The Green Ride: Bike-Sharing Platforms and Urban Carbon Reduction

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Abstract: *Can the sharing economy contribute to urban sustainability? This study explores this question using the staggered entry of bike-sharing platforms across Chinese cities as a quasi-natural experiment. Drawing on 2015-2017 city characteristics panel data and monthly CO_2 emission records, we employ a staggered difference-in-differences (DID) model to assess the impact of bike-sharing on per capita urban CO_2 emissions. The results show that bike-sharing platforms significantly cut emissions by replacing high-carbon transport and boosting public adoption of shared bikes. This effect is more potent in cities with less stringent environmental enforcement, more advanced digital economies, greater technological innovation, and where two platforms jointly entered. By elucidating the mechanisms underlying bike-sharing's carbon-reduction potential, this study highlights its role in urban sustainability. It offers policy insights for leveraging shared mobility to reduce city carbon emissions.*

Keywords: *sharing economy; bike-sharing; green transition; CO_2 emissions*

JEL Classification Codes: Q51; Q53; R40

DOI: 10.19602/j.chinaeconomist.2026.01.05

1. Introduction

The sharing economy is transforming the digital era by converting idle resources into shared assets via digital platforms. It redefines ownership, labor, and consumption—enhancing efficiency and streamlining daily life[1]. In China, this model resonates deeply with the nation's vision of "innovation, coordination, green development, openness, and sharing," laying the foundation for sustainable progress (Heinrichs, 2013; Mi & Coffman, 2019). Endorsed in the 13th Five-Year Plan (2016-2020) as a strategic economic priority, the sharing economy has surged with 5G and artificial intelligence (AI) integration, reaching a market value of 3.832 trillion yuan in 2022—a 3.9% increase year-over-year, according to the National Information Center. From ride-hailing to food delivery, the sharing economy now touches nearly every aspect of urban life. As such, it fosters eco-conscious behavior and supports China's ambitious "dual carbon" goals to peak emissions and achieve net carbon neutrality.

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Acknowledgement: This study was supported by the National Natural Science Foundation of China (NSFC) (Grant No. 72372048) and the "Young Top-Notch Talent" Cultivation Program of Hubei Province.

[1] This definition is from the *China Sharing Economy Development Report (2023)*, published by the State Information Center.

Bike-sharing, a pioneering sector in China's sharing economy, has expanded at a remarkable speed, leaving a broad imprint on urban development and industrial transformation and upgrading (Cao et al., 2023). It has actively supported the green transition of China's transportation sector and contributed to its "dual carbon" goals. According to the *Report on Bike-Sharing Contribution to Pollution and Carbon Reduction* by the Environmental Development Center of the Ministry of Ecology and Environment (MEE) and the China Environmental United Certification Center (CEC), shared bikes and e-bikes offered by Meituan, a Chinese online service platform, have reduced CO_2 emissions by 1.187 million tons since their launch—equivalent to taking 270,000 private cars off the road for a year. Yet, for all its promise, the environmental impact of bike-sharing remains underexplored. While experts agree it helps, the picture is clouded by the operational challenges during rapid expansion—bikes abandoned on sidewalks, blocking doorways, or piled in vacant lots. Additionally, the scale and mechanism of its carbon-cutting potential remain murky. Does a new bike-sharing platform truly reduce a city's emissions? If so, how enduring is its impact? This study addresses these questions, using the staggered entry of bike-sharing companies across Chinese cities as a natural experiment to explore their role in a low-carbon future.

We analyze city-level data from 2015-2017 alongside monthly CO_2 emissions, employing a staggered difference-in-differences (DID) model to measure the impact of bike-sharing platforms on per capita emissions. The results from this model were clear: cities with new platforms see a significant, lasting drop in emissions. A dynamic trend analysis, inspired by Bertrand & Mullainathan (2003), confirms this downward shift persists post-entry.

To ensure our findings are robust, we conducted rigorous tests. First, to address potential city-level confounding factors, we used propensity score matching (PSM) to pair treatment and control cities based on their characteristics in the year before bike-sharing platforms launched. Re-running the regressions on this matched sample yielded consistent results. Second, to rule out region-specific influences on platform locations, we performed a placebo test by randomly assigning "pilot" cities. In this scenario, the CO_2 reduction effect vanished, confirming that our results stem from bike-sharing, not chance or local factors. Finally, to address potential bias from heterogeneous treatment effects in our staggered DID design, we applied the Goodman-Bacon decomposition to identify sources of bias. We used the corrections from Cengiz et al. (2019) and Callaway & Sant'Anna (2021). From these added analyses, the results still hold. Together, these tests confirm that bike-sharing is a powerful, lasting solution for reducing urban carbon emissions.

Our findings reveal that bike-sharing platforms cut carbon emissions through two main channels: by substituting for other modes of transport and by inspiring more people to ride. In cities with extensive public transit networks and high private car ownership, shared bikes serve as a practical, low-carbon alternative, enhancing their emission-reduction effect. Meanwhile, higher urban metro development levels, better air quality, and stronger public eco-consciousness reinforce public willingness to use shared bikes, thereby amplifying the CO_2-reduction effects of bike-sharing platform deployment.

Regional differences also emerge. In areas where environmental regulations are relatively weak, bike-sharing platforms can step in as a market-based substitute for policy, delivering tangible emission cuts. Moreover, a strong local digital economy accelerates this process by creating fertile ground for the sharing economy and expanding platform reach. Strengthened regional sci-tech innovation capacity adds another push, supplying new momentum for the carbon-reducing potential of these platforms. The effect is most striking in cities where two bike-sharing providers operate side by side, resulting in deeper cuts in emissions than in cities served by just one provider.

This study makes two key contributions to the field. First, it examines the impact of bike-sharing platforms on per capita CO_2 emissions, offering a fresh and broadly applicable perspective. Previous studies explored sharing economy platforms like Uber (Kim et al., 2018; Nian et al., 2021; Barrios et al., 2022) and Airbnb (Zervas et al., 2017; Barron et al., 2021; Farronato & Fradkin, 2022), or analyzed bike-sharing's effects on housing prices, traffic congestion, and air pollution (Chu et al., 2021; Shr et al., 2023; Hamilton & Wichman, 2018; Huang et al., 2023; Xiao et al., 2021; Cao et al., 2023). While prior studies focus on single-city contexts (e.g., Zhang & Mi, 2018; Cao & Shen, 2019), our multi-city analysis spanning urban centers exploits the quasi-experimental nature of bike-sharing's phased expansion. Thus, yielding findings with broader generalizability.

