhance the EV adoption. However, these factors are neither unique to China nor sufficient to explain its rapid rise as the world leader in the production and sales of electric vehicles. For example, despite implementing comparable subsidy programs, the United States and Europe continue to lag far behind China in EV adoption rates. This raises several questions: What unique factors distinguish China's EV market? How do these factors interact with industrial policies to shape market dynamics and consumer behavior? Examining these interactions is the key to understanding the rapid expansion of the Chinese EV industry.

China's HSR network has several unique features that offer a valuable opportunity to address these questions. First, as the largest and one of the world's fastest HSR systems, it offers unparalleled connectivity, enabling people to travel conveniently to nearly any city in the country. This extensive and well-integrated network serves as a reliable complement to EVs, alleviating range anxiety by offering an efficient option for medium to long-distance travel. Second, the gradual expansion of HSR across cities allows a staggered Difference-in-Difference (DID) approach to evaluate its causal impact on EV adoption. Third, the significant variation in HSR characteristics across cities, including network length, number of lines, and train speeds, provides a valuable opportunity to examine the heterogeneity in the impacts of HSR connectivity. Together, these features make China's HSR network an ideal setting for investigating the causal relationship between infrastructure development and EV adoption.

Our analysis is based on a city-month panel dataset comprising new and pre-owned vehicle registrations and insurance records from 328 prefectural cities in China, covering the period from 2010 to 2023. Our primary identification strategy employs a staggered DID approach, leveraging the variation in the timing of HSR introduction across cities as a quasi-natural experiment. Specifically, we compare changes in EV market share and sales before and after HSR implementation in treatment cities (those newly connected to HSR) with those in control cities (those not yet connected). We also account for time-varying factors and city-specific characteristics that may confound the results. Our results show that HSR connectivity significantly increases EV market share and sales (volume), with average increases of 1.22 percentage points and 91.39%, respectively. Using the Callaway and Sant'Anna DID (CSDID) estimator (Callaway and Sant'Anna, 2021), which addresses concerns about treatment effects varying over time and/or across cohorts, we continue to observe robust and consistent results. Our dynamic analysis further validates the parallel pre-trends assumption, showing no significant differences in EV market share between treatment and control cities before HSR introduction; moreover, following HSR connectivity, a significant treatment effect emerges, with EV market share increasing by 1 percentage point initially and growing to 3.7 percentage points over time, reflecting sustained and intensifying growth.

To further address potential endogeneity concerns in estimating the impact of HSR connectivity on EV adoption, we complement the DID framework with an instrumental variable (IV) approach. The IV approach employs two plausible instruments for a city's HSR connectivity: first, the historical railway network from 1962, reflecting centralized planning objectives unrelated to modern transportation needs; and second, the least-cost straight-line network, which captures geographic and cost-driven variations in HSR connectivity. These instruments are strongly correlated with the timing of a city's HSR development, but are plausibly unrelated to unobserved factors that may affect EV adoption, satisfying the relevance and exclusion restriction criteria for valid IVs. By isolating exogenous variation in HSR expansion, the IV approach also reveals a significant and positive causal relationship between HSR connectivity and EV adoption. We also implement an alternative IV estimate using the Borusyak and Hull (2023) approach, where we replace the binary HSR treatment indicator by the associated growth in "market access" from HSR expansion; and we also find consistent results.

We then explore the possible competing and/or complementary mechanisms underlying the relationship between HSR connectivity and EV adoption, focusing on local industrial policies, charging infrastructure growth, supply-side factor and regional economic development. We find that consumer purchase subsidies are particularly effective in cities with HSR connectivity, highlighting the complementary role of HSR connectivity and policy support in driving the adoption of EVs. We also find that HSR remains an important driver of EV adoption after controlling for improvements in regional infrastructure, such as EV charging stations and road upgrades, as well as the entry of EV manufacturers and car dealerships. In addition, we find a positive interaction effect between HSR connectivity and charging infrastructure, which suggests that HSR connectivity amplifies the impact of charging stations on EV adoption.

This paper directly contributes to two main strands of literature. First, it adds to the growing literature on the EV market. Monetary incentives, such as purchase subsidies, tax exemptions, and rebates, have been extensively analyzed for their effectiveness in promoting EV adoption (Sallee, 2011; Gallagher and Muehlegger, 2011; Huse and Lucinda, 2014; Li et al., 2017; Gulati, McAusland, and Sallee, 2017; Jenn, Springel, and Gopal, 2018; Springel, 2021; Xing, Leard, and Li, 2021; Armitage and Pinter, 2021; Muehlegger and Rapson, 2022; Remmy, 2024; Barwick et al., 2023; He et al., 2023; Guo and Xiao, 2023). Non-monetary incentives, which reduce the marginal cost of EV usage, have also been shown to play a significant role (Li et al., 2022; Liu et al., 2023). Examples of non-monetary incentives include benefits such as free parking, toll reductions, exemptions from green license plate fees, access to bus and high-occupancy vehicle (HOV) lanes, exemptions from driving and purchasing restrictions (which is particularly relevant in China), and improvements to charging infrastructure (Bakker and Trip, 2013; Hackbarth and Madlener, 2013; Ajanovic and Haas, 2016; Wang, Pan, and Zheng, 2017; Ma, Fan, and Feng, 2017; Li et al., 2017; Jenn, Springel, and Gopal, 2018; Li, 2023; Springel, 2021; Dorsey, Langer, and McRae, 2022; Fournel, 2023; Li, Walls, and Zheng, 2023; Tian, 2024). Beyond these incentives, other studies have examined the effects of gasoline prices and regulatory bans on gasoline vehicles, which are increasingly shaping the EV market (Beresteanu and Li, 2011; Allcott and Wozny, 2014; Forsythe et al., 2023). Davis (2023) documents that EVs overwhelmingly tend to be in multi-vehicle households in the United States, presumably because many households perceive EVs to suffer from range limitations and the ability to substitute them with gasoline-powered vehicles for longer trips alleviates such concerns. Thus, the gasoline-powered vehicle serves as a complement to EVs to alleviate concerns about range limitations. Our paper is unique in that it examines the impact of China's high-speed rail system, which was planned before the EV take-off, thus not specifically designed as a policy to accelerate the adoption of EVs. Our findings underscore the potential complementarity between the high-speed rail system and EV adoption by addressing critical barriers such as range anxiety. In addition, Davis (2019) find that in multi-vehicle households, electric vehicles are driven considerably fewer miles per year on average than gasoline- powered vehicles, which undermines the environmental benefits of EVs. The wide availability of HSR in China provides a cleaner antidote to range anxiety associated with EVs than gasoline-powered vehicles. Our findings thus offer valuable lessons for the design of integrated strategies to accelerate EV adoption and foster more environmentally sustainable transportation systems around the world.

Second, this study contributes to the large body of literature on the economic impacts of HSR. Extensive research has highlighted the social and economic benefits of transportation infrastructure, such as roads and railways, examining their effects on urban growth, spatial structure, congestion reduction, and trade costs (Baum-Snow, 2007; Duranton and Turner, 2011, 2012; Zheng and Kahn, 2013; Faber, 2014; Baum-Snow et al., 2017; Donaldson and Hornbeck, 2016; Donaldson, 2018). Within this body of research, HSR stands out as a transformative mode of transportation with wide-ranging effects. Studies have documented its role in improving intercity mobility (Chen, 2012; Tierney, 2012), promoting market integration (Zheng and Kahn, 2013), reducing greenhouse gas emissions (Guo et al., 2020; Lin et al., 2021; Barwick et al., 2024), fostering economic development through increased population density, employment opportunities, and improved access to the labor market (Levinson, 2012; Lin, 2017; Ahlfeldt and Feddersen, 2018), and improving competition and quality of service in the airline industry (Fang, Wang, and Yang, 2024). Research also suggests that HSR disproportionately benefits larger cities, strengthening their economic ties while offering limited benefits to smaller or less developed regions (Qin, 2017). This study expands our understanding of the broader economic and environmental impacts of HSR by examining its underexplored role in facilitating EV adoption. The findings highlight the potential of HSR to accelerate sustainable mobility transitions, offering key policy insights on optimizing HSR investments to maximize both economic and environmental benefits.

The remainder of the paper is organized as follows. Section 2 provides an overview of the EV industry and the HSR network in China; Section 3 details the datasets and presents summary statistics; Section 4 describes the empirical strategies and reports the main findings; Section 5 explores the potential competing and/or complementary mechanisms driving the results; Section 6 conducts robustness checks and heterogeneity analysis; Section 7 concludes.

2 Background

2.1 China's EV Market and Policy Evolution

During the past decade, China's EV industry has undergone several stages of development, driven by a combination of technological progress, market forces, and supportive initiatives. Early R&D initiatives and pilot programs, such as the "*Ten Cities, Thousand Vehicles*" launched in 2009, provided the early momentum for consumer awareness and adoption. Between 2013 and 2015, purchase subsidies and tax incentives, which mainly targeted public institutions and buses, began to increase the visibility of EVs among private consumers in first-tier cities. Tesla's entry into the Chinese market in 2014 further sparked public interest and strengthened the development of the domestic supply chain for EV production. Although overall sales remained relatively modest during this period, these factors helped generate consumer interest, promote competition, and lay the foundation for the development of the industry.

Between 2016 and 2018, a strategic reduction in government fiscal support marked a shift toward fostering market competition and technological innovation, redirecting the focus from subsidies to a more sustainable, market-driven growth model. In 2018, China's EV sales exceeded one million units. We show that during this period, China's continued expansion of its HSR network had an unintended impact on consumers' EV adoption. The availability of convenient HSR routes for medium- to long-distance travel redefined the role of personal vehicles, with many consumers focusing on their EV use for daily commuting and short-distance trips. This shift in travel patterns fostered a supportive environment for the adoption of EVs, particularly models with moderate battery range, in areas where both HSR and urban charging infrastructure were well established.

From 2019 to 2021, improvements in vehicle range and technology contributed to the growing appeal of EVs. Combined with improving affordability and the continued rollout of public charging stations, these advancements helped push China's annual EV sales to three million units in 2021. At the same time, HSR continued its nationwide expansion, reinforcing the idea that many medium- and long-distance trips could be handled by trains, thereby making EVs an increasingly practical choice for everyday mobility. By 2022, China's EV market had begun to mature, with production reaching 7.06 million units and sales 6.89 million units, and EVs accounted for almost a third of new vehicle sales. In 2024, EVs accounted for 45% of all new car sales in China. As subsidies were phased out, infrastructure development, such as charging networks and battery-swapping facilities, supported the growth of the EV sector. The shift from subsidy-driven to market-driven dynamics, driven by competition, technology, and HSR-influenced consumer preferences, transformed the industry into a competitive and technologically advanced global leader in EV production and adoption.

2.2 HSR Network in China

Over the past two decades, China's HSR network has emerged as the largest and most extensively utilized HSR system in the world, accounting for more than 70% of the global HSR mileage. Operating at speeds of 250 to 350 kilometers per hour, the network has expanded significantly in both geographic reach and service capacity. By the end of 2023, the HSR network spanned 45,000 kilometers, connecting 96% of the cities that have populations exceeding 500,000. Our dataset covers comprehensive details on network coverage, line lengths, and connectivity attributes. In addition to this, the conventional railway system extends 160,000 km, ensuring connectivity to 99% of all cities with populations greater than 200,000.[3] China now leads the world in operational mileage, ongoing construction scale, the number of high-speed trainsets in service, and commercial operating speeds.

The rapid expansion of China's HSR network has been a cornerstone of the country's broader strategy to modernize transportation infrastructure, improve regional accessibility, and promote economic integration. Structured under the "Eight Vertical and Eight Horizontal" framework, the network consists of eight north-south and eight east-west corridors designed to connect major cities and facilitate the flow of people and goods across key economic regions. This framework is part of the Long-Term Railway Network Plan, initiated in the early 2000s and updated every five years to align with evolving economic and de-

[3] Source: https://www.gov.cn/yaowen/liebiao/202401/content_6925054.htm

mographic priorities. By 2023, 80% of the planned "Eight Vertical and Eight Horizontal" HSR corridors were operational, reflecting substantial progress in achieving the network's strategic development goals. Figure 2 presents the geographic expansion of the HSR network between 2003 and 2023.

[Figure 2 About Here]

3 Data and Summary Statistics

3.1 Vehicle Sales Data

Our analysis utilizes a city-month-level panel dataset of vehicle sales, including both new and pre-owned, spanning January 2010 to December 2023 in 328 prefectural cities. The data from 2010 to 2015 are derived from official vehicle registration records, while data from 2016 to 2023 are sourced from Compulsory Traffic Accident Liability Insurance records. This panel dataset provides comprehensive information on sales volumes and market shares by powertrain type, capturing spatial and temporal dynamics in market trends.

In this paper, we classify vehicles into three categories: pure battery-powered EVs, fuel-powered vehicles (referred to as fuel vehicles or FVs), and hybrid vehicles. Our primary focus is on how HSR alleviates range anxiety for potential EV buyers; hybrid vehicles's dual-fuel capability significantly reduces range anxiety, making HSR less relevant as a complementary transportation option for these vehicles. As such, only pure battery-powered vehicles are classified as EVs in the baseline analysis.[4]

We use two primary measures to evaluate the adoption of a specific type of vehicle: sales volume and market share. Sales volume is defined as the total number of units sold for the vehicle type within each city-month cell, while market share is calculated as the percentage of the vehicle type's sales relative to the total vehicle sales in the same city-month cell. Panels A and B of Table 1 present the summary statistics for the adoption measures at the city-month level, both for the full sample of 328 cities and for a subsample that excludes cities connected by HSR before 2015. Figure 1 presents trends in the EV market share and its relationship with HSR connectivity. Panel A shows the national trajectory of EV adoption along with the expansion of HSR from 2010 to 2023, with EV data derived from the China Stock Market & Accounting Research (CSMAR) database.[5] The EV market share remained negligible until 2015, followed by a gradual increase through the late 2010s and a sharp acceleration after 2020. Meanwhile, the HSR network expanded steadily over the entire

[4]To ensure the robustness of our findings, we include hybrid vehicles as a placebo test in Section 6 to provide further validation and consistency of the results.

