Platform Sharing Economy and Carbon Emission

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Abstract. This paper investigates the environmental impacts of the sharing economy against the backdrop of China's urban carbon reduction targets. Utilizing monthly panel data from 296 Chinese cities spanning the period 2015 to 2017, the study adopts a high-dimensional fixed effects model and treats the staggered Treat*Post of platform-based services as a quasi-natural experiment.The findings indicate that the Treat*Post associated with sharing economy platforms exerts a significant inhibitory effect on urban carbon emissions. To verify the credibility of these findings, a series of robustness checks have been conducted, encompassing placebo simulations, alternative model specifications, and sub-sample analyses, all of which confirm the reliability of the core results.Mechanism exploration reveals that the emission reduction effect is achieved through two key channels: the improvement of traffic efficiency and the enhancement of institutional synergy. This effect is particularly prominent in cities with stronger governance capabilities. Furthermore, heterogeneity analysis demonstrates that the carbon reduction effect of the sharing economy is more substantial in economically developed cities and those with a less industrialized economic structure.These research findings not only deepen the academic understanding of the interaction between digital platforms and environmental performance but also provide practical policy insights for promoting green innovation in urban governance practices.

Keywords: Carbon Emission, Platform Sharing Economy Policy, DID

1 Introduction

Against China’ s urban carbon reduction goals, this study explores the sharing economy’ s environmental impacts using 2015 – 2017 monthly panel data of 292 cities. Treating platform service rollouts as a quasi-natural experiment with a high-dimensional fixed effects model, it finds platform presence significantly cuts urban carbon emissions by 0.61% via traffic efficiency and institutional synergy. The effect is more prominent in developed, service-oriented cities, with robustness checks validating results, offering policy insights for green urban governance.

X. Pan et al. (eds.), *Proceedings of the 2026 11th International Conference on Financial Innovation and Economic Development (ICFIED 2026)*, Advances in Economics, Business and Management Research 382,
https://doi.org/10.2991/978-94-6239-642-5_52

2 Background and Literature Review

Nowadays cities in China urgently need to explore new pathways for green and low-carbon development. The sharing economy, also known as the platform economy, is characterized by efficient resource allocation, low marginal costs, and high resource utilization rates, which endows it with potential to contribute to urban carbon reduction. In recent years, platform-based services including ride-hailing bike-sharing and same-city delivery have experienced rapid expansion, thereby sparking an escalating academic debate on their environmental consequences. Specifically, the sharing economy may facilitate emission reduction by improving resource utilization efficiency; however, its penetration into transportation and logistics sectors could also trigger rebound effects, which might intensify energy consumption and carbon emissions.

Despite the growing academic attention on the sharing economy, empirical research focusing on its environmental impacts—particularly on urban carbon emissions—remains insufficient. From the perspective of research scope, most existing literature has centered on economic outcomes such as employment income distribution and industrial transformation, while the environmental effects have been relatively overlooked. From the perspective of research methods, studies that do address environmental impacts often rely on theoretical reasoning or case-specific evidence, lacking systematic identification based on large-scale multi-city panel data. Furthermore, considering the spatial heterogeneity in the expansion of the platform economy, its carbon reduction effect may exhibit variations across regions with different characteristics. These research gaps collectively indicate the need for a more holistic and dynamic analytical perspective to clarify two core questions: whether the sharing economy genuinely reduces urban carbon emissions, and under what mechanisms and conditions such effects occur.

Empirical evidence regarding the environmental impacts of the sharing economy remains inconsistent. Li et al. (2022) conducted an analysis on ride-splitting services in Chengdu and found that not all pooled rides achieve emission reduction, which reveals the existence of location-specific heterogeneity in the environmental effects of the sharing economy[1]. Similarly, Amatuni et al. (2019) demonstrated that car-sharing services can generate 3-18% life-cycle[2].

CO_2 savings, but rebound effects may undermine these environmental benefits. In the Chinese context, Jin, S. T., et al. (2018) reported that ride-hailing services can promote the use of public transit in small and medium-sized cities[3]; however, Tirachini, (2020) and Henao & Marshall, (2019)pointed out that such services may still increase total emissions if private vehicle use is displaced[4][5].