Second, this study demonstrates how market-driven mechanisms, such as bike-sharing, can advance low-carbon transitions. Prior research has linked carbon intensity to factors like urbanization, trade openness, economic agglomeration, and regional development (Lin & Liu, 2010; Li & Qi, 2011; Shao et al., 2019; Chen, 2020; Zheng et al., 2019). Studies have also examined how market-based environmental policies, such as carbon taxes and emissions trading, affect emissions (Chen, 2012; Qian et al., 2019; Cao et al., 2021; Hu et al., 2020). These policies often outperform command-and-control approaches because they rely on market incentives (Chen, 2022). Since bike-sharing expansion is primarily driven by operator decisions rather than government mandates (Gu et al., 2019), our findings highlight how the sharing economy can fuel China's low-carbon urban shift. As such, it offers empirical evidence that market forces can drive sustainable progress.

2. Literature Review and Research Hypotheses

2.1 Literature Review

2.1.1 Economic and environmental benefits of the sharing economy

As cities strive for high-quality urbanization, the sharing and low-carbon economies have emerged as key paths to sustainable development. By enabling efficient resource allocation and circulation, the sharing economy enhances resource use, reduces environmental pollution, and fosters low-carbon, eco-friendly growth (Zhu, 2017). Notably, research on the sharing economy primarily focuses on ride-sharing and short-term rental platforms, with less attention on bike-sharing's broader impacts.

Ride-sharing platforms like Uber have been extensively studied for their social welfare effects. Kim et al. (2018) found that Uber's entry into Manhattan forced taxis to expand their geographic coverage and serve previously underserved customers to remain competitive. Nian et al. (2021) demonstrated that Uber's staggered entry across regions reduced personal bankruptcy rates by providing alternative sources of income. Furthermore, Barrios et al. (2022) highlighted how Uber and Lyft create gig opportunities that lower entrepreneurial risks, encouraging new business formation.

Short-term rental platforms, notably Airbnb, have also drawn significant attention. Zervas et al. (2017) showed that Airbnb's entry into Texas over a decade lowered hotel prices by leveraging the sharing economy's flexible supply, benefiting all consumers. This is particularly true at low-cost and non-business-oriented hotels. Additionally, Barron et al. (2021) found that Airbnb increases house prices and rents by shifting housing supply from long-term to short-term rentals. Furthermore, Farronato & Fradkin (2022) modeled competition between flexible Airbnb hosts and professional lodging providers, showing that responsive hosts expand supply when hotel capacity is constrained, driving down hotel prices.

Bike-sharing platforms offer unique social and environmental benefits, including zero emissions, reduced car usage, alleviated traffic congestion, lower energy consumption, and increased daily bike use (Shaheen et al., 2010). Socio-economically, Chu et al. (2021) found that bike-sharing lowers travel costs between homes and subway stations, reducing the price premium of subway-adjacent apartments and boosting the appeal of more distant ones. Using a spatial DID approach, Shr et al. (2023) found that bike-sharing facilities significantly increased nearby rental prices, based on data from China's Taiwan region. Hamilton & Wichman (2018) demonstrated that Washington D.C.'s Capital Bikeshare reduced traffic congestion by over 4%, particularly in highly congested areas. Huang et al. (2023) confirmed similar congestion relief from bike-sharing in Chinese cities. Environmentally, bike-sharing's benefits are well-documented. Zhang & Mi (2018) used big data to estimate that Shanghai's bike-sharing programs saved energy and reduced CO_2 and NOx emissions, with greater impacts during evening rush hours. Cao & Shen (2019) modeled Beijing's Mobike data to quantify bike-sharing's contribution to CO_2 reduction. Chen et al. (2020) employed a complete life-cycle assessment (LCA) model covering the production, operation, and recycling phases to quantify the sector's critical thresholds for emission reduction. Sun et al. (2021) showed that dockless bike-sharing in Beijing enhances resource utilization and reduces consumption in urban cycling systems. Additional studies explore bike-sharing's development trends (Guo et al., 2017) and government regulation (Cai, 2017).

2.1.2 Factors influencing urban low-carbon transition

Extensive research has explored the drivers of urban low-carbon economies and transitions. Notably, these have focused primarily on how urbanization, trade openness, economic clustering, and regional development shape carbon emissions. Studies on low-carbon transitions often emphasize the role of environmental policy tools, such as carbon taxes and emissions trading schemes, in achieving sustainable outcomes.

Urbanization's impact on emissions has been widely studied. Grossman & Krueger (1995) used cross-country panel data to establish a strong correlation between urbanization and greenhouse gas emissions. He et al. (2009) noted that rapid urbanization increases inflexible energy demand, exacerbating environmental challenges. Lin & Liu (2010) argued that China's low-carbon transition should balance GDP growth with controlled urbanization, prioritizing energy conservation while developing clean energy as a secondary strategy.

Trade openness presents mixed effects. Li & Qi (2011) used static and dynamic panel models and found that international trade increases CO_2 emissions and carbon emission intensity across Chinese provinces. In contrast, Chen (2020), leveraging China's WTO entry as a quasi-natural experiment, showed that reduced trade barriers significantly lowered SO_2 emission intensity, suggesting that greater openness can enhance environmental and social welfare. Likewise, economic clustering also influences emissions. Lu & Feng (2014) demonstrated that higher spatial concentration of population and economic activity reduces industrial pollutant emissions per unit of GDP. Shao et al. (2019) identified an inverted N-shaped relationship between economic clustering, carbon intensity, and per capita emissions, noting that beyond a certain threshold, clustering yields both energy savings and emission reductions. Zheng et al. (2019), using the Log Mean Divisia Index (LMDI), found that since 2012, regional structural shifts—measured by provincial economic growth shares—have significantly cut CO_2 emissions, advocating for regional cooperation to optimize development models. Additional studies highlight the roles of industrial structure (Wang et al., 2010), technological progress (Shi et al., 2018), smart city pilots (He & Gai, 2022), and urban transport systems (Liang & Xi, 2016; Fan & Zheng, 2020) in reducing urban carbon emissions.