[5]https://data.csmar.com/.

period, showing consistent linear growth. Panel B examines the market share of EVs in cities according to the timing of their HSR connections, based on the vehicle sales data used in our analysis. Cities with earlier HSR connections saw earlier and more sustained adoption, while those connected later exhibited a delayed but comparable rise. Cities without HSR connectivity experienced slower growth, with a noticeable increase only after 2020. These patterns suggest that HSR connectivity plays a role in accelerating EV adoption, with the timing of connection influencing the pace of growth.

[Table 1 About Here]

3.2 Supplementary Data Sets

To investigate several competing and/or complementary mechanisms, we collect additional data sets that capture both demand and supply side factors. Specifically, we examine whether the registrations of EV-related firms and the improvements in regional infrastructure, such as enhanced road networks and expanded EV charging stations, contributed to the increase in EV market share. The data set for EV charging facilities contains the geographic locations of charging stations across China and is constructed using historical map data from Gaode Maps, covering the period from 2010 to 2023.[6] From the Gaode Maps platform, we systematically extract the geographic coordinates of key points of interest (POIs) associated with EV charging stations in each city using geographic information system (GIS) techniques. This allows us to further construct a detailed city-year panel dataset that captures the temporal and spatial evolution of EV charging infrastructure in China's major urban areas. Figure 3 illustrates the expansion of China's EV charging infrastructure and road network from 2010 to 2023. The expansion of charging stations has been steady but accelerated markedly after 2018, with the most significant growth observed in 2018, when the number increased by over 300%, rising from 5,952 in 2017 to 23,869 in 2018. The number of charging stations in the 328 sample cities grew significantly from 3,277 in 2015 to 74,469 in 2023, suggesting the possible role of the rapid expansion of charging infrastructure in support of the adoption of EVs.[7]

[Figure 3 About Here]

To account for regional variations in road infrastructure investments over time, we compile a comprehensive city-year level dataset of road network information for the period 2010–2023.

[6] Gaode Maps (https://www.amap.com/) is a leading electronic mapping service provided by Gaode Software Co., Ltd., widely recognized as one of the most prominent map services in mainland China.

[7] Each charging station typically consists of multiple charging *piles* and functions as a designated facility for recharging EVs. By 2023, China had more than 8 million charging piles nationwide.

Covering 328 cities at the prefecture level, this dataset is sourced from the China Statistical Yearbook, the China City Statistical Yearbook, and various provincial and municipal statistical yearbooks. It includes granular information on road types, lengths, and network connectivity, classified into highways, national roads, local roads, and graded versus ungraded roads. Figure 3 also illustrates that the length of China's road network increased steadily and consistently throughout the period.

In addition, to analyze supply-side responses, we use firm registration data from the Chinese State Administration for Industry and Commerce (SAIC). The firm registration data includes almost the universe of registered firms in China from the founding of the People's Republic of China.[8] This dataset provides detailed firm-level information, including geographic location, years of establishment and exit (if applicable), registered capital, etc. We construct city-month level (cumulative) counts of the EV manufacturers and car dealerships to control for the supply-side effects. Lastly, to capture regional economic and demographic dynamics that may shape the EV adoption, we collect city-year data on GDP, population growth, and local fiscal expenditure for the period 2010–2023 from the China City Statistical Yearbook. The summary statistics for these variables are presented in Panel C of Table 1 and Appendix Table A1.

3.3 Industrial Policy Data

It is important to consider the role of various government policies that may have played an important role in both the development of the EV industry and the adoption of EVs. We use systematic coding of industrial policies using large language models (LLMs) based on government documents from Fang, Li, and Lu (2024), from which we extract 15,513 industrial policies targeting the EV industry for the period from 2010 to 2022. For each policy document, the dataset includes detailed information on the issuing government (including central, provincial, or city), policy tone (supportive, regulatory, or discouraging), classification of policy tools (see below for details), and other relevant attributes. Among the 15,513 industrial policy documents related to EVs, 2,045 were issued by the central government, 5640 by provincial governments, 7,413 by city-level governments, and 389 by county- or township-level governments. Since we focus on city-level variations in EV adoption rates in this paper, it is natural to incorporate only the 7,413 industrial policy documents issued by city-level governments; in particular, we focus on 6,476 of the 7,413 policy documents issued

[8] The firm registration data has been used in many studies. See, e.g., Fang et al. (2024) for a detailed description of the dataset.

by city-level governments that have a supportive tone.[9, 10]

To investigate the mechanisms through which the HSR network interacts with industrial policies, we separately analyze *demand*- and *supply*-side policy tools. Demand-side policies are classified into three types: *consumer incentives*, such as purchase subsidies and sales tax reductions; *public procurement* by government agencies or public institutions; and government-sponsored *trade fairs* and promotional events. On the supply side, we identify four policy tools: *R&D* policies (which promote technology development through subsidies, tax benefits, and public-private partnerships); *investment* policies (which aim to attract foreign and regional investment); *industrial cluster* policies (which promote supply chain integrations through special economic zones); and *entry promotion* policies (which include market regulations, entrepreneurship incentives, and other measures to improve the business environment). In our empirical analysis below, we will examine the effects of these city-level industrial policies on EV adoption, particularly their interaction effects with HSR connectivity.

4 Empirical Methods and Results

4.1 Identification Challenges and Strategies

One of the main objectives of this paper is to estimate the effect of HSR connectivity on EV adoption. However, establishing causality is challenging due to the omitted variable bias and reverse causality. The omitted variable bias arises when unobserved factors, such as local consumers' preferences for clean environment, can simultaneously lead to greater HSR investment and higher EV adoption. For example, cities experiencing rapid economic growth and launching new infrastructure projects may simultaneously build HSR lines and witness rising EV usage due to higher incomes and greater environmental awareness. Reverse causality further complicates identification, as regions with higher EV penetration may indirectly drive demand for HSR development, reflecting preexisting preferences for sustainable transportation or economic characteristics.

For simplicity, we first employ a staggered DID approach as our baseline model. We start with a simple Two-Way Fixed Effect (TWFE) regression, which facilitates a flexible analysis of the impact of control variables on EV adoption and, more importantly, the interaction effects between HSR and key factors such as charging infrastructure expansion

[9]While high-level national initiatives are prevalent during the sample period, we emphasize local actions because market dynamics and consumer behavior are primarily shaped by local policy implementations. Note that national-level policies related to EVs, including consumer purchase subsidies, are effectively captured in our empirical models through time fixed effects.

[10]Figure A1 presents the word cloud generated from the identified EV policy documents, where the size of each word represents its relative frequency within the text.

and industrial policies. However, it is important to note that TWFE estimators can be subject to potential biases in the presence of variation in treatment timing and dynamic treatment effects (Callaway and Sant'Anna, 2021). The issue arises in part because TWFE estimates incorporate already-treated units as part of the control group. To the extent that already-treated units exhibit systematically higher growth in outcomes of interest relative to the yet untreated units, incorporating them as controls can bias point estimates toward zero. This concern is particularly relevant in our setting, as HSR expansion has spanned a long time horizon from 2003 to the present. However, the EV market was virtually nonexisting until 2015, with a market share of just 0.06% in 2014 and less than 0.2% in 2015. By the time the EV market began to develop in 2015, 155 cities were already connected to the HSR network.[11] As illustrated in Figure 1, these cities were the earliest participants in the EV market. Benefiting from more advanced transportation networks, higher consumer awareness, and better infrastructure, they have experienced faster growth in the EV market share over time. If we employ a simple TWFE estimator to implement the staggered DID approach, these early connected cities would be classified as the treated group for the entire market growth period, thus serving as the control group for the later connected cities in the staggered DID design, which can bias the true treatment effect.[12]

To mitigate potential biases inherent in the TWFE estimator and strengthen the robustness of our findings, we employ a comprehensive set of empirical strategies. First, in the baseline analysis, we exclude cities with HSR stations established before 2015, which improves comparability between the treatment and control groups and mitigates the potential bias arising from the inclusion of the always-treated cities as part of the control group. Second, we use the heterogeneity-robust semi-parametric CSDID estimator for staggered treatment timing, as proposed by Callaway and Sant'Anna (2021), to account for variations in treatment effects across city groups and over time. By aggregating treatment effects by event year, the CSDID estimator also allows us to estimate the dynamic treatment effect. Because the CSDID estimator effectively mitigates biases from the dynamic treatment effect, only the always-treated group, i.e. cities connected to HSR before 2010, are excluded from the estimation sample.

In addition, we adopt two alternative empirical strategies to address concerns about the potential endogenous timing of the HSR expansion and to demonstrate the robustness of our results. First, we employ an IV approach that isolates exogenous variation in HSR connectivity, drawing on two well-established instruments in the literature: the historical

[11] Appendix Table A1 provides detailed statistics for three subsamples: 155 cities connected to HSR before 2015; 107 cities connected in and after 2015; and 66 cities not yet connected to HSR. These early connected cities differ considerably from their later connected and unconnected counterparts in terms of local economic conditions, industrial composition, and geographic characteristics (Fang, Wang, and Yang, 2024).

[12] In Appendix A, we follow Goodman-Bacon (2021) and decompose the traditional TWFE estimator into a set of 2-by-2 DID estimators over the entire sample period to illustrate the source of bias.

railway network from 1962 (Baum-Snow, 2007; Duranton and Turner, 2011, 2012; Baum-Snow et al., 2017; Agrawal, Galasso, and Oettl, 2017) and a least-cost straight-line network connecting major target cities (Banerjee, Duflo, and Qian, 2020; Faber, 2014; Hornung, 2015). Using these two IVs to instrument for the HSR expansion over the sample period, we are able to causally identify the cumulative effect of the HSR expansion on EV adoption. Second, we employ an alternative treatment measure by calculating the *"market access"* (MA) growth induced by HSR expansion. MA is a continuous measure of the connectivity of the transportation network, incorporating information on the geographical distribution of economic activities and the reduction in travel time facilitated by HSR; as such, it captures a richer effect than the binary treatment measure of whether the city has been connected to the HSR. Endogeneity concerns may arise due to the non-random selection of HSR stations and the non-random exposure to shocks due to omitted geographic characteristics. As such, we follow Borusyak and Hull (2023) to construct an IV for this measure by recentering the measure around its expectation under a random counterfactual shock assignment process. The recentered treatment measure isolates the variation in HSR-induced MA growth that is not related to unobserved confounders, allowing us to causally identify the impact of HSR-induced MA growth on EV adoption.

4.2 Baseline Results: Staggered DID

We first use a staggered DID approach that takes advantage of the rapid and phased expansion of the HSR network across Chinese cities. This rollout is treated as a plausibly exogenous source of variation in complementary transportation infrastructure. By comparing changes in EV adoption before and after HSR implementation in cities receiving HSR connections to those in cities not yet connected during the study period, we aim to estimate the causal impact of HSR connectivity on EV adoption.

For illustration, consider cities that initially lacked HSR connections, where consumers were concerned about range anxiety due to the limitations of EV battery distance for long trips. Before the introduction of HSR, long travel times and the inability to cover long distances could easily discourage EV adoption in favor of FVs. With the introduction of HSR, travel times are significantly reduced, making long-distance travel more convenient and alleviating range anxiety. In this context, cities with newly established HSR connections can serve as the treatment group, while cities without HSR connections act as the control group. The availability of HSR enables consumers to use EVs for daily short-distance travel while relying on HSR for longer trips. This combination enhances the practicality of EVs, alleviates concerns about limited battery range, and encourages greater EV adoption. HSR acts as a complement to EVs and a substitute for FVs for medium- and long-distance intercity travel. By comparing changes in EV adoption before and after the introduction of HSR in both treatment and control cities, we can estimate the causal impact of HSR on EV adoption.

4.2.1 TWFE Estimation Results

For simplicity, we start with the conventional TWFE model. The regression model is specified as follows:

$$Y_{i,ym} = \alpha + \beta \mathit{Treatment}_{i,ym} + \theta_i + \delta_{ym} + \epsilon_{i,ym}, \tag{1}$$

where $Y_{i,ym}$ represents the share of sales of a specific type of vehicle (i.e., EV or FV) among all vehicles, or the logarithmic sales of that vehicle type, in city i during the year-month period ym; $\mathit{Treatment}_{i,ym}$ is a dummy variable that takes the value 1 if city i has established an HSR connection by year-month ym; θ_i represents city fixed effects, which account for time-invariant unobserved characteristics of each city that could affect EV sales (such as consumer preferences or regional differences in market structure); δ_{ym} represents year-month fixed effects, which control for common shocks or trends that affect all cities during a given period, such as macroeconomic conditions, seasonal effects, or nationwide policies that impact all cities; and $\epsilon_{i,ym}$ is the error term.[13] Standard errors are clustered at the city level to account for potential autocorrelation or heteroskedasticity in the residuals. The main coefficient of interest is β, which captures the differential effect of the introduction of HSR on EV adoption measures in treatment cities compared to control cities.