To address the aforementioned research gaps, this paper employs a city-level panel dataset from China and adopts a high-dimensional fixed effects model. By treating the Treat*Post of the platform economy as a quasi-natural experiment, this study identifies the impact of the sharing economy on urban carbon emissions. Additionally, this paper further explores the potential mechanisms through which the platform Treat*Post affects carbon emissions and conducts heterogeneity analysis based on regional development levels and industrial structures. The ultimate goal of this study is to provide empirical evidence and policy insights for promoting the environmentally sustainable development of the sharing economy.

3 Theoretical Framework and Research Hypotheses

As a digital platform-based model that facilitates the temporary allocation and multi-party sharing of idle resources, the sharing economy may influence carbon emissions through several interrelated mechanisms. These mechanisms include the improvement of resource integration efficiency the shift of transportation behaviors and the effect of institutional substitution. From a business model perspective, sharing economy platforms reconfigure value propositions by monetizing idle assets, a practice exemplified by the enhancement of vehicle utilization in services like Uber. This reconfiguration may lead to carbon leakage if the consumption induced by platforms offsets the gains from efficiency improvement, such as the stimulation of discretionary travel through low-cost ride-hailing services.

3.1 Resource Optimization and Efficiency Gains

Compared with traditional models, the sharing economy enables more efficient and flexible reallocation of underutilized assets, which cover private cars housing and labor. Endowed with advantages in dynamic pricing algorithmic matching and real-time dispatching, platforms can reduce idle capacity and redundant supply. Specifically, ride-hailing services can promote carpooling and the optimization of routing, which in turn cuts down unnecessary urban trips and potentially reduces overall carbon emissions. Sharing economy models are consistent with the principles of circular economy, and they promote sustainability by enhancing the utilization of idle assets (Boar et al., 2020; Faraji, M., 2024)[6][7]. In addition, Tirachini, (2020) emphasize that the built environment and platform services jointly affect commuting emissions, a finding that is in line with the transport-efficiency mechanism proposed in this study[4].

3.2 Dual Effects of Behavioral Responses and Modal Shifts

Nevertheless, the environmental impact of platform-based services, especially in the field of transportation, may exhibit rebound effects. Owing to lower transaction costs and high convenience, platform services may induce new travel demand, particularly in cities with underdeveloped public transit systems. In such contexts, users may replace low-carbon travel options, such as subways and buses, with platform-based alternatives. If the gains from efficiency improvement are insufficient to offset the increased travel volume, carbon emissions may rise accordingly.

3.3 Institutional Substitution and Policy Synergy

The expansion of the sharing economy may also result in institutional substitution. As platforms operate on a large scale, they often drive local governments to adjust regulatory frameworks, including data supervision eco-certification and congestion charges, thereby promoting more adaptive governance. Furthermore, many platforms implement their own green initiatives, such as carbon credits and eco-friendly algorithm preferences. These initiatives may align with urban climate goals and amplify positive externalities. Based on the above analysis, this study proposes the following hypotheses:
Hypothesis 1 (H1): The platform economy services exerts a significant inhibitory effect on urban carbon emissions.

4 Empirical Strategy

4.1 Data Sources and Sample Construction

This study employs a balanced panel dataset at the city-month level, covering 292 Chinese cities over the period from January 2015 to December 2017. The dataset comprises a total of 10236 observations, ensuring sufficient sample size for empirical analysis. City-level carbon emissions, a key dependent variable in this study, are sourced from the Center for Global Environmental Research. The data provider aggregates 1km × 1km gridded remote sensing data through systematic processing to calculate monthly carbon dioxide emissions for each city. The unit of measurement for this variable is tons, which enables precise quantification of urban carbon emission levels.Data related to the Treat and Post variables, which are core explanatory variables for identifying the causal effect of the platform economy, are collected from two authoritative sources namely the City Statistical Yearbook and the City Development Report. This dual-source approach enhances the reliability and accuracy of the Treat and Post indicators.In addition city-level socioeconomic data, which serve as control variables to mitigate potential omitted variable bias, are obtained from the China City Statistical Yearbook. The socioeconomic variables included in this study cover gross domestic product per capita income industrial structure government expenditure and land area. These variables capture the key socioeconomic characteristics of cities and help isolate the independent impact of the platform economy on urban carbon emissions.