Environmental policy tools—both price and quantitative tools—are critical for low-carbon transitions. Chen (2012) developed a dynamic assessment index using the SBM-DDF-AAM framework to evaluate and predict China's provincial low-carbon progress since reforms. Qian et al. (2019) proposed a multi-factor carbon allowance allocation model that accounts for regional variations in low-carbon technologies from both consumption and production perspectives. Xu & Sun (2023) showed that carbon emissions trading pilots, as market-based regulations, accelerate the restructuring of energy consumption and support "dual control" goals for total emissions and intensity. While Cao et al. (2021) found no impact of emissions trading systems (ETS) on coal efficiency in regulated power plants, Hu et al. (2020) used a DID model to demonstrate significant energy savings and emission reductions from CO_2 ETS in developing countries, driven by improved technical efficiency and industrial restructuring, with more potent effects in regions with robust enforcement and high marketization. Chen (2022) argued that market-driven environmental policies, which harness economic incentives, outperform administrative mandates in driving efficient, low-carbon economic transitions.

While these studies provide robust insights into the sharing economy and low-carbon transitions, a key gap persists: the specific impact of bike-sharing platform entry—a cornerstone of the sharing economy—on urban carbon emissions remains underexplored. Building on this foundation, this study investigates whether bike-sharing can deliver measurable carbon-reduction effects in cities, offering a novel contribution to the literature.

2.2 Research Hypotheses

Bike-sharing platforms, as a mode of urban transportation, may reduce city carbon emissions through two primary channels: substituting for regional transport vehicles and increasing public willingness to use shared bikes.

Bike-sharing exerts substitution effects on regional transport modes. Shared bikes address the "last-mile" challenge, complementing urban public transit systems and meeting diverse travel needs. Urban rail transit reduces air pollution primarily by substituting for taxis (Liang & Xi, 2016). As a feeder service, bike-sharing synergistically complements metro systems. Chen et al. (2018) found that bike-sharing and rail transit together significantly reduce air pollution, with shared bikes amplifying the rail transit's emission-reduction effects. Xiao et al. (2021) similarly noted that integrating bike-sharing with metro systems boosts environmental improvements. Cao et al. (2023) used a DID model and showed that the air quality benefits of bike-sharing increase as subway networks expand. Niu et al. (2022) quantified this substitution effect by modeling the full life-cycle carbon emissions of shared bikes, accounting for China's electric vehicle penetration and bike wear rates, and demonstrated significant carbon savings from replacing cars. Beyond emissions, bike-sharing reduces traffic congestion and travel costs, supporting greener urban transport. Yang et al. (2018) found that shared bikes shorten average travel times, enhance public transit network efficiency, and address uneven spatial distribution, alleviating congestion and cutting carbon emissions. Additionally, Chu et al. (2021) showed that bike-sharing lowers travel costs between homes and subway stations, increasing the appeal of distant apartments and reducing price premiums for those near subways. Huang et al. (2023) used a DID approach to confirm bike-sharing's role in mitigating traffic congestion in major Chinese cities, further reducing transport-related carbon emissions.

In contrast, public willingness to use shared bikes critically shapes their utilization rates. Higher usage rates amplify the platforms' environmental impact, influenced by both objective and subjective factors. When public preference favors bike-sharing, it amplifies the platforms' efficacy in reducing urban CO_2 emissions. Objective factors—particularly the quality of cycling infrastructure and service accessibility—are the primary determinants of this preference. Liu et al. (2012) proposed bike-sharing as a solution to the "last-mile" problem, emphasizing the need to improve cycling environments alongside promoting the system. Xiang et al. (2018) found a strong negative correlation between urban air pollution and bike-sharing demand, indicating that cleaner air boosts bike-sharing usage. Wang et al. (2019) showed that higher bike accessibility increases the substitution of shared bikes for cars in commuting, enhancing environmental benefits. Subjective elements such as environmental consciousness are equally pivotal. Zheng et al. (2013) demonstrated that heightened public concern for the environment pushes local governments to prioritize ecological governance, such as pollution control and industrial restructuring, to improve air quality. Using a game-theoretic model, Wu et al. (2022) established theoretically that public environmental awareness drives market demand for green products and eco-friendly firms, ultimately enhancing environmental outcomes.

Drawing on these findings, we hypothesize that the entry of bike-sharing platforms reduces per capita urban CO_2 emissions by replacing higher-emission transport modes and encouraging public use of sustainable travel options.

3. Research Design

3.1 Data Sources and Sample Selection

To ensure robust results, we focus on city-level data from the Chinese mainland between 2015 and 2017 to avoid noise from the 2018 bike-sharing deposit crisis involving platforms like ofo[2]. We also excluded samples from China's Taiwan region, Macau Special Administrative Region (SAR), and Hong Kong SAR. Missing city characteristic data were imputed using the ARIMA method.

[2] Reports from CNR (December 30, 2017) noted that six bike-sharing companies, including Wukong, Dingding, Kuqi, 3V Bike, Xiaolan, and Xiaoming, ceased operations due to financial difficulties, impacting millions of users. Additionally, *Legal Daily* (December 21, 2018) reported that ofo's "new refund policy" on December 17, 2018, led to over 10 million users queuing for refunds by December 19, with numbers continuing to rise.

Following Cao et al. (2021) and Chu et al. (2021), we compiled entry dates for the major bike-sharing platforms ofo and Mobike. Monthly city-level CO_2 emissions (in tons) were aggregated from 1 km × 1 km satellite data provided by the Center for Global Environmental Research. Other economic and demographic variables were drawn from the China City Statistical Yearbook. To reduce the effects of outliers, continuous variables were Winsorized at the 1% and 99% percentiles. The final balanced panel includes 296 cities and 10,656 city-month observations.

3.2 Model Specification and Variable Definitions

This study treats the staggered entry of bike-sharing platforms into cities as a quasi-natural experiment with time-varying treatment periods. As such, this enables us to evaluate their impact on urban CO_2 emissions. We employed a staggered DID model, widely recognized in policy evaluation for its ability to address endogeneity and isolate the net effect of interventions. Cities with bike-sharing platforms (ofo or Mobike) formed the treatment group, while those without served as the control group. Since platform entry dates vary across cities, we defined the treatment event as the earliest entry date of either ofo or Mobike in a given city, based on data from 2015-2017. The period selected for this study was chosen deliberately. Dockless bike-sharing emerged in China in 2015, and from 2015 to 2017, ofo and Mobike collectively held over 90% of the market share, operating in a dynamically competitive yet stable environment (Cao et al., 2023). Post-2018, the industry faced significant disruptions: financial difficulties led to deposit refund issues, notably for ofo, which faced a refund backlog affecting millions. Concurrently, major market shifts occurred, including Didi's launch of Qingju Bike, Hello Bike's introduction of a nationwide credit-based deposit waiver, and Meituan's acquisition of Mobike. These events reshaped the competitive landscape, introducing volatility that could obscure the net impact of bike-sharing on CO_2 emissions. By focusing on 2015-2017, we capture a representative period of market stability, minimizing confounding factors.