[Table 2 About Here]

Column (1) of Table 2 presents the results. The coefficient estimate of *Treatment* is positive and statistically significant at the 1% level, indicating that HSR connectivity is associated with a 1.22 percentage point increase in EV market share, providing initial evidence of the impact of HSR connectivity on the adoption of EVs. A 1.22 percentage point increase is significant, as the average EV market share during the sample period was only 4% (as shown in Table 1). Notably, this estimate likely represents a lower bound, as the initial increase in EV adoption facilitated by HSR connections may create a multiplier effect. We will show later in Table 7, that increased EV adoption spurs the development of more charging infrastructure, further accelerating EV adoption in a self-reinforcing cycle.[14]

[13] We do not include province by year-month fixed effects because the connection of HSR often impacts multiple cities in the same province at the same time. Including province by year-month fixed effects would absorb some of the effects of HSR connectivity on EV adoption, leading to a downward bias.

[14] Columns (2)-(6) of Table 2 report the regression results that include various control variables, such as local infrastructure (charging stations and road lengths), the number of EV manufacturers and car dealerships, etc. to further account for possible confounders, which we will discuss in detail in Section 5.

HSR and EV Sales. Column (1) of Appendix Table A2 analyze the impact of HSR connectivity on the natural logarithm of (1+EV sales) (Panel A) and (1+FV sales) (Panel B), respectively. In both cases, the coefficients on *Treatment* are positive and statistically significant at the 1% level, indicating that HSR connectivity significantly boosts vehicle sales. The effect on EV sales is significantly greater, indicating the critical role of HSR connectivity in accelerating EV adoption. Although smaller in magnitude, the positive and significant effect on FV sales indicates that HSR connectivity also drives a general increase in vehicle demand, including both EVs and conventional FVs.

4.2.2 Callaway and Sant'Anna (2021) DID Results

As discussed in Section 4.1, the traditional TWFE estimator may be biased in the presence of heterogeneous or dynamic treatment effects in a staggered rollout design such as ours. To address these issues, we follow Callaway and Sant'Anna (2021) and use the CSDID estimator that allows us to estimate and flexibly aggregate group-time average treatment effects on the treated (ATTs) across multiple treatment groups and time periods. The CSDID procedure is computationally intractable for long panels, so we take the time period t to be a year.

CSDID estimates group-time ATTs separately for each treated cohort and then aggregates them appropriately to obtain an overall treatment effect. Specifically, each city i belongs to a group g that first introduces HSR in year T_g. For each group–time pair (g, t) with $t \geq T_g$, the method estimates a group–time average treatment effect, $\widehat{\text{ATT}}(g, t)$, by comparing the EV market share of cities in group g at time t with that of an appropriate comparison group of cities that have not yet introduced HSR or never did. City and year fixed effects are controlled for. After estimating the group-time ATTs, the overall ATT is obtained by aggregating across treatment cohorts and time periods. This approach avoids the potential bias of standard TWFE regressions, which may fail to account for treatment effect heterogeneity across groups and/or over time.

We report the results in Table 3, with Panel A using the never-treated cities as the control group and Panel B using the not-yet treated cities as the control group. The results in both panels confirm the robustness of our findings. Specifically, Column (1) shows that HSR connectivity increases EV market share by 2.74 to 2.98 percentage points. Columns (2) and (3) confirm that HSR connectivity has positive impacts on both EV and FV sales, but the effect on EV sales is much larger in magnitude. The CSDID method yields larger estimates, consistent with the literature that contrasts it with the conventional TWFE model. In particular, two key factors contribute to these larger estimates: First, the CSDID estimator rectifies the negative weight issue by avoiding the use of already-treated groups as controls, thus reducing the downward bias from this inappropriate control group specification. Second, leveraging the entire sample in the CSDID method allows us to capture the substantial growth in the EV market share among earlier connected cities, which contributes to the larger magnitude of the estimates.

[Table 3 About Here]

4.2.3 Dynamic Effects

We now examine the dynamic response of EV adoption to HSR entry and validate the parallel pre-trend assumption required for the DID estimation. By aggregating the aforementioned group-time-specific ATTs by event year, the CSDID estimator allows us to estimate the dynamic treatment effect. In particular, we define *event time* as $s = t - T_g$, where $s = 0$ denotes the year of HSR introduction, $s < 0$ refers to the pre-treatment (lead) years, and $s > 0$ corresponds to the post-treatment (lag) years. After estimating $\widehat{\text{ATT}}(g, t)$ for each group g and corresponding times $t \geq T_g$, we aggregate these estimates by event time, $s = t - T_g$, to construct a dynamic event-study representation of the effect of HSR on EV adoption. Formally, the dynamic average treatment effect is defined as:

$$\widehat{\text{ATT}}_s \; = \; \sum_{g=1}^{G} w_{g,s} \, \widehat{\text{ATT}}\big(g, \; T_g + s\big), \tag{2}$$

where $w_{g,s}$ is a weight representing the probability of being first treated in year T_g conditional on being observed at each relative year s. The term $\widehat{\text{ATT}}_s$ measures the effect of HSR introduction on EV adoption s years relative to the year in which HSR service becomes operational. Specifically, it captures any anticipatory effects when $s < 0$ and the dynamic effect of HSR connectivity on EV adoption in the years following HSR introduction when $s > 0$. Similarly, we can also aggregate the group-time-specific ATTs by calendar year to estimate the dynamic effect of HSR connectivity on EV adoption over time.

Figure 4 presents the dynamic effects of HSR connectivity on EV market share by event year (Panel A) and calendar year (Panel B), along with 95% confidence intervals. Panel A shows that the pre-treatment coefficients are close to zero and statistically insignificant, suggesting that treated and untreated cities exhibited similar trends in EV market share before HSR introduction. This finding supports the parallel pre-trends assumption, indicating that the timing of HSR adoption is plausibly exogenous conditional on the included fixed effects. Examining the dynamic treatment effect, Panel A indicates that, following the introduction of HSR, the estimated coefficients increase in magnitude and become statistically significant starting in the second year, indicating a sustained impact of HSR connectivity on EV market share. The coefficients continue to increase through the eighth year, suggesting that the effect of HSR on EV adoption intensifies over time. The results indicate a strong and growing treatment effect in the post-treatment period, with minimal evidence of anticipatory effects in the pre-treatment period. Panel B aggregates the treatment effects by calendar year and confirms the growing impact of HSR connectivity over time. The magnitude of the treatment effect is consistent with the baseline TWFE estimates. For example, in 2018, the treatment effect of HSR on EV market share is approximately 1 percentage point, compared to a national EV market share of 3.2%. By 2022, the treatment effect rises to about 5 percentage points, while the national average EV market share reaches 19.3%. Overall, the treatment effect accounts for about 30% of the annual national average market share.

[Figure 4 About Here]

4.3 Instrumental Variable Approach

So far, we have obtained causal estimates using a staggered DID framework, which treats HSR connections as exogenous shocks to EV adoption. We have also demonstrated that the parallel pre-trends assumption for the identification strategy holds. However, a potential concern is that the timing of when cities receive their HSR connections may not be entirely random, as HSR expansion might be prioritized for cities with certain predetermined characteristics, such as geographic centrality, economic importance, or urban planning efforts. Although the DID approach accounts for the time-invariant differences between cities and common time-varying shocks, it may not fully address unobserved factors that jointly influence HSR connection and EV adoption, thus introducing concerns of reverse causality and omitted variable bias.

To address potential endogeneity concerns and improve the robustness of our results, we employ an IV approach that isolates exogenous variation in HSR connectivity, drawing on two well-established instruments from the literature: the historical railway network from 1962; and a least-cost straight-line network connecting major target cities. Specifically, the historical railway network reflects the centralized planning objectives of the 1960s, designed to transport raw materials and goods between major cities and provincial capitals under China's five-year plans. These historical functions differ from the market-driven transportation needs of modern China. While the historical railroad network influenced the spatial distribution of infrastructure, it is unlikely to directly affect EV adoption and instead provides exogenous variation through its role in shaping the modern HSR network. Similarly, the least-cost straight-line network, based on geographic constraints and cost-minimization principles, provides an exogenous measure of HSR connectivity. Cities along direct lines connecting major megacities are more likely to gain HSR access by chance, independent of modern travel demand or economic conditions. This makes the network a valid instrument, capturing variation in HSR connectivity unrelated to unobserved factors influencing EV adoption. These instruments satisfy the key requirements of relevance and exclusion restriction, being strongly correlated with the timing and spatial distribution of HSR development while uncorrelated with unobserved factors directly affecting EV adoption.

We estimate the following equations at the city level:

$$\Delta\text{Treatment}_i = \alpha_1 + \delta\,\text{IV}_i + \mathbf{\Gamma}_1'\mathbf{X}_i + \eta_i \quad \text{(First Stage)}, \tag{3}$$

$$\Delta Y_i = \alpha_2 + \beta\,\Delta\widehat{\text{Treatment}}_i + \mathbf{\Gamma}_2'\mathbf{X}_i + \epsilon_i \quad \text{(Second Stage)}. \tag{4}$$

where $\Delta\text{Treatment}_i = \text{HSR}_{i,2010-2023}$ denotes the change in HSR connectivity over the same period (e.g., moving from no HSR to having HSR by 2023); $\Delta Y_i = Y_{i,2023} - Y_{i,2010}$ is the long difference in EV share for city i between 2010 and 2023; IV_i represents the instrumental variables, including historical railway networks and least-cost paths, which predict $\Delta\text{Treatment}_i$, but do not directly affect ΔY_i; $\mathbf{X}_i$ is a vector of additional city-level controls (e.g., number of charging stations, road mileage, and economic indicators) measured in the end year 2023 that capture observable differences across cities; η_i and ϵ_i are error terms in the first and second stages, respectively. δ, β are the key coefficients of interest, measuring the effect of the instrument on treatment (first stage) and the effect of the predicted treatment on ΔY_i (second stage). This long-difference approach exploits the net change in EV share and HSR connectivity over a substantial horizon, mitigating concerns about time-invariant unobserved heterogeneity and short-term fluctuations.

[Table 4 About Here]

Table 4 reports the results of the long-difference IV specification estimating the impact of HSR connectivity on changes in EV market share from 2010 to 2023. Panel A presents the first-stage estimates, which strongly support the validity of the instruments. The 1962 railway network is consistently and significantly associated with HSR connectivity in all specifications, confirming its strength as an instrument. The least-cost path IV also exhibits a positive relationship with HSR connectivity, although its significance varies across models. The Cragg-Donald F-statistics, ranging from 17.4 to 47.4, exceed conventional thresholds against weak instruments.

Panel B presents the second-stage estimates, which capture the cumulative effect of HSR connectivity on EV adoption. The IV estimates indicate that cities where HSR expansion was exogenously driven by the instruments experienced a substantially greater long-term increase in EV adoption compared to those without HSR. Column (1) in Panel B suggests that HSR connectivity leads to a cumulative increase in EV market share by 13 percentage points, and the positive impact of HSR connectivity on EV adoption remains robust with various control variables. It should be noted that the long-difference IV estimates yield larger effect sizes than the staggered DID estimates. This discrepancy arises because the IV approach captures the *cumulative* effect of HSR connectivity over the sample period, whereas the staggered DID approach identifies the *average* effect on an annual or monthly basis. As documented in Section 3.3, the treatment effect exhibits an increasing dynamic pattern over time. Therefore, a larger cumulative effect compared to the average annual or monthly effect is expected.

4.4 Market Access as Exposure to HSR Shock: Borusyak and Hull (2023) Approach

Our baseline analysis considers HSR connectivity as a binary indicator, which only varies at the first time when a city is connected to the HSR network. This binary treatment indicator fails to capture the "quality" of the connectivity, which can be affected by further expansion and upgrade of the HSR network. In this subsection, we employ an alternative *continuous* treatment measure by calculating the "market access" (MA) growth induced by the HSR expansion. In particular, following Borusyak and Hull (2023), MA is calculated as:

$$MA_{it} = \sum_{j \neq i} \exp(-0.02\tau_{ijt}) \cdot Pop_{j,2010}, \tag{5}$$

where $Pop_{j,2010}$ represents the 2010 population of city j, and τ_{ijt} denotes the predicted travel time between regions i and j in year t (measured in minutes). Travel time predictions are derived from the operational speed of each HSR line and the geographic distance between the city pair (i, j). We then calculate the growth of MA in city i from 2009 to 2020 as $(\log MA_{i,2020} - \log MA_{i,2009})$. The year 2009 serves as the pre-sample baseline, while 2020 is chosen as the endpoint to exclude disruptions caused by the COVID-19 pandemic. During this period, a total of 107 HSR lines became operational, and an additional 26 lines were completed between 2021 and 2023. Compared to a binary treatment indicator for HSR connection, the MA growth measure provides a richer representation of the impact of HSR expansion. It accounts for (i) the number of connected cities, (ii) the economic significance of those connections (proxied by population size), and (iii) the speed of travel enabled by HSR. By incorporating these factors, this alternative treatment measure allows us to estimate how the intensity of integration into the HSR network affects EV adoption, rather than just the binary presence of an HSR connection.

As with our baseline treatment measures, the MA growth measure may also be subject to endogeneity concerns due to the nonrandomness of the HSR connectivity. In addition, even when HSR connections are randomly assigned to different cities, MA growth may still be affected by unobserved confounders. To address the endogeneity concern and ensure the robustness of our estimates, we adopt the approach proposed in Borusyak and Hull (2023). To instrument for actual MA growth, we recenter the actual growth around an expected MA growth. In particular, we perform a permutation of the 2020 completion status of built and unbuilt (but planned) HSR lines, and this procedure generates a counterfactual HSR network. We repeat the permutations 2,000 times, and the expected MA growth takes the average of these permutations. By recentering the MA growth around its expectation, it isolates variation in HSR-induced MA growth unrelated to unobserved confounders, mitigating omitted variable bias arising from unobserved determinants that could simultaneously influence both HSR expansion and EV adoption. Thus, this recentered MA growth is used as the instrument for the actual MA growth.