4.2 Variable Definitions

In this study, the dependent variable is the natural logarithm of monthly carbon emissions at the city level, denoted as $\ln(CO_2)$, which captures the intensity of urban carbon output over time. The core explanatory variable is the product of and, in which is a binary indicator which takes the value of 1 once a sharing economy platform enters a city and takes the value of 0 when a sharing economy platform doesn't enter the city. is a binary indicator which takes the value of 1 once the year is the year or after the year the sharing economy platform enters the city and takes the value of 0 once the year is before the year the sharing economy platform enters the city. This setup allows us to isolate the effect of platform economy Treat*Post on carbon emissions.

To mitigate potential confounding influences, we include a set of control variables that reflect key city-level characteristics. These include the natural logarithm of per capita GDP ($\ln(\text{GDP\_per\_capita})$), which proxies for the level of economic development, and the proportion of the secondary industry in GDP (Industry_2), capturing the degree of industrialization. Additionally, the share of the tertiary industry in GDP (Industry_3) reflects the structure of the service economy. We also control for the natural logarithm of a city's administrative land area (ln(Land)) and the ratio of public fiscal expenditure to GDP (Govern_public), which serves as a measure of government size.Besides, we also control for the fixed investment input of the city (ln_INV) and the urbanization of the city (URB) to capture the construction level of the city and the population density of the city.

The empirical model adopts a high-dimensional fixed effects (HDFE) approach to account for unobserved heterogeneity. Specifically, we control for both city fixed effects and time fixed effects (including year and month, denoted by ym), thereby capturing city-invariant and time-specific shocks that may otherwise bias the estimates. To further explore heterogeneity in treatment effects, we interact the Treat*Post variable with key structural features, such as a binary indicator for developed versus less-developed regions (Treat*Post × Developed) and the level of industrialization (Treat*Post × Industry_2). These interaction terms enable us to investigate how the impact of platform Treat*Post varies across different regional and economic contexts.

4.3 Model Specification

We estimate the following high-dimensional fixed-effects panel model:

$$\ln(CO_2)_{it} = \beta_0 + \beta_1 Treat * Post_{it} + \lambda X'_{it} + +\lambda_t + \varepsilon_{it} \quad (1)$$

In model (1), $\ln(CO_2)_{it}$ represents the natural logarithm of carbon dioxide emissions in city at time t , capturing the intensity of urban carbon output. The key explanatory variable, treat, is a binary indicator which takes the value of 1 once a sharing economy platform enters a city and takes the value of 0 when a sharing economy platform doesn't enter the city. Post is a binary indicator which takes the value of 1 once the year is the year or after the year the sharing economy platform enters the city and takes the value of 0 once the year is before the year the sharing economy platform enters the city. The term X'_{it} denotes a vector of control variables, including economic, industrial, and geographic characteristics of the city. To account for unobserved heterogeneity, the model incorporates city fixed effects $\mu_i$and time fixed effectsλ_t, which control for time-invariant city-specific factors and temporal shocks common to all cities, respectively. Finally, $\varepsilon_{it}$is the random disturbance.

To ensure causal identification, all regressions employ city-clustered robust standard errors. We also include event-time interaction terms for parallel trend testing and conduct robustness checks via parallel trend test placebo tests and subsample heterogeneity analysis.

5 Empirical Results and Analysis

Based on model (1) and data achieved, this paper conducts the specific regression and the results are displayed in table 1.

Fixed Effects: City (cityid) and Month (ym); Observations: 5,532; Clusters: 167 cities; Adjusted R^2: 0.9992; Model: HDFE clustered at city level.

Table 1. Basic regression result

	$LnCO_2(1)$	$LnCO_2(2)$	$LnCO_2(3)$	$LnCO_2(4)$
*Treat * Post*	-0.0113***	-0.0069***	-0.0052**	−0.0061***
	(0.0028)	(0.0027)	(0.0022)	(0.0028)
ln(GDP_per_capita)	---	0.0051*	0.0114	0.0098**
× 2016		(0.0024)	(0.0072)	(0.0040)
ln(GDP_per_capita)	---	0.0148***	0.0056	0.0312**
× 2015		(0.0028)	(0.0032)	(0.0123)
Industry_2 ×	---	---	-0.0877	0.0114
2016			(0.0992)	(0.0311)
Industry_2 ×	---	---	0.0475*	0.0567
2015			(0.0241)	(0.0874)
Industry_3× 2016	---	---	-0.0224	0.0638*
			(0.0754)	(0.0317)
Industry_3× 2015	---	---	0.1084**	0.1075
			(0.0479)	(0.1121)
ln(Land)	---	---	-0.0014	−0.0047***
× 2016			(0.0011)	(0.0012)
ln(Land)	---	---	-0.0056**	−0.0121***
× 2015			(0.0022)	(0.0033)
Govern_public	---	---	---	0.0378**