The staggered difference-in-differences (DID) approach rests on the parallel trends assumption—that is, before bike-sharing platforms enter, the treatment and control cities should exhibit broadly similar trends in per capita CO_2 emissions. In practice, however, platform entry is far from random; economic conditions, social factors, and local development strategies may all shape when and where a platform launches. Such influences risk breaking the parallel trends assumption and biasing the results. To guard against this, we control for each city's pre-treatment characteristics as of the end of 2014—factors that could plausibly influence platform entry—by interacting them with a complete set of year dummy variables. This allows us to capture time-varying effects of those initial conditions and strip them out from the estimated treatment effect. The resulting baseline regression model is:

$$Ln\ (CO_{2}\_per\_capita)_{i,y,m}=\alpha_0+\beta_1 Entry_{i,y,m}+\gamma Controls_{i,2014}\times\delta_y+\mu_i+\lambda_{y,m}+\varepsilon_{i,y,m} \qquad (1)$$

Variables are defined as follows. $Ln(CO_2\_per\_capita)_{i,y,m}$ represents the natural logarithm of per capita CO_2 emissions for city i in year y and month m. $Entry_{i,y,m}$ is a dummy variable equal to 1 if a bike-sharing platform (ofo or Mobike) had entered city i by year y, month m, and 0 otherwise. Its coefficient β_1 is our primary focus: a significantly negative value would indicate that platform entry helps reduce per capita CO_2 emissions.

$Controls_{i,2014}$ denotes pre-treatment city i's characteristics measured at the end of 2014, interacted with year fixed effects (δ_y). These controls capture factors that could influence both platform entry and emissions trends: Economic development (*Ln(GDP_per_capita)*), the natural log of per capita GDP; Industrialization level (*Industry_2*), measured by the secondary industry's share of GDP; Industrial structure (*Industry_3*), measured by the tertiary industry's share of GDP; Land area (*Ln(Land)*), the natural log of administrative land area in square kilometers; Government scale (*Govern_public*), measured by public fiscal expenditure as a share of GDP.

We also include city fixed effects to absorb time-invariant characteristics and year-month fixed effects to capture common temporal shocks. Standard errors are clustered at the city level to account for potential serial correlation. Descriptive statistics are reported in Appendix A.

4. Empirical Results and Analysis

4.1 Baseline Regression

To test our hypothesis, we defined the treatment event as the earliest entry of either ofo or Mobike into a city. We applied the staggered DID model to assess its impact on per capita CO_2 emissions. Results are presented in Table 1. Column (1) excludes control variables, while Column (2) includes interactions between 2014 city characteristics and year fixed effects. Both regressions reveal a significant negative effect of bike-sharing platform entry on per capita CO_2 emissions, confirming a robust emission-reduction impact. In Column (1), the coefficient for *Entry* is -0.012, significant at the 1% level. In Column (2), after controlling for city characteristic trends, the coefficient is -0.006, significant at the 5% level, indicating that platform entry reduces monthly per capita CO_2 emissions by 0.60% on average.

TABLE 1. Baseline regression results

Variable	(1)	(2)
	Ln(CO_2_per_capita)	*Ln(CO_2_per_capita)*
Entry	-0.012*** (0.003)	-0.006** (0.002)
Constant	-2.012*** (0.000)	-2.076*** (0.019)
Control variable	No	Yes
City fixed effects	Yes	Yes
Year-month fixed effects	Yes	Yes
Observations	10656	10656
Adjusted R^2	0.999	0.999

Note: *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively, with robust standard errors clustered at the city level in parentheses.

4.2 Parallel Trends Test

The staggered DID model assumes that, before bike-sharing platform entry, treatment and control cities followed parallel trends in per capita CO_2 emissions. To verify this, we use an event-study framework with a dynamic DID model:

$$Ln\ (CO_2\_per\_capita)_{i,y,m}=\alpha_0+\sum_{s=-6(s\neq-1)}^{s=12}\beta_S Entry_{i,y,m}^{S}+\gamma Controls_{i,2014}\times\delta_y+\mu_i+\lambda_{y,m}+\varepsilon_{i,y,m}\ (2)$$

where, $Entry_{i,y,m}^{S}$ represents dummy variables for time periods relative to platform entry. Due to limited data, all months ≥6 before entry are grouped into $Entry_{i,y,m}^{-6}$ (1 if ≥6 months pre-entry, 0 otherwise), and months ≥12 after entry are grouped into $Entry_{i,y,m}^{+12}$ (1 if ≥12 months post-entry, 0 otherwise). Other periods, such as $Entry_{i,y,m}^{-5}$ (1 if 5 months pre-entry, 0 otherwise), are defined similarly. All other variables are as in the baseline model.

Dynamic estimates and trends show that pre-entry coefficients are all statistically insignificant, confirming no significant differences in emission trends between treated and control cities and thus satisfying the parallel trends assumption. Post-entry coefficients become significantly negative from the fifth month onward, indicating that platform entry produces a persistent reduction in CO_2.

4.3 Robustness Checks

The baseline regression indicates that the entry of bike-sharing platforms reduces per capita CO_2 emissions. To ensure that confounding factors do not drive this finding, we conducted multiple robustness tests, including propensity score matching DID (PSM-DID), placebo tests, handling treatment effect heterogeneity in the staggered DID framework, and additional checks to confirm the reliability of the results.

4.3.1 PSM-DID

Although bike-sharing platform entry is relatively exogenous, differences in city characteristics could introduce bias from reverse causality or omitted variables. To address this, we applied propensity score matching (PSM) using 2014 city characteristics (e.g., per capita GDP, industrial structure) as matching variables, employing 1:1 nearest-neighbor matching with replacement. Re-running the baseline model on this matched sample produced consistent results, with the Entry coefficient remaining significantly negative, reinforcing the robustness of our findings.