[Table 5 About Here]

Table 5 presents regression results on the relationship between the share of EV sales and MA growth. Columns (1) and (2) report OLS estimates using unadjusted MA growth as the treatment variable, showing a positive and significant relationship between HSR-induced market access expansion and EV sales share. Columns (3) and (4) report the IV results in which this treatment is instrumented by MA growth recentered by expected MA growth from the permutation practice. Columns (5) and (6) report results from OLS regressions in which recentered MA growth is used as the treatment variable, controlling for expected MA growth based on the same HSR counterfactuals. The results are consistent with our baseline estimates and the magnitudes of the effects remain robust across all specifications, indicating that the observed relationship is not driven by spurious correlations or unaccounted-for factors. In particular, based on the IV estimation results with full set of covariates—our preferred model—in Column (4), with an average MA growth of 0.58 log points over the period, it implies 1.18 (= 0.58 * 2.04) percentage points of EV sales share growth attributable to HSR, accounting for more than 42% of the 2.8 percentage points average EV sales share growth observed during the period.

5 Competing and/or Complementary Mechanisms

In this section, we discuss the possible competing and/or complementary mechanisms to ensure that the observed relationship between HSR and EV adoption is not spurious.

5.1 Industrial Policies for the New Energy Vehicle Sector

A potential concern with our baseline results is the possibility that industrial policies, both demand- and supply-side, such as purchase subsidies or tax incentives, and other support schemes targeting EV manufacturers and consumers, could confound the observed relationship between HSR connectivity and EV adoption. These policies, implemented by central, provincial, and city governments, differ significantly in scope and timing across regions. For example, local consumer purchase subsidies could drive EV adoption independently of HSR connectivity, introducing a confounder if HSR connections positively correlate with broader expansions of industrial policies.

In this section, we account for the impact of industrial policies in our empirical analysis. As detailed in Section 3.3, we categorize 6,476 supportive policy documents issued by the city-level government with seven distinct target-oriented policy tools, and each document can contain several tools. These tools include consumer purchase subsidies (*PurchaseSubsidy*), government procurement (*Procurement*), trade fairs and promotion events (*TradeFair*), R&D subsidies and other policies (*R&D*), investment policies (*Investment*), industrial cluster policies (*Cluster*), and entry incentives (*Entry*). We construct city-year-level indicators to capture whether a city i has issued EV supporting policy documents with each of the above policy tools. We include these policy indicators and their interactions with HSR connectivity (*Treatment*) in our baseline regression Eq. (1) to assess whether industrial policies independently influence the adoption of EVs and whether their effects are amplified by the presence of HSR connectivity.

[Table 6 About Here]

Table 6 presents the regression results. In Column (1), we add in the baseline regression (1) an indicator for whether city i had a consumer purchase subsidy policy in place in year y and its interaction with *Treatment*; and then in Colums (2) to (7) we additionally incorporate other policy controls. Table 6 offers several insights. First, in all except the last specification, the coefficient on *Treatment* remains positive and statistically significant, underscoring the critical role of HSR infrastructure in driving EV adoption and reinforcing the robustness of our baseline results. Second, and most notably, the interaction term *Treatment*PurchaseSubsidy* consistently yields a positive and statistically significant coefficient, highlighting a strong complementarity between HSR infrastructure and targeted consumer incentives for EV purchases. These results suggest that consumer EV purchase subsidies are particularly effective in fostering EV adoption when combined with complementary HSR connectivity. By providing a convenient long-distance travel alternative, HSR reduces the perceived limitations of EVs (particularly range anxiety), thereby amplifying the effect of consumer subsidies on EV adoption.

Third, other demand-side policies, such as government procurement and trade fair promotions, demonstrate limited effectiveness. Although these policies are intended to expand markets, their primary beneficiaries are suppliers rather than consumers. As shown in Columns

(2) and (3), their coefficients are generally insignificant or negative, and their interactions with HSR connectivity do not produce meaningful effects. These findings indicate that procurement and regulatory initiatives do not have a direct impact on EV adoption, nor do they exhibit complementarity with HSR infrastructure.

Fourth, supply-side policies, including R&D, investment, industrial clusters, and entry incentives (Columns (4) to (7)), show no significant effect on EV adoption. These policies, which aim to enhance technological innovation, production capacity, or market entry, do not appear to significantly influence consumer decisions. In addition, the interaction terms with HSR connectivity are consistently insignificant or negative, suggesting that supply-side instruments are less sensitive to the presence of HSR infrastructure.

Overall, these findings highlight the critical role of demand-side interventions, particularly consumer subsidies, in driving EV adoption when complemented by HSR connectivity. While supply-side policies remain essential for long-term technological and industrial development, they do not exhibit immediate synergies with HSR infrastructure in promoting EV adoption. By reducing range anxiety, HSR connectivity enhances the effectiveness of consumer subsidies, enabling a shift toward greater EV adoption for daily commutes and routine travel. These results provide broader policy implications that combining complementary infrastructure with targeted demand-side incentives is a highly effective strategy for accelerating EV adoption.

5.2 Regional Infrastructure Improvements

Another potential mechanism behind the observed increase in EV adoption is the broader regional infrastructure development that often accompanies HSR expansion. These improvements include road upgrades and EV charging station deployment, which reduce barriers to EV adoption by enhancing accessibility, convenience, and range confidence. For instance, better road networks improve connectivity, while charging infrastructure mitigates range anxiety, making EVs more practical for both medium- and long-distance travel. However, if unaccounted for, these infrastructure investments may introduce upward bias in the estimated effects of HSR, as HSR-connected cities tend to attract greater public and private investment in complementary infrastructure.

To address this potential confounder, we incorporate two supplementary datasets: one capturing the geographic locations and temporal expansion of EV charging stations across 328 Chinese cities from 2010 to 2023, constructed using GIS techniques and historical data from Gaode Maps, and another covering China's road networks through 2023, including road types, spatial coverage, and connectivity.

In Columns (2) and (3) of Table 2, we introduce the number of EV charging stations *ln(1+#Charging Stations)* and total road mileage *ln(Road Length)* as additional control variables to investigate whether the observed effect of HSR connectivity on EV market share operates partially through the development of charging infrastructure and road networks. Specifically, including *ln(1+#Charging Stations)* reduces the coefficient on *Treatment* from 0.0122 in Column (1) to 0.0082 in Column (2), a decrease of approximately one-third. This reduction suggests that the expansion of EV charging stations explains part of the relationship between HSR connectivity and EV market share growth, though not entirely. Importantly, the coefficient on *Treatment* remains positive and statistically significant, indicating that while charging station expansion contributes to EV adoption, HSR connectivity remains a significant and robust driver of the observed increase in EV market share. In Column (3), the inclusion of *ln(Road Length)* barely changes the HSR effect, indicating that traditional road infrastructure plays a limited role in influencing vehicle adoption patterns. The results in Columns (2) and (3) demonstrate that the positive and significant effect of HSR connectivity on EV market share remains robust even after accounting for variations in charging infrastructure and road development.

[Table 7 About Here]

Table 7 further examines the interacting effects of HSR connectivity and charging infrastructure. Columns (1) and (2) show that HSR connectivity is positively associated with the development of EV charging stations, as evidenced by the significant coefficients on *Treatment* (0.5244 and 0.4313, respectively), indicating that cities connected to HSR are more likely to expand charging infrastructure. Columns (3) to (5) examine EV share as the dependent variable and provide evidence of a positive interaction effect between HSR connectivity and charging infrastructure. Specifically, the positive and highly significant interaction term between *Treatment* and *ln(Charging Stations)* indicates that HSR connectivity amplifies the effect of charging stations on EV adoption, pointing to the synergistic relationship between HSR and charging infrastructure.

5.3 Entry of EV Manufacturers and Car Dealerships

A related supply-side concern is the potential impact of HSR connectivity on the entry and operations of EV manufacturers. While primarily designed for passenger mobility, HSR indirectly enhances logistics by reducing freight traffic on parallel highways and freeing up capacity on conventional railways through its substitution effect on passenger rail (Lin et al., 2021; Cheng and Chen, 2021). These improvements lower transportation costs and increase the efficiency of distributing goods, including EVs, making HSR-connected cities more attractive for manufacturers (Baek and Park, 2022).

To explore this potential mechanism, we compute the cumulative number of active EV manufacturers and car dealerships in city i in year-month (y, m) based on firm registrations data from SAIC, as described in Section 3. We examine whether the observed increase in EV sales is influenced by supply-side changes by estimating a regression model that includes HSR connectivity and *ln(1+#EV Manufacturers)* and *ln(1+#Car Dealerships)*. In Column (4) of Table 2, the coefficient on *Treatment* remains positive and statistically significant, though the magnitude of the effect is somewhat smaller.

5.4 Socio-economic Factors

One potential concern is that the observed relationship between HSR connectivity and EV adoption may be confounded by endogenous factors such as economic development and population dynamics. Cities with HSR connections may experience significant economic growth, reflected in higher regional GDP and increased disposable income (Lin, 2017; Diao, 2018; Donaldson, 2018). This economic development can influence EV adoption, as wealthier residents are more likely to purchase environmentally friendly technologies due to greater purchasing power, heightened environmental awareness, and exposure to technological advancements. Similarly, HSR connectivity can stimulate migration to connected cities by improving accessibility, reducing commuting costs, and enhancing economic opportunities, leading to population growth. The resulting influx of residents can increase overall vehicle demand, including EVs. If economic growth and population changes are correlated with both HSR connectivity and EV adoption but are not considered in the analysis, they can introduce omitted variable bias, leading to an upward bias in the estimated causal impact of HSR on EV adoption.

To address these potential confounding factors, we incorporate data on GDP, population growth, and fiscal expenditure at the city-year level into our empirical analysis. In Column (5) of Table 2, the coefficient on *Treatment* decreases to 0.0082 but remains positive and statistically significant at the 1% level, suggesting that the impact of HSR on EV market share persists even after controlling for these variables. Among the additional controls, *ln(GDP)* exhibits positive and statistically significant coefficient, indicating that higher income levels indeed promote EV adoption. However, population growth and local fiscal expenditures exhibit negligible magnitudes or lack statistical significance, indicating minimal direct impact on the EV market share.

Column 6 of Table 2 provides evidence that HSR connectivity increases EV market share even after controlling for all key economic and policy factors. Although the magnitude is smaller than in other columns, the coefficient estimate of *Treatment* remains positive and statistically significant, suggesting that HSR connectivity has a significant impact on EV adoption and reinforces the robustness of its effect on EV adoption patterns.

6 Robustness Checks and Heterogeneity Tests

6.1 Robustness Checks

Potential Arbitrariness in Year Selection. To ensure the robustness of our findings, we address the potential concerns arising from the COVID-19 pandemic in 2020, which significantly disrupted economic conditions and policy environments in the post-COVID period. Notable changes during this period include supply chain disruptions, government stimulus packages, expanded subsidies for EV purchases to boost economic recovery, and possible shifts in consumer preferences toward private vehicles due to health and safety concerns. Given these unique factors, there is a concern that including the post-2020 period could bias our results. One may also question the arbitrariness in the cutoff year when we choose to exclude cities with HSR connections before 2015 in our baseline analysis. To test the robustness of our estimates, we report the results in the Appendix Table A3 where we use conduct the same analyses but excluding cities with HSR connections before 2014, 2013, and 2012, respectively.

Column (1) of Appendix Table A3 uses the full sample and it shows a small and statistically insignificant coefficient, suggesting that early connected cities and sample heterogeneities may obscure the effect of HSR on EV adoption.[15] Columns (2) through (4), which exclude cities connected before 2014, 2013, and 2012 respectively, yield positive and statistically significant coefficients (ranging from 0.007 to 0.101), demonstrating that removing earlier connected cities reveals a robust association between HSR connectivity and increased EV share. Column (5), excluding observations after 2020, produces a smaller but statistically significant coefficient, indicating that the observed impact of HSR connectivity on EV adoption is not fully driven by the special circumstances surrounding the COVID-19 period. These results highlight the sensitivity of the treatment effect to sample composition while consistently confirming that HSR connectivity promotes EV adoption.

Impact of HSR on Hybrid Vehicles. Hybrid vehicles are excluded from the baseline analysis because their dual-fuel capability alleviates range anxiety, reducing their dependence on HSR as a complementary transportation option. To further test the robustness of the results, we use hybrid vehicles as a placebo and examine the effects of HSR connectivity on their market share using various estimation methods. As shown in Table A4, although the treatment effect remains positive and statistically significant in Columns (1) and (2), which

[15] Cities connected to the HSR network in 2010 and 2011, including the 26 cities served by the Beijing-Shanghai HSR line inaugurated on June 30, 2011, drive the insignificant coefficients in the full sample. As the first to benefit from medium- to long-distance HSR routes, these early connected cities exhibit distinct characteristics that differ significantly from later connected cities.

use the staggered DID approach, it becomes statistically insignificant in the IV estimations presented in Columns (4), (8), and (10). This suggests that the impact of HSR connectivity on hybrid vehicles is weaker and non-robust compared to that on the EVs. The positive impact of HSR connectivity on hybrid vehicles in the staggered DID specification may be driven by the endogeneity of the HSR expansion, or by the spillover effect of EVs on hybrid vehicles— as the market for EVs expands, there is heightened consumer awareness and more charging stations being built, both may benefit hybrid vehicles. However, when we address these omitted variable concerns with different IV designs, the positive effect disappears. This placebo test further confirms the role of HSR on relaxing consumers' range anxiety, thereby supporting the robustness of the baseline findings.