× 2016				(0.0202)
Govern_public × 2015	---	---	---	0.0654**
				(0.0301)
Constant	-2.0121***	-2.0076***	-1.2317***	−1.7232***
	(0 .0002)	(0.0187)	(0.0287)	(0.0321)
Other Control variables	Y	Y	Y	Y
City	Y	Y	Y	Y
Year	Y	Y	Y	Y
N	10236	10236	10236	10236
Adj R2	0.9993	0.9993	0.9993	0.9994

6 Robustness Checks

To confirm the robustness of our empirical findings, we conduct multiple checks, including placebo tests, subgroup robustness estimations, and alternative variable specifications.

6.1 Parallel Trend Test

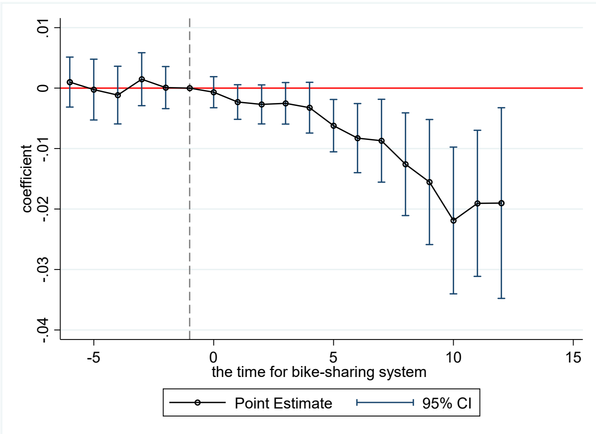

Fig. 1. Parallel Trend Test

To validate the identification assumption underlying the difference-in-differences (DID) strategy, this study conducts an event study to examine the parallel trend assumption—a critical prerequisite for ensuring the causal inference validity of the DID framework. Figure 1 presents the estimated coefficients of the platform economy's Treat*Post variable across each period before and after the policy-relevant event, alongside the corresponding 95% confidence intervals. The vertical axis of the figure denotes the estimated marginal effect of the platform Treat*Post on urban carbon dioxide emissions, while the horizontal axis represents the relative time with respect to the Treat*Post event. Notably, the value of 0 on the horizontal axis corresponds to the month in which the platform Treat*Post occurs.

As illustrated in Figure 1, the estimated coefficients for the pre-treatment periods (i.e., event time from −5 to −1) are numerically close to zero and fail to reach statistical significance at conventional levels. This result indicates that the treatment group (cities affected by the platform Treat*Post) and the control group (cities not affected) exhibited parallel trends in carbon dioxide emissions prior to the implementation of the platform Treat*Post. In contrast, the estimated coefficients for the post-Treat*Post periods demonstrate an increasingly negative trajectory, with several coefficients achieving statistical significance. This pattern suggests that urban carbon emissions underwent a gradual and cumulative reduction subsequent to the occurrence of the platform Treat*Post, which aligns with the theoretical expectation that platform economies generate environmental benefits by enhancing resource allocation efficiency and optimizing transportation systems.

Collectively, the findings from the event study provide empirical support for the parallel trend assumption of the DID strategy. By confirming that the pre-treatment emission trends of the two groups are comparable, this result reinforces the credibility of the DID estimation framework in identifying the causal effect of the platform economy's Treat*Post on urban carbon emissions, thereby mitigating concerns about potential omitted variable bias or endogeneity in the causal inference process.

6.2 Placebo Test

To mitigate potential threats to causal inference—such as model misspecification or spurious associations between the platform economy and urban carbon emissions—this study implements a placebo test. The test follows a rigorous design: we restrict the sample to cities that were never exposed to the actual platform Treat*Post (i.e., the control group) and randomly assign artificial placebo treatment statuses (fake Treat*Post events) to these untreated cities. Under this randomized framework, we re-estimate the baseline empirical model 500 times to generate a distribution of placebo-estimated coefficients, which reflects the range of effects that could arise purely from random variation rather than the actual platform intervention.