4.3.2 Placebo test

To ensure unobserved factors do not drive our staggered DID results, we conducted a placebo test. We randomly selected 106 cities (the same number as in the actual treatment group), assigned them fictitious bike-sharing entry dates, and re-estimated the DID model from Equation (1) 1,000 times, saving the estimated coefficients and corresponding p-values from each run. We then computed descriptive statistics for these 1,000 estimates and plotted their kernel density distribution. The placebo coefficients are distributed around zero in an approximately normal shape. In contrast, the baseline DID coefficient of −0.006 (with controls) lies far to the left of the placebo distribution's left tail, ruling out the possibility that random or unobserved factors drive the observed CO2 reduction from bike-sharing entry.

4.3.3 Robustness checks for staggered DID

In the staggered DID framework, the two-way fixed effects (TWFE) estimator has long been regarded in the literature as equivalent to the DID estimator. However, recent studies (Goodman-Bacon, 2021; Sun & Abraham, 2021; Liu et al., 2022) show that, under heterogeneous treatment effects, the TWFE estimator may be biased. To obtain an unbiased estimate of the average treatment effect (ATE), in addition to satisfying the parallel trends assumption, the TWFE estimator also requires that the treatment effect be constant across both groups and time periods. In multi-period settings with staggered treatment timing, this condition may be violated due to the "bad control group" problem—where individuals who received treatment earlier are used as controls for newly treated individuals, even though their outcome variables already incorporate the treatment effect. When such "contaminated" controls carry substantial weight, the TWFE estimator is more likely to exhibit bias that is difficult to interpret due to cross-period contamination (Goodman-Bacon, 2021). Following Goodman-Bacon (2021), we begin by decomposing the TWFE estimator in Equation (1) for analysis, and subsequently apply the approaches of Cengiz et al. (2019) and Callaway & Sant'Anna (2021) to obtain heterogeneity-robust estimators.

Following Goodman-Bacon (2021), we decompose the two-way fixed effects (TWFE) estimator from Equation (1). The final average treatment effect (ATE) from the TWFE estimator is -0.012. The DID estimate using "never-treated" cities as controls is -0.012 (weight share: 88.7%), the estimate using "not-yet-treated" cities is -0.002 (weight share: 7.8%), and the estimate using "already-treated" cities is 0.000 (weight share: 3.5%). The last type of 2×2 DID comparison—using "already-treated" cities as controls—has minimal influence on the final TWFE estimate, with the bulk of the weight (88.7%) coming from the "never-treated" group. These results indicate that, in our setting, bias from heterogeneous treatment effects is small.

We further validate our findings using the stacked DID approach proposed by Cengiz et al. (2019) and, following Callaway & Sant'Anna (2021), the weighted group-time ATT method, with "not-yet-treated" and "never-treated" cities as controls. The results confirm the robustness of the baseline model in Equation (1). Figure 1 plots the dynamic treatment effects from the baseline DID, PSM-DID, and the above heterogeneity-robust estimators. Before the bike-sharing platform entry, coefficient estimates across different samples and estimation methods are statistically insignificant, satisfying the parallel trends assumption. After entry, the treatment effects become progressively significant, indicating that our main results are robust.

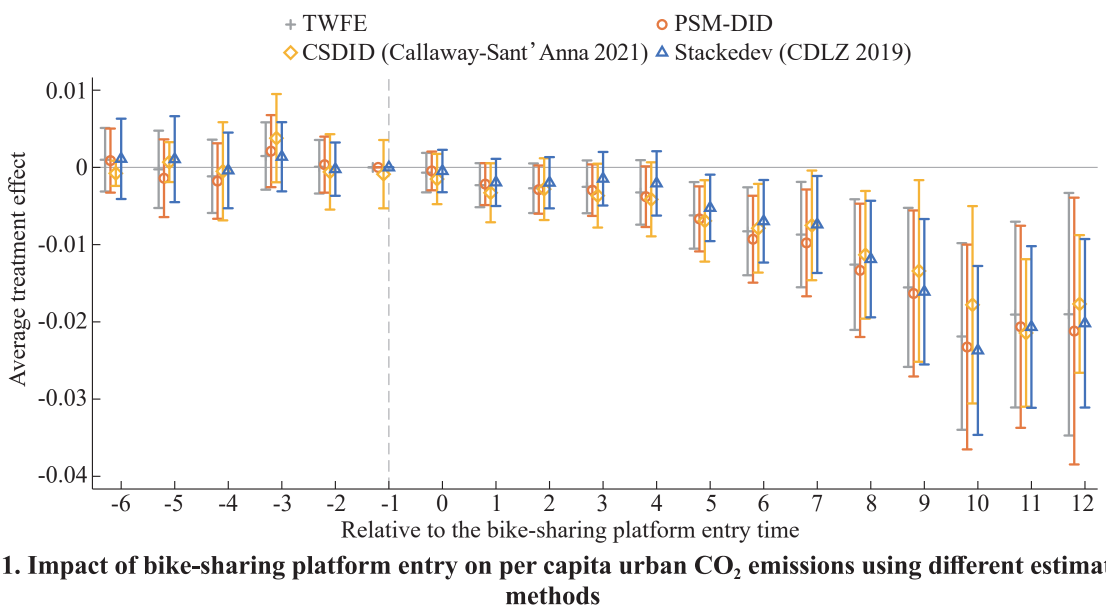

Fig.1. Impact of bike-sharing platform entry on per capita urban CO_2 emissions using different estimation methods

4.3.4 Additional robustness checks

To ensure other factors do not confound our conclusions, we conducted further robustness tests addressing the potential impact of air quality, the Air Pollution Prevention and Control Action Plan (APPCAP), and the Low-Carbon City Pilot policy.

(1) Accounting for the impact of Air Quality. Prior studies have found that the entry of bike-sharing platforms can improve urban air quality (Cao et al., 2023; Huang et al., 2022). To control for air quality's potential influence on CO_2 emissions, we further included the monthly Air Quality Index (AQI) as a control variable and re-estimated the baseline model (Equation 1). Results in Appendix B, Column (1), show that the coefficient for *Entry* remains significantly negative at the 1% level, indicating that the CO_2 reduction effect of bike-sharing is robust to changes in air quality.