6.2 Heterogeneity Effects

The impact of HSR connectivity on EV adoption is unlikely to be uniform across regions or market segments, as differences in HSR design and regional characteristics can lead to heterogeneous effects. To explore the mechanisms driving these variations, we examine how specific HSR characteristics and regional factors influence EV adoption. Specifically, we incorporate interactions between *Treatment* and various characteristic variables, such as HSR speed, line lengths, number of lines, number of stations, and geographic regions. The results are detailed in Appendix Table A5.

We first analyze the role of HSR network characteristics. Cities with more extensive or faster HSR networks may experience higher EV adoption rates due to enhanced regional accessibility and improved market connectivity. Column (1) shows that the interaction term *Treatment*SpeedDummy* is positive and statistically significant at the 1% level, indicating that high-speed HSR lines (above 300 km/hour) have a stronger positive impact on EV share. This finding highlights the importance of faster travel speed and greater regional integration in driving EV market growth. Conversely, the coefficients for interaction terms in Columns (2) through (4), which examine the effects of HSR line lengths, number of lines, and number of stations, are statistically insignificant. This indicates that these characteristics do not contribute to differential impacts on EV adoption.

Next, we examine regional heterogeneity by categorizing cities into four areas—East, Middle, West, and Northeast—based on socio-economic development policies outlined by the Central Committee and the State Council.[16] Column (5) uses cities in the Northeast as

[16]The regions in China are categorized into four major economic zones based on the socio-economic development framework outlined in key policy documents, including the Opinions of the Central Committee of the Communist Party of China and the State Council on Promoting the Rise of the Central Region and the Implementation Opinions on Several Policies and Measures for Western Development issued by the State Council. The East includes provinces such as Beijing, Shanghai, Jiangsu, and Guangdong, reflecting the country's most developed areas. The Middle region comprises Shanxi, Anhui, and similar provinces, while

the benchmark to assess geographic variation. The interaction terms between *Treatment* and geographic dummies (*East*, *Middle*, and *West*) reveal significant regional differences. HSR connectivity has a stronger impact on EV adoption in eastern and middle regions, reflecting higher income levels, better infrastructure, and greater consumer readiness in these areas. In contrast, the impact in western regions is weaker, probably due to lower economic development and less developed EV-related infrastructure. In the northeast, colder climates can pose a challenge to EV adoption due to concerns about battery performance at low temperatures, highlighting the role of climatic and regional factors in modulating the effectiveness of HSR connectivity. These findings highlight the importance of accounting for both the characteristics of HSR and the regional context to understand the heterogeneous effects of HSR on the adoption of EVs.

7 Conclusion

This study provides novel insights into the relationship between transportation infrastructure and EV adoption, using the rapid expansion of China's HSR network as a quasi-natural experiment. Our findings reveal that HSR connectivity plays a significant role in increasing EV market share and sales by alleviating range anxiety, a primary barrier to EV adoption. HSR offers an efficient and practical solution for long-distance travel, complementing the use of electric vehicles for short-distance commutes. Dynamic analyses confirm a substantial treatment effect, with sustained growth in EV adoption following the introduction of HSR connections. In addition, faster and extensively connected networks show more pronounced effects, while regional disparities in the effects may stem from differences in income levels, infrastructure quality, and climatic conditions. We examine competing and/or complementary mechanisms such as regional development, industrial policies, infrastructure improvements, and supply-side factors. The results suggest the critical role of HSR in fostering sustainable mobility when integrated with supportive industrial policies, particularly consumer subsidies for EV purchases. We document interesting synergies between the HSR network and the construction of charging stations. While the HSR connection enhances early EV adoption by alleviating consumers' range anxiety, the larger consumer base creates an agglomeration effect and further fosters the construction of charging stations, and the two jointly benefit future consumers. The synergy between the HSR network and other infrastructure and policies may explain why the HSR connection has a persistent and growing effect on EV adoption. We also perform extensive robustness checks to ensure the validity and reliability

the West covers less developed areas such as Sichuan, Tibet, and Xinjiang. Finally, the Northeast includes Liaoning, Jilin, and Heilongjiang, which represent historically industrial regions. https://www.stats.gov.cn/zt_18555/zthd/sjtjr/dejtjkfr/tjkp/202302/t20230216_1909741.htm of the results.

Our study offers valuable information for policymakers formulating comprehensive policies to promote the adoption of electric vehicles. First, beyond conventional monetary and non-monetary incentives, policymakers should recognize the significant role that efficient and convenient intercity public transportation systems play in supporting EV adoption. Second, the synergy between transportation infrastructure and policy interventions highlights the need for cohesive, regionally tailored approaches to maximize the effectiveness of EV adoption initiatives. The rapid expansion of China's HSR network from 2008 onward contributed significantly to China's EV adoption miracle in recent years. Our estimates suggest that the HSR expansion could account for about one third of the increase in EV market share during our sample period. Regardless of whether this miracle happened inadvertently or by design, the lessons for the rest of the world are clear. High-speed rail systems that provide a reliable and efficient alternative for long-distance travel can help accelerate EV adoption by alleviating range anxiety, because HSR complements EV use for short trips and enhances their overall practicality. Investing in high-speed rail systems can therefore align economic development with environmental sustainability.

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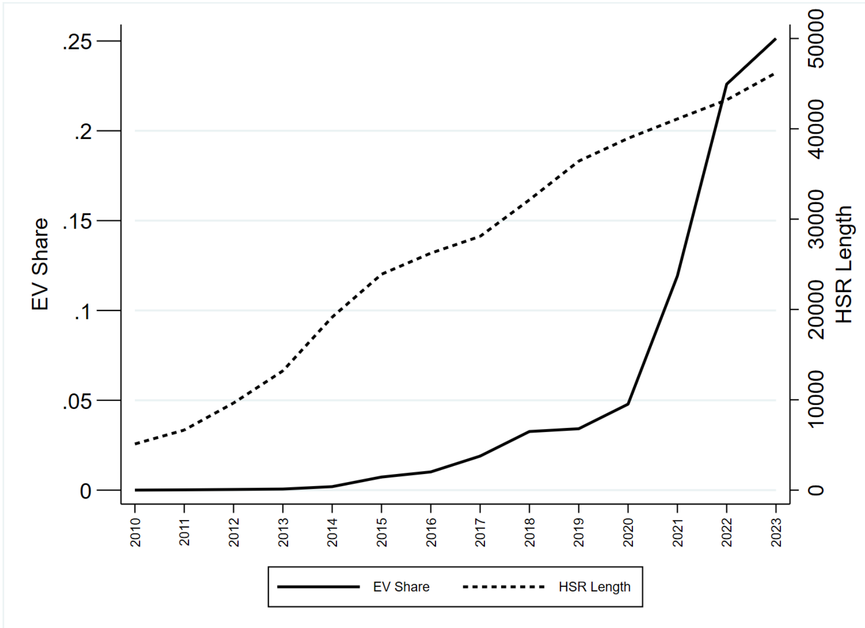
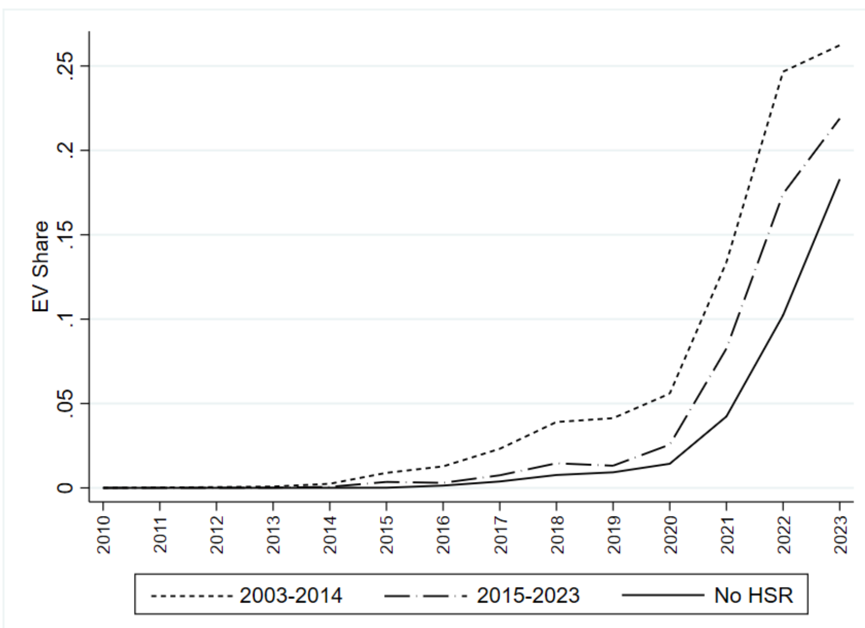
Figure 1: Trends in EV Adoption and HSR Expansion

Panel A: National Trends in EV Market Share and HSR Network Expansion

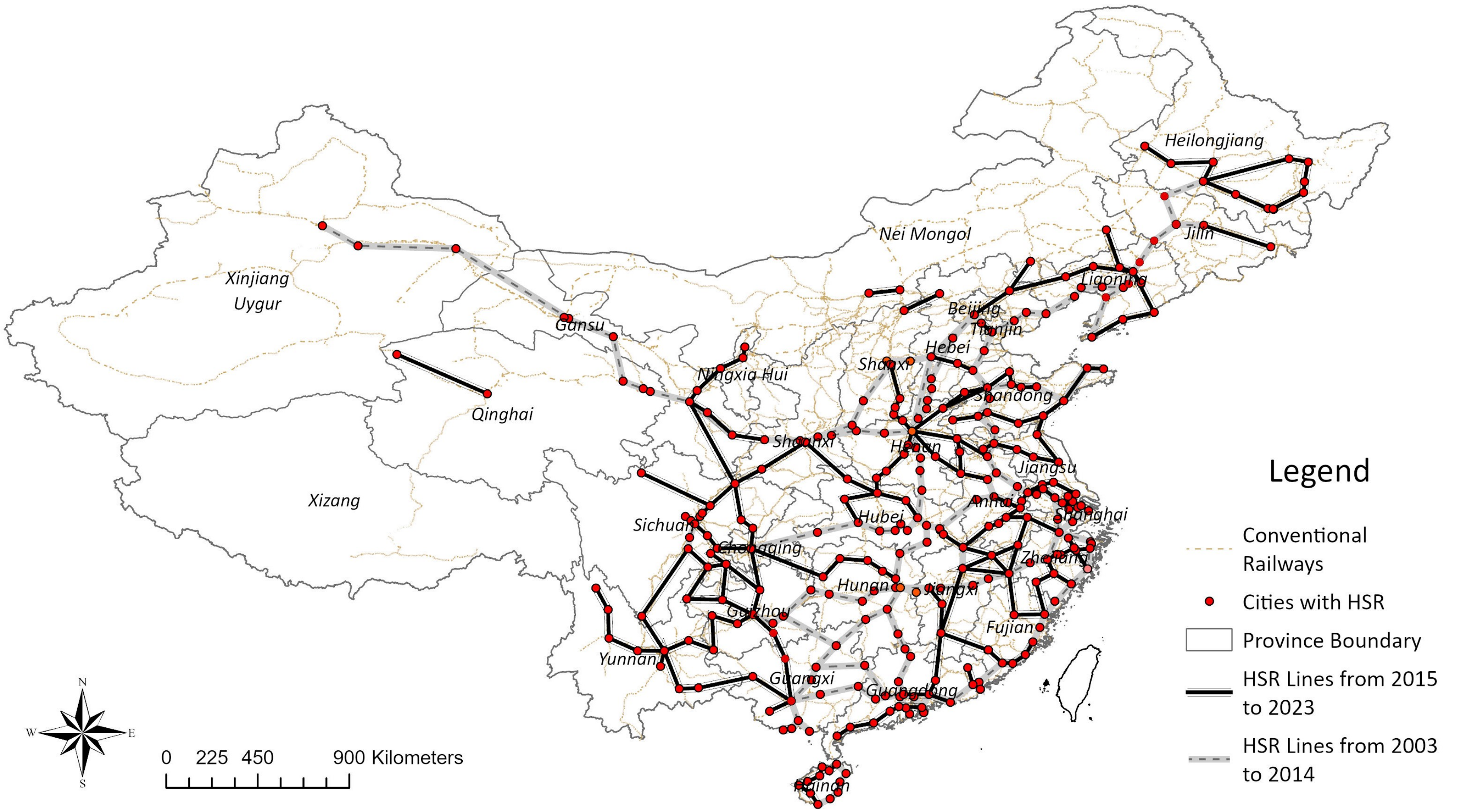


Panel B: Changes in EV Market Share by City Groups with HSR Connectivity



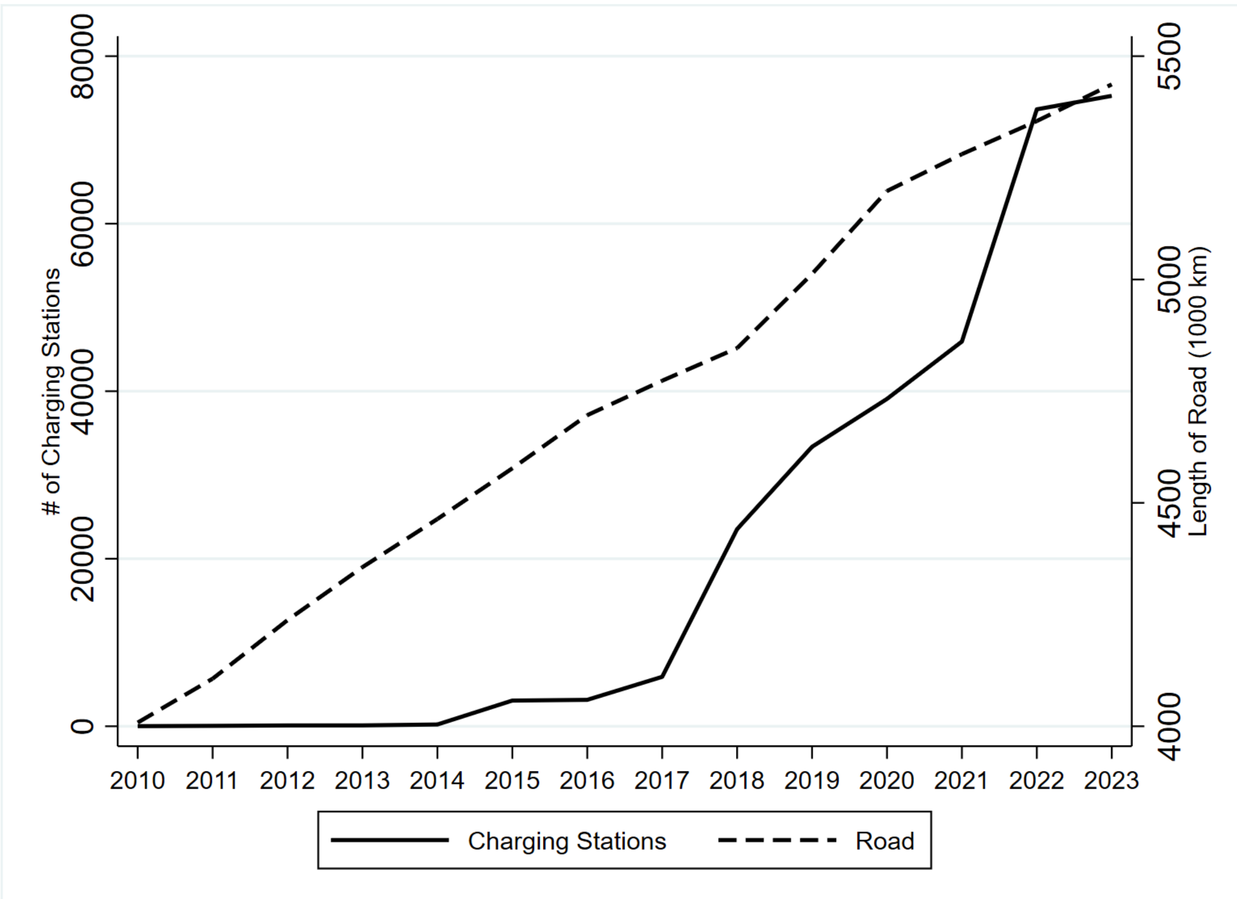
Notes: This figure illustrates trends in EV adoption and HSR expansion, using EV market share excluding hybrids for consistency with the baseline analysis. Panel A presents the national trend in EV market share (solid line) and total HSR network length (dashed line) from 2010 to 2023, with EV data derived from the CSMAR database and HSR network data from official railway statistics. Panel B tracks EV market share over time across city groups categorized by HSR connectivity, based on the sample data used in the analysis: cities connected in 2003–2014 (dashed line), those connected in 2015–2023 (dash-dotted line), and cities without HSR (solid line).

Figure 2: High-Speed Rail Network in China (2003–2023)



Notes: This figure illustrates the spatial expansion of China's HSR network from 2003 to 2023, created using ArcGIS Pro. Cities with HSR connections are marked with red dots. HSR lines established between 2003 and 2014 are shown by grey dashed lines, while lines constructed from 2015 to 2023 are shown by black solid lines. The map also includes conventional railway lines in brown and province boundaries for geographical reference. For illustrative purposes, HSR connections between cities are represented as straight lines, which may not correspond to the actual routes or alignments of the railways.

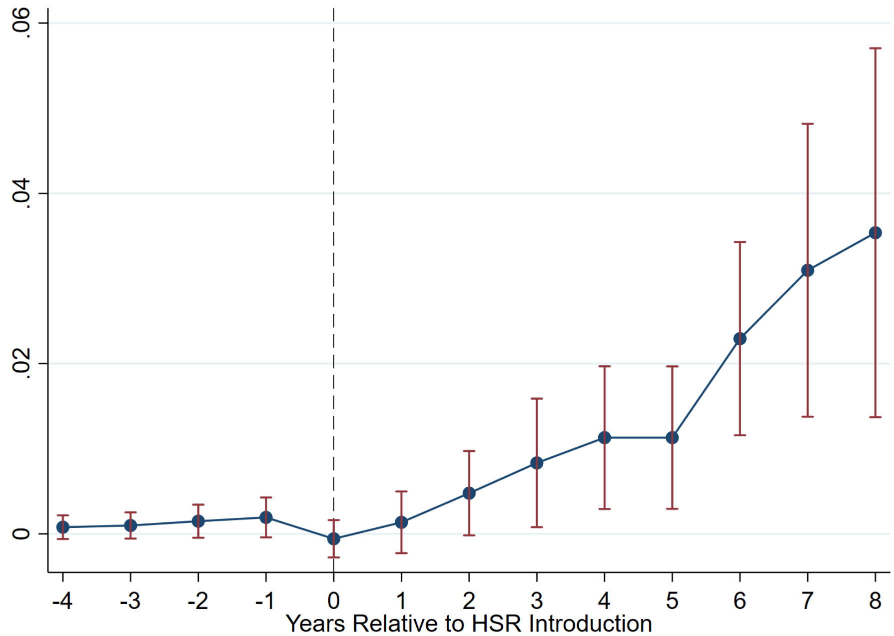
Figure 3: Trends in Charging Stations and Road Length in China (2010–2023)



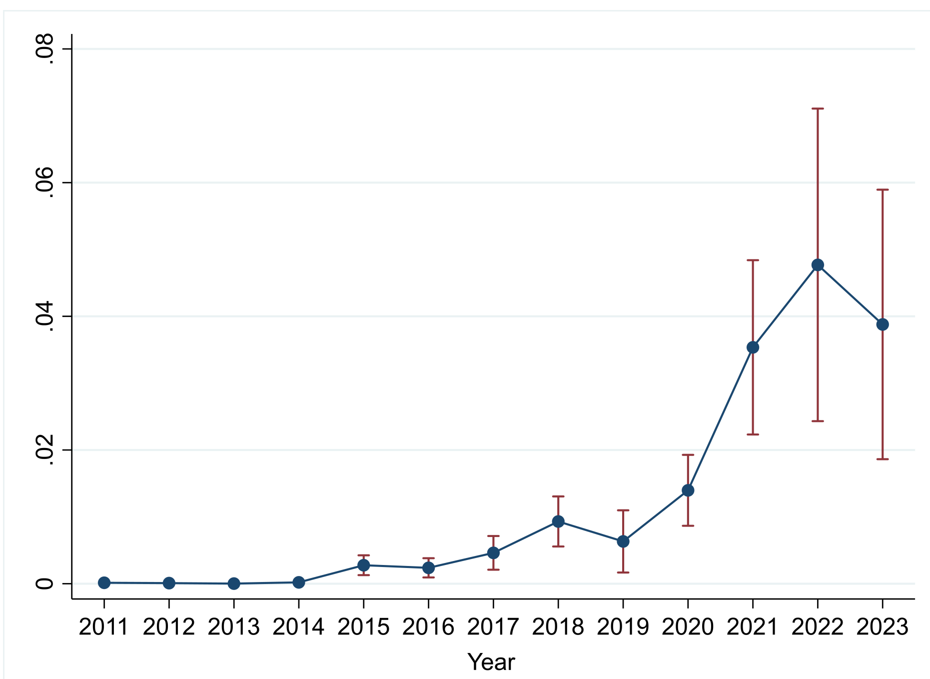
Notes: The figure shows the cumulative number of charging stations (solid line, left axis) and road length in thousands of kilometers (dashed line, right axis) in China from 2010 to 2023.

Figure 4: The Dynamic Response of EV Market Share

Panel A: By Event Year



Panel B: By Calendar Year



Notes: This figure presents the dynamic effects of HSR connectivity on EV market share. The sample period is 2010-2023. All cities are included in the analysis. The unit of observation is city-year. Panel A shows the change in EV market share relative to the event year of HSR introduction (year 0). Panel B depicts the change in EV market share by calendar year (2011–2023), highlighting a sharp upward trend beginning in 2016 and accelerating after 2020. The vertical axis depicts the estimated changes in EV market share.

Table 1: Descriptive Statistics

	N	Mean	S.D	Min	Max
Panel A. City-Month Variables					
EV Sales	55,104	305.05	1,410.29	0	57,536
Fuel Sales	55,104	4,443.78	6,909.99	1	116,453
EV Share	55,104	0.04	0.08	0	0.92
# of Car Dealerships	55,104	24.69	32.18	0	734
# of EV manufacturers	55,104	0.03	0.22	0	8
Panel B. City-Month Variables (Exclude Connected Cities before 2015)					
EV Sales	29,064	93.73	348.94	0	7,729.00
Fuel Sales	29,064	2,169.94	2,442.08	1	35,398.00
EV Share	29,064	0.03	0.07	0	0.92
# of Car Dealerships	29,064	19.29	22.87	0	393
# of EV manufacturers	29,064	0.03	0.23	0	8
Panel C. City-Year Variables					
# of Charging Stations	4,592	106.81	565.94	0	13750.81
Road Lengths (Km)	4,592	13,709.32	10,599.47	268.40	186,137.00
GDP (Mill. CNY)	4,592	253,103.89	395,808.28	3,186.00	4,721,866.00
Population Growth	4,592	0.01	0.05	-0.33	0.67
Fiscal Expenditure (Mill. CNY)	4,592	42,250.47	65,188.51	727.44	966,192.74

Notes: This table presents descriptive statistics for key variables. Panel A reports city-month-level data for the full sample (2010–2023), while Panel B focuses on a subsample excluding cities with HSR connections established before 2015 (baseline analysis, 2015–2023). Panel C provides city-year-level data on infrastructure and socio-economic characteristics (2010–2023).

Table 2: Baseline Results: Staggered Difference-in-Difference Estimation

Dep. Variable	EV Share					
Model	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	0.0122***	0.0082**	0.0121***	0.0102***	0.0113***	0.0065*
	(0.0040)	(0.0038)	(0.0040)	(0.0039)	(0.0040)	(0.0037)
ln(1+ #Charging Stations)		0.0076***				0.0067***
		(0.0011)				(0.0011)
ln(Road Length)			0.0115***			0.0119***
			(0.0038)			(0.0034)
ln(1+ #EV Manufacturers)				0.0093*		0.0068***
				(0.0049)		(0.0023)
ln(1+ #Car Dealerships)				0.0166*		0.0041
				(0.0093)		(0.0049)
ln(GDP)					0.0171**	0.0113*
					(0.0078)	(0.0068)
Population Growth					-0.0219	-0.0234
					(0.0148)	(0.0147)
ln(Fiscal Expenditure)					0.0073	0.0036
					(0.0065)	(0.0059)
Observations	29,064	29,064	29,064	29,064	29,064	29,064
R-squared	0.725	0.733	0.726	0.728	0.728	0.737
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table presents the results using the DID estimations. The sample period is 2010-2023. Cities connected before 2015 are excluded from the estimation sample. The unit of observation is city-month. Fixed effects for city and year-month are included in all columns. Robust standard errors, clustered at the city level, are reported in parentheses. Statistical significance is denoted by *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.10$.

Table 3: CSDID Estimation Results

Panel A: Never-Treated Cities as the Control Group			
Dep. Variable	EV Share	ln(1+EV Sales)	ln(1+FV Sales)
Model	(1)	(2)	(3)
Treatment	0.0298***	1.7747***	0.3224***
	(0.0051)	(0.1807)	(0.0737)
Observations	3,808	3,808	3,808
City FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

Panel B: Not-Yet-Treated Cities as the Control Group			
Dep. Variable	EV Share	ln(1+EV Sales)	ln(1+FV Sales)
Model	(1)	(2)	(3)
Treatment	0.0274***	1.5215***	0.2638***
	(0.0051)	(0.1680)	(0.0642)
Observations	3,808	3,808	3,808
City FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

Notes: This table reports the estimation results using CSDID. The sample period is 2010-2023. Cities connected before 2010 (i.e. the always treated group during the sample period) are excluded from the estimation sample. The unit of observation is city-year. Panel A uses never-treated observations as the control group and Panel B uses the not-yet treated observations as the control group. All models include city fixed effects and year fixed effects. Standard errors, clustered at the city level, are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 4: Results from Instrumental Variable Approach

	Panel A. First Stage					
Dep. Variable	Treatment					
Model	(1)	(2)	(3)	(4)	(5)	(6)
1962 Railways	0.2705***	0.1946***	0.2707***	0.2049***	0.2436***	0.1947***
	(0.0404)	(0.0368)	(0.0404)	(0.0369)	(0.0373)	(0.0362)
Least Cost Path	0.2220***	0.1900***	0.2228***	0.1226*	0.1503**	0.1021
	(0.0735)	(0.0663)	(0.0748)	(0.0713)	(0.0743)	(0.0751)
ln(1+ #Charging Stations)		0.0980***				0.0827***
		(0.0127)				(0.0294)
ln(Road Length)			-0.0025			-0.0193
			(0.0345)			(0.0324)
ln(1+ #EV Manufacturers)					0.0706***	0.0404**
					(0.0190)	(0.0188)
ln(1+ #Car Dealerships)					0.0499	0.0207
					(0.0333)	(0.0290)
ln(GDP)				0.2153***		0.1149**
				(0.0479)		(0.0582)
Population Growth				-0.7936***		-0.9712***
				(0.2872)		(0.2972)
ln(Fiscal Expenditure)				-0.1251*		-0.1473**
				(0.0644)		(0.0710)
R-squared	0.226	0.326	0.226	0.341	0.286	0.372
Cragg-Donald Wald F-statistic	47.370	28.838	45.722	21.793	29.269	17.377