(2) Excluding the impact of *Air Pollution Prevention and Control Action Plan* (APPCAP). On September 10, 2013, the State Council issued the APPCAP to address severe PM2.5 pollution. The policy includes 10 measures targeting reduced coal dependence, stricter vehicle emissions standards, the promotion of renewable energy, and updated emission standards, along with specific high-target PM2.5 reduction goals for regions such as Beijing-Tianjin-Hebei, the Yangtze River Delta, and the Pearl River Delta. Due to variations in the intensity of APPCAP implementation across Chinese cities, this policy inevitably affects urban CO_2 emissions. Following Yu et al. (2022) and Zhou et al. (2022), we identified 73 high-target cities under APPCAP. Given that APPCAP began in 2013 and continued through the end of our 2015-2017 sample period, we excluded these cities from the initial sample and re-estimated the staggered DID model. Results in Appendix B, Column (2), show the Entry coefficient remains significantly negative at the 1% level, indicating the CO_2 reduction effect is robust to APPCAP's influence.

(3) Excluding the impact of Low-Carbon City Pilot Policy. To accelerate the green transition of China's development, the National Development and Reform Commission (NDRC) officially launched the first batch of Low-Carbon City Pilot programs in 2010. It expanded the scope twice more in 2012 and 2017. The pilot list grew from the initial 5 provinces and 8 cities to 45 cities in the third batch, with the pilot scope gradually radiating nationwide. Drawing from official NDRC notices, we compiled the approval dates and city lists for all three batches. The list included provinces, prefecture-level cities, and county-level cities. We included all prefecture-level cities within the pilot provinces. We retained only pilot regions at the prefecture-level or above, resulting in a total of 131 pilot cities across all three batches. We then created a dummy variable, *LCC_entry*, which is 1 if a city was a low-carbon pilot after its official approval date and 0 otherwise. By including this variable as a control in our staggered DID model, we obtained the results shown in Appendix B, Column (3). The regression results show that even after controlling for the influence of the low-carbon pilot policy, the coefficient for *Entry* remains significantly negative at the 1% level. This confirms that the carbon-reduction effect of bike-sharing platforms' entry is robust.

4.4 Potential Mechanisms

Bike-sharing reduces urban per capita CO_2 emissions through two channels: substituting for high-emission transport modes and enhancing public preference for green travel. By integrating with public transit, bike-sharing boosts system efficiency and mitigates traffic congestion (Wang

& Zhou, 2017; Hamilton & Wichman, 2018; Huang et al., 2023). The synergy between bike-sharing and rail transit promotes the substitution of motorized vehicles, reducing commute times and air pollution (Fan & Zheng, 2020; Xiao et al., 2021). As a sustainable transport option, bike-sharing also benefits from heightened public environmental awareness, which increases adoption by fostering a preference for eco-friendly travel.

To test the substitution effect, we used public bus/trolley passenger volume and private car ownership as indicators, and present the results in Table 2. In Column (1), the interaction between *Entry* and annual public transit passenger volume at the prefecture-level city level yields a significantly negative coefficient at the 1% level, indicating more substantial CO_2 reductions in cities with robust transit systems. In Column (2), the interaction with private car ownership is also significantly negative at the 1% level, showing greater reductions in cities with more cars. In congested cities with high transit use or car ownership, bike-sharing's on-demand, stop-and-go flexibility—unconstrained by fixed routes—replaces car trips, reducing traffic-related greenhouse gas emissions and lowering per capita CO_2 levels.

TABLE 2. Mechanism test—substitution effect of transportation

Variable	(1)	(2)
	Ln(CO₂_per_capita)	*Ln(CO₂_per_capita)*
Entry	-0.002 (0.002)	0.003 (0.003)
Entry×Ln(traffic)	-0.006*** (0.002)	
Ln(traffic)	-0.002 (0.002)	
Entry×Ln(car)		-0.013*** (0.004)
Ln(car)		-0.055*** (0.019)
Constant	-2.009*** (0.025)	-2.090*** (0.034)
Control variable	Yes	Yes
City fixed effects	Yes	Yes
Year-month fixed effects	Yes	Yes
Observations	9888	8244
Adjusted R^2	0.999	0.999

Note: *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively, with robust standard errors clustered at the city level in parentheses.

To examine the mechanisms underlying public willingness to adopt bike-sharing, we use three indicators—urban rail transit scale, air pollution levels, and public environmental awareness—and report the results in Table 3. In Column (1), we measure rail transit scale by the total operational length of rail lines and interact it with the *Entry* variable. The interaction term's coefficient is significantly negative at the 1% level, indicating that bike-sharing's CO_2 reduction effect is stronger in cities with more developed rail systems. In Column (2), we use the PM2.5 index to gauge air pollution and find the interaction term significantly positive at the 1% level, suggesting that severe air pollution weakens bike-sharing's CO_2 reduction effect. In Column (3), we proxy public environmental awareness[3] with the Baidu Search Index for "environmental pollution" and interact it with *Entry*. The significantly negative coefficient at the 1% level indicates that greater environmental awareness amplifies bike-sharing's effect on CO_2 reduction. These findings align with theoretical expectations. In cities with extensive rail transit, bike-sharing complements subways by facilitating seamless transfers, reducing commute times, and boosting usage (Fan & Zheng, 2020; Xiao et al., 2021). Conversely, high PM2.5 levels deter cycling due to health concerns, reducing bike-sharing's emission-reduction potential (Xiang et al., 2018). Stronger public environmental awareness enhances the preference for sustainable transport, increasing bike-sharing adoption and strengthening its CO_2 mitigation effect.

TABLE 3. Mechanism test: willingness to use bike-sharing

Variable	(1)	(2)	(3)
	Ln(CO₂_per_capita)	*Ln(CO₂_per_capita)*	*Ln(CO₂_per_capita)*
Entry	-0.003 (0.002)	-0.007^{***} (0.002)	0.002 (0.003)
Entry×Ln (rail)	-0.004^{***} (0.001)		
Ln(rail)	0.006 (0.008)		
Entry×Ln (PM2.5)		0.027^{***} (0.008)	
Ln(PM2.5)		-0.010 (0.019)	
Entry×Ln (PEC)			-0.009^{***} (0.003)
Ln (PEC)			-0.006 (0.004)
Constant	-2.057^{***} (0.020)	-2.069^{***} (0.019)	-2.074^{***} (0.021)
Control variable	Yes	Yes	Yes
City fixed effects	Yes	Yes	Yes
Year-month fixed effects	Yes	Yes	Yes
Observations	10656	10656	10476
Adjusted R^2	0.999	0.999	0.999

Note: *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively, with robust standard errors clustered at the city level in parentheses.