	Panel B. Second Stage					
Dep. Variable	Change in EV Share					
Model	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	0.1299***	0.0725**	0.1362***	0.1027***	0.1349***	0.1001***
	(0.0260)	(0.0296)	(0.0258)	(0.0346)	(0.0303)	(0.0366)
ln(1+ #Charging Stations)		0.0255***				0.0358***
		(0.0045)				(0.0083)
ln(Road Length)			-0.0092			-0.0099
			(0.0074)			(0.0062)
ln(1+ #EV Manufacturers)					0.0128**	0.0108**
					(0.0053)	(0.0048)
ln(1+ #Car Dealerships)					-0.0115	-0.0121*
					(0.0080)	(0.0063)
ln(GDP)				0.0109		-0.0207
				(0.0170)		(0.0160)
Population Growth				0.2412**		0.1428
				(0.1007)		(0.0986)
ln(Fiscal Expenditure)				0.0062		-0.0014
				(0.0173)		(0.0177)
Observations	328	328	328	328	328	328
R-squared	-0.019	0.241	-0.033	0.107	-0.016	0.228
Hansen J-statistic	2.095	4.683	2.440	5.117	2.150	8.443

Notes: This table presents the results of a long-difference IV specification (Equations 3 and 4). Changes in EV share and Treatment are measured as the long difference between 2010 and 2023, and control variables are 2023 values. All cities are included. The unit of observation is city. Robust standard errors are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 5: Robustness Tests using the Borusyak and Hull IV

Dep. Variable	EV Share					
	Panel A. Unadjusted OLS		Panel B. Recentered IV		Panel C. Recentered OLS	
Model	(1)	(2)	(3)	(4)	(5)	(6)
Market Access Growth	0.0307***	0.0150***	0.0192*	0.0204**		
	(0.0047)	(0.0053)	(0.0111)	(0.0103)		
Recentered Market Access Growth					0.0234***	0.0186**
					(0.0081)	(0.0080)
Expected Market Access Growth					0.0323***	0.0139***
					(0.0047)	(0.0053)
ln(1+ #Charging Stations)		0.0046***		0.0044***		0.0047***
		(0.0014)		(0.0014)		(0.0014)
ln(Road Length)		-0.0060**		-0.0059**		-0.0060**
		(0.0027)		(0.0027)		(0.0027)
ln(1+ #EV Manufacturers)		0.0023		0.0019		0.0025
		(0.0026)		(0.0027)		(0.0027)
ln(1+ #Car Dealerships)		-0.0058***		-0.0058***		-0.0058***
		(0.0022)		(0.0022)		(0.0023)
ln(GDP)		0.0039*		0.0032		0.0039*
		(0.0023)		(0.0026)		(0.0023)
Population Growth		-0.011		-0.0081		-0.0111
		(0.0189)		(0.0190)		(0.0188)
ln(Fiscal Expenditure)		0.0067		0.0074		0.0066
		(0.0044)		(0.0045)		(0.0044)
Observations	324	324	324	324	324	324
R-squared	0.102	0.294	0.088	0.291	0.104	0.294

Notes: This table reports the results of regressions analyzing the relationship between the share of EV sales growth and market access (MA) growth across Chinese cities from 2009 to 2020, using the Borusyak and Hull IV approach. Control variables use 2020 values. All cities are included. The unit of observation is city. Columns (1) and (2) use unadjusted MA growth as the treatment. Columns (3) and (4) instrument MA growth with expected values based on permutations of built and planned HSR connections. Columns (5) and (6) estimate OLS regressions with recentered MA growth as the treatment, controlling for expected MA growth from the same HSR counterfactual. Robust standard errors are reported in parentheses. Statistical significance is denoted by *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.10$.

Table 6: Interacting Effects of HSR Connection and EV-Related Industrial Policies

Dep. Variable				EV Share			
Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Treatment	0.0095**	0.0097**	0.0100**	0.0099**	0.0095**	0.0085*	0.0078
	(0.0042)	(0.0043)	(0.0044)	(0.0048)	(0.0046)	(0.0048)	(0.0052)
Policy_Demand	-0.0040**	-0.0021	-0.0021	-0.0019	-0.0029	-0.0018	-0.0038**
	(0.0020)	(0.0020)	(0.0020)	(0.0019)	(0.0022)	(0.0019)	(0.0019)
Treatment*Policy_Demand	0.0094**	0.0100**	0.0109**	0.0097**	0.0092*	0.0078	0.0091*
	(0.0047)	(0.0047)	(0.0054)	(0.0045)	(0.0049)	(0.0049)	(0.0046)
Policy_Procurement		-0.0033*					
		(0.0017)					
Treatment*Policy_Procurement		-0.0014					
		(0.0044)					
Policy_TradeFair			-0.0040*				
			(0.0021)				
Treatment*Policy_TradeFair			-0.0026				
			(0.0047)				
Policy_R&D				-0.0041**			
				(0.0019)			
Treatment*Policy_R&D				-0.0011			
				(0.0042)			
Policy_Investment					-0.0024		
					(0.0020)		
Treatment*Policy_Investment					0.0004		
					(0.0047)		
Policy_Cluster						-0.0049**	
						(0.0020)	
Treatment*Policy_Cluster						0.0032	
						(0.0043)	
Policy_Entry							-0.0038**
							(0.0018)
Treatment*Policy_Entry							0.0035
							(0.0040)
Observations	26,988	26,988	26,988	26,988	26,988	26,988	26,988
R-squared	0.725	0.725	0.726	0.726	0.725	0.726	0.726

Notes: This table presents the estimates of EV market share regressed on HSR connectivity, different industrial policy dummies, and their interaction terms. The sample period is 2010-2022. Cities connected before 2015 are excluded from the estimation sample. The unit of observation is city-month. Fixed effects for city and year-month are included in all columns. Heteroscedasticity-consistent standard errors, clustered at the city level, are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 7: Interacting Effects of HSR Connections and Charging Stations on EV Adoption

Dep. Variable	ln(1+ #Charging Station)		EV Share		
Model	(1)	(2)	(3)	(4)	(5)
Treatment	0.5244***	0.4313***	0.0082**	-0.0145***	-0.0148***
	(0.1092)	(0.1049)	(0.0038)	(0.0042)	(0.0042)
ln(1+ #Charging Stations)			0.0076***	0.0041***	0.0034***
			(0.0011)	(0.0013)	(0.0013)
Treatment*ln(1+ #Charging Stations)				0.0077***	0.0073***
				(0.0017)	(0.0017)
ln(Road Length)		-0.0471			0.0111***
		(0.0780)			(0.0034)
ln(1+ #EV Manufacturers)		0.4068***			0.0064***
		(0.0800)			(0.0023)
ln(1+ #Car Dealerships)		0.0285			0.0035
		(0.1596)			(0.0046)
ln(GDP)		0.4648**			0.0115*
		(0.1866)			(0.0065)
Population Growth		0.1414			-0.0216
		(0.2505)			(0.0145)
ln(Fiscal Expenditure)		-0.0674			0.0024
		(0.1770)			(0.0057)
Observations	29,064	29,064	29,064	29,064	29,064
R-squared	0.806	0.815	0.733	0.737	0.741
City FE	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes

Notes: This table presents the results of the staggered DID estimation examining the interacting effects of HSR connectivity and charging infrastructure on EV adoption. Columns (1) and (2) analyze the impact of HSR connectivity on the natural logarithm of charging stations, while Columns (3) to (5) focus on EV share as the dependent variable. The sample period is 2010-2023. Cities connected before 2015 are excluded from the estimation sample. The unit of observation is city-month. Fixed effects for city and year-month are included. Robust standard errors, clustered at the city level, are reported in parentheses. Statistical significance is denoted by *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.10$.

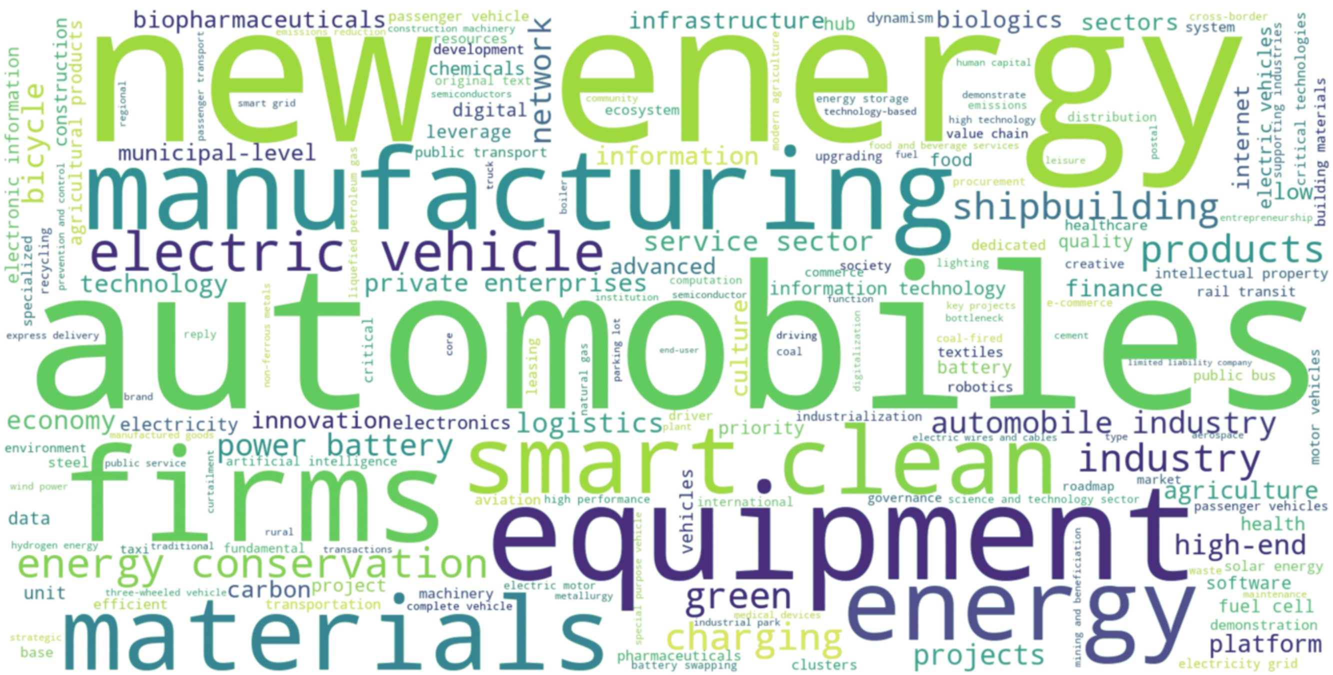
Appendix

A Goodman-Bacon (2021) Decomposition of TWFE Biases

We follow Goodman-Bacon (2021) and decompose the traditional TWFE estimator into a set of 2-by-2 DID estimators over the *full* sample of cities and over the full sample period (2010-2023) to illustrate the source of bias. Using the terminology from Goodman-Bacon (2021), we classify all units into three groups: the "always treated group" (units treated before the first period), the "timing group" (units treated during the sample period), and the "never-treated" group (units that never received treatment). Then the TWFE-DID estimator can be expressed as a weighted average of DID estimators derived from all two-group/two-period comparisons, including comparisons between the timing group and the never-treated group, the timing group and the always-treated group, and pre- vs. post-treatment within the timing group. When the assumptions of parallel pre-trend and constant treatment effect are violated, the latter two types of estimators can be biased, leading to what is commonly referred to as the "negative weighting problem" (Goodman-Bacon, 2021).

Figure A2 presents the decomposition result to illustrate the source of bias inherent in the TWFE estimation. When the never-treated or later-treated group is used as the control group, the treatment effects are almost always positive, while when the always-treated and the early-treated ones are used as controls, the treatment effects are constantly negative. This negative bias arises due to dynamic treatment effects, as early adopters follow a steeper growth trajectory once connected by the HSR network. This increasingly dynamic treatment effect is likely a result of the concurrent advancements in infrastructure like charging stations and the enhanced consumer awareness that arises as the market broadens. Moreover, the comparisons between the timing group and the always-treated group yield large weights, indicating that this group of comparisons is a significant contributor to the overall bias in the TWFE estimates. Panel B of Figure A2 further zooms into the early market development period before 2020, from which we observe a sharper contrast between the two comparisons within the timing group— the comparison of the earlier treated group vs. the later treated group, and that of the later treated group vs. the earlier treated group. We can see that when the later treated group is used as the control group, the treatment effect is constantly positive and the negative effect mainly comes from the comparison when the earlier treated group is used as the control group.