4.5 Heterogeneity Analysis

Bike-sharing's carbon-reduction effect, driven by market dynamics, varies with a city's macroeconomic context. We examine this heterogeneity across three dimensions: environmental regulation intensity, digital economy development, and technological innovation. Stringent

[3] The index was constructed using the Baidu search index for the keyword "environmental pollution."

environmental regulations heighten green oversight, pushing firms toward sustainability and curbing urban emissions (Zhang & Wei, 2014). The digital economy, fueled by cloud computing and big data, drives innovations in the sharing economy, such as peer-to-peer commerce and accommodation (Wang et al., 2023). Grounded in collaborative consumption theory, rapid IT advancements further accelerate the sharing economy, while technological innovation fosters digital urban growth, creating opportunities for bike-sharing expansion.

We measure these dimensions using the following indicators: environmental regulation intensity via the frequency of environment-related keywords in municipal government work reports and the share of pollution control investment in GDP; digital economy development via the digital inclusive finance index and internet penetration rate (internet users as a percentage of year-end registered population); and technological innovation via regional patent applications.

Table 4 presents the results. In Columns (1) and (2), interaction terms with environmental regulation indicators—keyword frequency and pollution control investment (sourced from China's Ministry of Ecology and Environment and National Bureau of Statistics)—are significantly positive at the 5% level. This indicates that when environmental keywords appear less frequently in government work reports and pollution control investments constitute a smaller share of GDP, bike-sharing platforms achieve stronger carbon reduction effects upon entering cities. This evidence confirms bike-sharing's role as a market-based complement to China's multi-tiered environmental governance system. In regions where regulatory enforcement is still developing, it provides an effective emission-reduction solution.

In Columns (3) and (4), interaction terms with digital economy indicators—digital inclusive finance index (from Peking University's Digital Finance Research Center) and internet penetration—are significantly negative at the 1% level, indicating that advanced digital economies amplify bike-sharing's CO_2 reduction by providing robust digital infrastructure and data resources that drive sharing economy growth.

TABLE 4. Heterogeneity analysis: environmental regulation, digital economy, and technological innovation

Variable	(1)	(2)	(3)	(4)	(5)
	Intensity of environmental regulation		Level of digital economy development		Tech innovation
	Ln(CO_2_per_capita)	*Ln(CO_2_per_capita)*	*Ln(CO_2_per_capita)*	*Ln(CO_2_per_capita)*	*Ln(CO_2_per_capita)*
Entry	-0.006*** (0.002)	-0.007** (0.003)	0.012*** (0.004)	0.002 (0.003)	0.002 (0.003)
Entry×Ln(ER)	4.460** (1.731)				
Ln(ER)	0.314 (0.844)				
Entry×Ln(ER_2)		3.305** (1.634)			
Ln(ER_2)		-1.777 (1.439)			
Entry×Ln(digital_eco)			-0.143*** (0.032)		
Ln(digital_eco)			-0.113*** (0.033)		

TABLE 4 Continued

Variable	(1)	(2)	(3)	(4)	(5)
	Intensity of environmental regulation		Level of digital economy development		Tech innovation
	$Ln(CO_2\_per\_capita)$	$Ln(CO_2\_per\_capita)$	$Ln(CO_2\_per\_capita)$	$Ln(CO_2\_per\_capita)$	$Ln(CO_2\_per\_capita)$
Entry×Ln(internet)				-0.021*** (0.005)	
Ln(internet)				0.007 (0.004)	
Entry×Ln(patent)					-0.006*** (0.002)
Ln(patent)					0.003 (0.002)
Constant	-2.059*** (0.023)	-1.843*** (0.031)	-2.038*** (0.022)	-2.044*** (0.022)	-2.053*** (0.020)
Control variable	Yes	Yes	Yes	Yes	Yes
City fixed effects	Yes	Yes	Yes	Yes	Yes
Year-month fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	10,512	4,032	10,584	10,656	10,656
Adjusted R^2	0.999	0.999	0.999	0.999	0.999

Note: *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively, with robust standard errors clustered at the city level in parentheses.

In Table 4, Column 5 examines the interaction between technological innovation, measured by regional patent applications from the China City Statistical Yearbook, and missing values are imputed using the ARIMA method. The significantly negative coefficient (at the 1% level) for the innovation interaction term empirically confirms that technological advancement progressively amplifies bike-sharing's carbon-reduction efficacy. Advanced innovation fosters low-carbon growth by enhancing digital networks and data utilization, empowering the sharing economy, and amplifying the emission-reduction impact of bike-sharing.

We also explore how the number of bike-sharing platforms affects urban carbon emissions, following Cao et al. (2023). The baseline *Entry* variable is split into two dummies: *Single Entry* (one platform enters) and *Joint Entry* (two platforms enter), with the joint entry event defined as the later entry month of ofo or Mobike. Results are reported in Table 5. Column (1) excludes pre-determined city characteristics, while Column (2) controls for their interactions with year fixed effects. In both columns, *the single-entry coefficients are small and statistically* insignificant. In contrast, Joint *Entry* coefficients are significantly negative at the 1% level, demonstrating a more substantial CO_2 reduction when two platforms enter a city, consistent with Cao et al. (2023).

TABLE 5. Heterogeneity analysis: joint vs. single entry

Variable	(1)	(2)
	$Ln(CO_2\_per\_capita)$	$Ln(CO_2\_per\_capita)$
Single Entry	-0.000 (0.002)	0.002 (0.002)
Joint Entry	-0.016*** (0.004)	-0.009*** (0.003)

TABLE 5 Continued

Variable	(1)	(2)
	Ln(CO_2_per_capita)	*Ln(CO_2_per_capita)*
Constant	-2.012*** (0.000)	-2.071*** (0.019)
Control variable	No	Yes
City fixed effects	Yes	Yes
Year-month fixed effects	Yes	Yes
Observations	10,656	10,656
Adjusted R^2	0.999	0.999

Note: *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively, with robust standard errors clustered at the city level in parentheses.