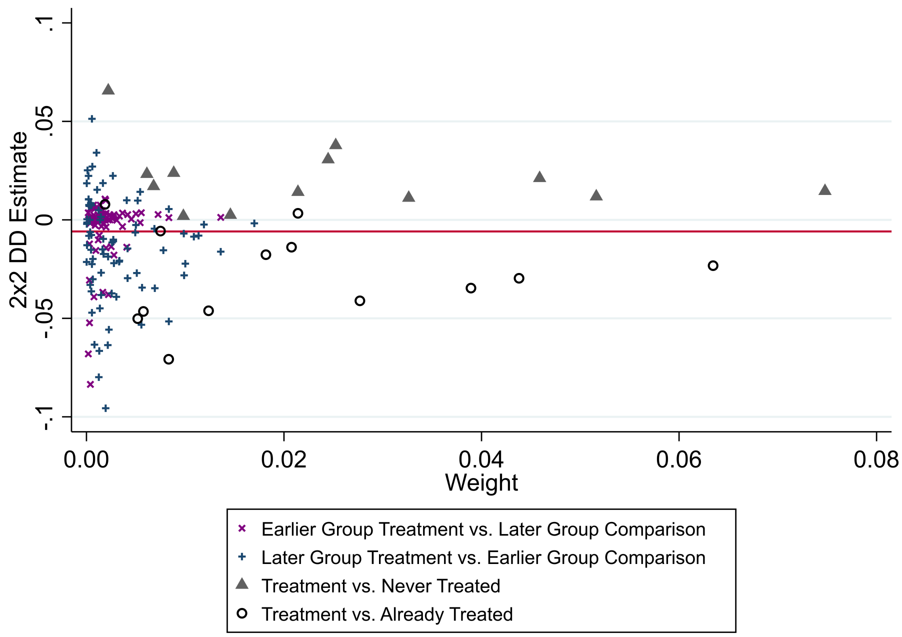
Figure A1: Word Cloud of EV Policy Documents



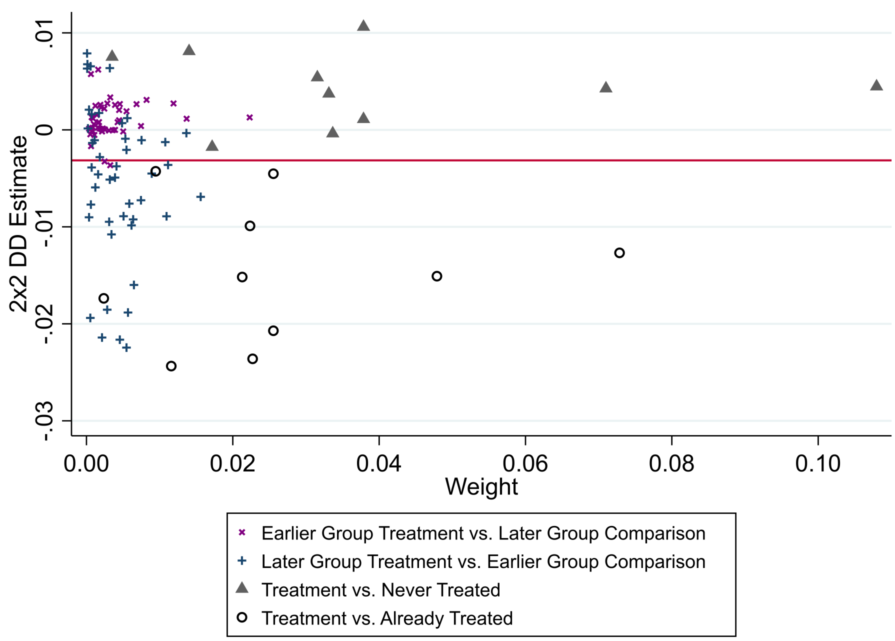
Notes: This figure illustrates a word cloud generated from the text of EV policy documents identified in the dataset. The size of each word reflects its relative frequency in the documents, highlighting the key themes and priorities emphasized in EV-related policies during the sample period.

Figure A2: Goodman-Bacon Decomposition for TWFE-DID Estimation

Panel A: 2010-2023



Panel B: 2010-2019



Notes: This figure illustrates the Goodman-Bacon decomposition of the TWFE-DID estimation, decomposing the overall treatment effect into its constituent 2x2 DID estimates. Panel A covers the full sample period (2010–2023), while Panel B restricts the analysis to the pre-2020 period (2010–2019). All cities are included. The unit of observation is city-month. The x-axis represents the weight assigned to each comparison group, and the y-axis shows the corresponding 2x2 DID estimate. The decomposition includes four types of comparisons, and the red line indicates the overall TWFE-DID estimate.

Table A1: Cities Connected before 2015 v.s. Cities Connected after 2015 vs. Cities Never Connected

Sample	Cities Connected before 2015 (155 Cities)		Cities Connected after 2015 (107 Cities)		Cities Never Connected (66 Cities)	
	Mean	S.D	Mean	S.D	Mean	S.D
EV Sales	540.9	1,991.87	131.6	426.5	32.35	134.81
Fuel Sales	6,981.68	9,065.01	2,840.96	2,792.37	1,082.06	1,038.23
EV Share	0.05	0.09	0.03	0.07	0.02	0.06
# Car Dealerships	29.05	37.20	25.23	27.01	12.02	15.26
# EV manufacturers	0.029	0.199	0.050	0.331	0.005	0.072
# of Charging Stations	185.37	716.01	44.60	117.24	12.95	38.41
Road Lengths (Km)	13,311.96	13,133.55	15,233.96	7,710.91	12,170.73	7,108.61
GDP (Mill. CNY)	387,903.48	527,981.38	164,863.75	139,503.67	79,585.07	84,282.65
Population Growth	0.01	0.05	0.00	0.05	0.00	0.05
Fiscal Expenditure (Mill. CNY)	58,383.63	90,370.88	31,618.56	18,014.94	21,598.56	14,026.38

Notes: This table provides descriptive statistics for three groups of cities: those connected to HSR before 2015, those connected after 2015, and those never connected to HSR.

Table A2: Baseline TWFE DID Analysis using ln(1+Sales) as the Dependent Variables

Dep. Variable	Panel A. ln(1+EV Sales)					
Model	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	0.9139***	0.7073***	0.9159***	0.7686***	0.8766***	0.6064***
	(0.1361)	(0.1105)	(0.1361)	(0.1230)	(0.1328)	(0.1000)
ln(1+ #Charging Stations)		0.3941***				0.3311***
		(0.0290)				(0.0272)
ln(Road Lengths)			-0.1478			-0.0706
			(0.1138)			(0.0872)
ln(1+ #EV Manufacturers)				0.7899***		0.6177***
				(0.0925)		(0.0757)
ln(1+ #Car Dealerships)				0.0568		-0.0118
				(0.2287)		(0.1821)
ln(GDP)					0.8507***	0.5220**
					(0.2935)	(0.2273)
Population Growth					-0.1532	-0.2302
					(0.1961)	(0.1739)
ln(Fiscal Expenditure)					-0.1482	-0.2738*
					(0.2302)	(0.1569)
Observations	29,064	29,064	29,064	29,064	29,064	29,064
R-squared	0.841	0.862	0.841	0.856	0.846	0.873

Dep. Variable	Panel B. ln(1+FV Sales)					
Model	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	0.2104***	0.1835***	0.2103***	0.1790***	0.1913***	0.1568***
	(0.0528)	(0.0493)	(0.0530)	(0.0497)	(0.0505)	(0.0451)
ln(1+ #Charging Stations)		0.0513***				0.0300**
		(0.0122)				(0.0124)
ln(Road Lengths)			0.009			-0.0029
			(0.0397)			(0.0344)
ln(1+#EV Manufacturers)				0.1621***		0.1149***
				(0.0415)		(0.0380)
ln(1+#Car Dealerships)				0.0699		-0.0039
				(0.0968)		(0.0841)
ln(GDP)					0.3906***	0.3474***
					(0.1045)	(0.0988)
Population Growth					-0.0699	-0.0794
					(0.0832)	(0.0821)
ln(Fiscal Expenditure)					0.2527**	0.2287**
					(0.0993)	(0.0933)
Observations	29,064	29,064	29,064	29,064	29,064	29,064
R-squared	0.88	0.881	0.88	0.882	0.886	0.888

Notes: This table repeats the baseline DID analysis using the natural logarithm of EV sales volume (Panel A) and FV sales volume (Panel B) as the dependent variables. The sample period is 2010-2023. Cities connected before 2015 are excluded from the estimation sample. The unit of observation is city-month. All models include city fixed effects and year-month fixed effects. Standard errors, clustered at the city level, are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table A3: Robustness Tests using Different Samples

Dep. Variable	EV Share				
Sample	Full Sample	Exclude Connected Cities before 2014	Exclude Connected Cities before 2013	Exclude Connected Cities before 2012	Exclude Sample after 2020
Model	(1)	(2)	(3)	(4)	(5)
Treatment	-0.0038	0.0101***	0.0081***	0.0068**	0.0051***
	(0.0032)	(0.0029)	(0.0031)	(0.0031)	(0.0008)
Observations	55,104	36,456	39,480	43,008	26,040
R-squared	0.758	0.743	0.740	0.746	0.232
City FE	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes

Notes: This table presents the results of TWFE DID, namely, Eq. (1), various subsamples to examine the effect of HSR connectivity on EV market share. The sample period is 2010-2023. The unit of observation is city-month. Column (1) includes the full sample without excluding any cities. Columns (2) through (4) exclude cities connected to HSR before 2014, 2013, and 2012, respectively. Column (5) excludes observations after 2020 to address potential distortions caused by COVID-19-related economic disruptions. All models include city and year-month fixed effects. Robust standard errors, clustered at the city level, are reported in parentheses. Statistical significance is denoted by *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.10$.

Table A4: Robustness Tests for the Effects of HSR Connectivity on Hybrid Vehicle Share

Dep. Var	Hybrid Vehicle Share									
	DID		Long-difference IV		Unadjusted OLS		Recentered IV		Recentered OLS	
Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Treatment	0.0054***	0.0047***	0.0351**	-0.0092						
	(0.0014)	(0.0013)	(0.0149)	(0.0240)						
MA Growth					0.0064***	-0.0043**	0.0054	0.0013		
					(0.0022)	(0.0017)	(0.0051)	(0.0039)		
Recentered MA Growth									0.0058	-0.0006
									(0.0035)	(0.0029)
Expected MA Growth									0.0066***	-0.0054***
									(0.0024)	(0.0020)
ln(1+ #Charging Stations)		0.0016***		0.0022		0.0006		0.0004		0.0007
		(0.0004)		(0.0035)		(0.0005)		(0.0005)		(0.0005)
ln(Road Length)		-0.0016*		-0.0198***		-0.0104***		-0.0103***		-0.0105***
		(0.0010)		(0.0026)		(0.0011)		(0.0011)		(0.0011)
ln(1+ #EV Manufacturers)		0.001		-0.0025		-0.0017***		-0.0022***		-0.0015**
		(0.0007)		(0.0016)		(0.0006)		(0.0007)		(0.0006)
ln(1+ #Car Dealerships)		-0.0015		-0.0007		-0.0007		-0.0007		-0.0008
		(0.0017)		(0.0028)		(0.0012)		(0.0012)		(0.0012)
ln(GDP)		-0.0051**		0.0217***		0.0045***		0.0039***		0.0045***
		(0.0023)		(0.0058)		(0.0011)		(0.0013)		(0.0011)
Population Growth		0.0065		0.0459		-0.0147		-0.0117		-0.0148
		(0.0043)		(0.0344)		(0.0100)		(0.0107)		(0.0100)
ln(Fiscal Expenditure)		0.0014		0.012		0.0127***		0.0134***		0.0125***
		(0.0020)		(0.0079)		(0.0022)		(0.0023)		(0.0022)
Observations	26,988	26,988	328	328	324	324	324	324	324	324
R-squared	0.807	0.810	0.100	0.573	0.018	0.633	0.018	0.622	0.018	0.635
City FE	Yes	Yes	No	No	No	No	No	No	No	No
Year-Month FE	Yes	Yes	No	No	No	No	No	No	No	No

Notes: This table presents the results of placebo test using various estimation methods to examine the effects of HSR connectivity on the hybrid vehicle share. Columns (1) and (2) use the staggered DID approach and include city fixed effects and year-month fixed effects. Cities connected before 2015 are excluded from the estimation sample. The unit of observation is city-month. Columns (3) and (4) implement long-difference IV estimations. Columns (5) to (10) apply the Borusyak and Hull IV approach for additional validation. All cities are included for Columns (3)-(10). The unit of observation is city. Robust standard errors, clustered at the city level, are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table A5: Heterogeneity by HSR Characteristics and Cities

Dep. Variable	EV Share				
Heterogeneity	Speed	Length	# of Lines	# of Stations	Cities
Model	(1)	(2)	(3)	(4)	(5)
Treatment	0.0041	0.0122**	0.0128***	0.0129***	-0.0413***
	(0.0053)	(0.0054)	(0.0041)	(0.0035)	(0.0071)
Treatment*SpeedDummy	0.0209***				
	(0.0069)				
Treatment*LengthDummy		-0.0012			
		(0.0071)			
Treatment*LinesDummy			-0.0060		
			(0.0091)		
Treatment*StationDummy				-0.0032	
				(0.0079)	
Treatment*East					0.0762***
					(0.0092)
Treatment*Middle					0.0719***
					(0.0082)
Treatment*West					0.0410***
					(0.0070)
Observations	29,064	29,064	29,064	29,064	29,064
R-squared	0.728	0.725	0.725	0.725	0.742
City FE	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes

Notes: This table examines the heterogeneity in the impact of HSR connectivity on EV market share by incorporating interactions between *Treatment* and various HSR characteristics, including *SpeedDummy* (=1 for HSR speed above 300km/h), *LengthDummy* (=1 for connected HSR length above 1500km), *LinesDummy* (=1 for connected HSR lines above 5), and *StationDummy* (=1 for connected HSR stations above 10). Column (5) explores regional heterogeneity using geographic categories (East, Middle, West, and Northeast), with the Northeast serving as the benchmark. The sample period is 2010-2023. Cities connected before 2015 are excluded from the estimation sample. The unit of observation is city-month. All specifications include city fixed effects and year-month fixed effects. Standard errors are clustered at the city level and reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.