4.6 Further Analysis: Environmental and Economic Benefits of Bike-Sharing

We assess the environmental and economic impacts of entry into bike-sharing platforms using the regression results. For environmental benefits, we draw on the coefficient of -0.006 from Table 1, Column (2). Given average monthly per capita CO2 emissions of 0.198 tons and an average city population of 4.35 million, this yields an annual per capita reduction of 0.014 tons. Scaled to the average city population (4.35 million), the yearly aggregate reduction reaches 62,000 tons. When two platforms operate in the same city, as shown in Table 5, Column (2), the annual reduction rises to roughly 93,000 tons, reflecting market expansion and increased usage (Cao et al., 2021). These magnitudes are broadly consistent with prior evidence: Cao & Shen (2019) estimate Mobike's CO_2 reduction in Beijing during May 2017 at 0.375-7.87 million tons, while Zhang & Mi (2018) find a 25,240-ton reduction in Shanghai in August 2016. Our broader city coverage and longer study period help explain the differences in scale.

For economic analysis, we follow Cao & Shen (2019) and assume that each liter of gasoline emits 2.23 kg of CO_2, with an average cost of 7.00 yuan per liter. Based on Table 1, Column (2), a single platform's entry generates about 0.195 billion yuan in annual economic gains from reduced CO_2 emissions. With two platforms, as indicated in Table 5, Column (2), this rises to approximately 0.292 billion yuan. The results underscore that bike-sharing delivers substantial economic and environmental dividends.

5. Conclusion and Policy Implications

Using city characteristics panel data from 2015-2017 and monthly CO_2 emissions, with city and month fixed effects, this study employs a staggered DID model and propensity score matching to examine the impact of bike-sharing platforms on per capita urban CO_2 emissions. The results demonstrate that bike-sharing significantly reduces per capita emissions, with effects persisting over time.

Mechanism validation confirms dual carbon-reduction pathways. First, bike-sharing substitutes for higher-emission transport modes, particularly in cities with high car ownership or public transit demand, alleviating congestion and curbing traffic-related emissions. Second, public preference for bike-sharing, shaped by environmental awareness and integration with rail transit, amplifies its

CO_2 reduction. Advanced rail systems increase adoption, while severe air pollution (high PM2.5) reduces ridership, weakening the effect. Moreover, heterogeneity analysis shows that bike-sharing serves as a market-driven complement to environmental regulation. Notably, its CO_2 reduction effect is stronger in cities with weaker regulations, in regions with advanced digital infrastructure, and in cities with higher technological innovation. Furthermore, joint entry by multiple platforms generates significantly greater emission reductions than single platform entry.

To advance the sharing economy and urban low-carbon goals, this study's findings offer several policy insights. First, promoting bike-sharing platforms can harness their positive role in reducing urban per capita CO_2 emissions. As bike-sharing drives low-carbon travel, policymakers should leverage this innovative model to support the dual carbon goals by expanding service coverage, planning dedicated bike lanes and greenways, and enhancing urban infrastructure to boost usage. Operators should use big data to enable precise operations, maintain bikes regularly, and adopt lightweight, eco-friendly designs to enhance convenience and durability, thereby increasing ridership, improving social welfare, and reducing CO_2 emissions.

Second, integrating bike-sharing with rail transit can amplify its CO_2 reduction effect. In cities with advanced rail systems, bike-sharing's transfer function enhances public willingness to use it, particularly when paired with subways. Policymakers should expand bike-sharing's use cases by deploying tailored bikes based on local travel patterns and adding parking areas near transit hubs to address the "last-mile" challenge, accelerating low-carbon progress.

Third, fostering public environmental awareness is key to enhancing bike-sharing's voluntary CO_2 reduction. By promoting low-carbon lifestyles through government and media campaigns that emphasize environmental protection and emissions reduction, society can shift toward greener practices and encourage the public to adopt bike-sharing and maximize its impact.

Fourth, by synergizing with governmental environmental regulations, bike-sharing serves as a market-based regulatory instrument to achieve carbon-reduction effects. Our findings show that, as a market-driven mechanism with positive environmental externalities, bike-sharing's CO_2 reduction effect is stronger in regions with weaker regulations. Policymakers should therefore optimize governance systems to coordinate government policies and market forces, achieving mutual benefits for CO_2 reduction and economic development.

Fifth, the digital economy and technological innovation are critical enablers of the sharing economy. Higher digital and innovation levels amplify bike-sharing's CO_2 reduction by providing robust digital infrastructure. Thus, policymakers should encourage innovation and digital transformation to integrate the digital and sharing economies, driving China's low-carbon, digital, and intelligent economic transition.

Sixth, regulating the sharing economy is essential to support carbon peaking and neutrality goals. While bike-sharing reduces CO_2 emissions, issues like disorderly parking and unhealthy competition highlight its negative externalities as a quasi-public good. As the sharing economy diversifies, regulatory policies should standardize its development, promote healthy competition among operators, and encourage civilized user behavior. Doing so will harness its positive externalities and ensure orderly growth.

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Appendix A. Descriptive statistics

Variable	Observations	Mean	SD	Min	Median	Max
Entry	10656	0.108	0.310	0.000	0.000	1.000
CO_2_per_capita	10656	0.198	0.207	0.015	0.144	1.320
Ln(CO_2_per_capita)	10656	-2.013	0.898	-4.200	-1.938	0.277
Ln(GDP_per_capita)	296	10.744	0.519	9.680	10.703	12.065
Industry_2	296	0.448	0.094	0.184	0.461	0.634
Industry_3	296	0.430	0.085	0.282	0.416	0.706
Ln(Land)	296	9.417	0.864	7.375	9.427	12.112
Govern_public	296	0.230	0.155	0.084	0.190	1.168

Appendix B. Results of additional robustness tests

Variable	(1)	(2)	(3)
	Considering air quality as control variable	Excluding 73 APPCAP pilot cities	Considering the implementation time of Low-Carbon City Pilot Policy as control variable
	Ln(CO_2_per_capita)	*Ln(CO_2_per_capita)*	*Ln(CO_2_per_capita)*
Entry	-0.006^{***} (0.002)	-0.005^{**} (0.002)	-0.006^{**} (0.002)
AQI	-0.000 (0.000)		
LCC_entry			-0.005 (0.003)
Constant	-2.036^{***} (0.024)	-2.182^{***} (0.020)	-2.071^{***} (0.020)
Control variables	Yes	Yes	Yes
City fixed effects	Yes	Yes	Yes
Year-month fixed effects	Yes	Yes	Yes
Observations	10340	8028	10656
Adjusted R^2	0.999	0.999	0.999

Note: Same as TABLE 1.