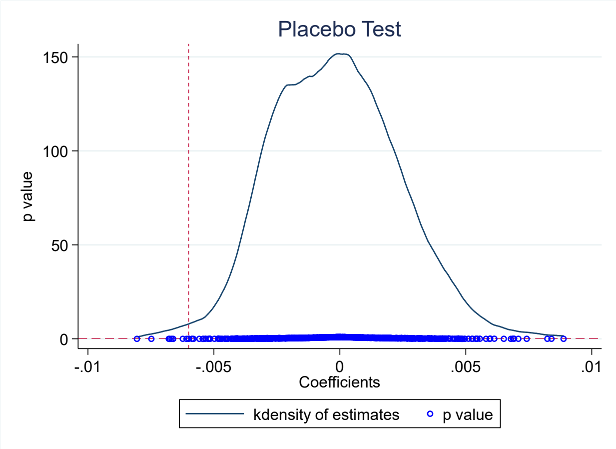

Fig. 2. Placebo Test

To further validate the causal interpretation of the baseline findings, this study conducts a placebo test designed to rule out confounding effects from sample selection bias or pre-existing unobserved trends. The test is implemented by restricting the analysis sample to non-treated cities (i.e., cities never exposed to the actual platform Treat*Post) and randomly assigning artificial Treat*Post timing to these cities. Under this randomized framework, the baseline empirical model is re-estimated multiple times to generate a distribution of placebo-estimated coefficients—this distribution reflects the range of effects that could arise purely from random variation rather than the substantive impact of the platform economy. As visualized in Figure 2, the actual estimated coefficient of the platform Treat*Post (−0.0061) deviates significantly from the distribution of placebo estimates, lying outside the 95% confidence interval of the placebo distribution. This result confirms that the identified negative effect of the platform Treat*Post on urban carbon emissions is unlikely to be driven by sample selection bias or pre-existing trends, thereby reinforcing the robustness of the study's core findings.

Table 1 presents the baseline estimation results derived from the high-dimensional fixed effects (HDFE) model, which controls for unobserved heterogeneity across cities and time. The coefficient of the key explanatory variable, Treat*Post, is −0.0061 and statistically significant at the 1% level. From an economic perspective, this coefficient indicates that the Treat*Post of platform economy services is associated with a significant reduction in urban carbon emissions, with an average reduction magnitude of approximately 0.61%. This empirical result directly supports Hypothesis 1 (H1), which posits a negative relationship between the platform economy's Treat*Post and urban carbon emissions.

Regarding the control variables included in the model: First, the coefficient of per capita gross domestic product ($\ln(\text{GDP\_per\_capita})$) is significantly positive, reflecting that more economically developed cities tend to have higher energy demand—this demand may stem from increased industrial activity and household consumption, thereby leading to higher carbon emissions. Second, the proportion of the secondary industry (Industry_2) exerts a positive effect on carbon emissions, which aligns with the fact that secondary industry (e.g., manufacturing, construction) is typically energy-intensive and emission-heavy; in contrast, the share of the tertiary sector (Industry_3) shows no statistically significant effect on carbon emissions, possibly due to the relatively low energy intensity of most service sectors. Third, land area (ln_Land) and public budget expenditure (ln_Govern_public) exhibit partial statistical significance through their year-specific interaction terms, suggesting that the impact of these variables on urban carbon emissions varies across different years, potentially due to changes in urban planning policies or public investment priorities.

Collectively, these results imply that the sharing economy (as represented by the platform economy's Treat*Post) can generate environmental co-benefits by enhancing resource allocation efficiency—for instance, by reducing idle capacity of transportation assets and optimizing travel routes. These mechanisms help mitigate the pressure of urban carbon emissions, providing empirical support for the role of the sharing economy in promoting urban green development.

6.3 Subsample Robustness

To account for potential structural differences across cities, we conduct robustness checks by re-estimating the baseline model on several refined subsamples. First, we exclude direct-administered municipalities and mega-cities, which may exhibit distinct administrative and economic dynamics. Second, we limit the sample to the year 2016, which marks the peak of platform expansion and may represent a critical period for evaluating environmental impacts. Third, we remove border and non-mainland regions such as Hong Kong, Macau, and Taiwan to ensure comparability in institutional and geographic contexts. Across all of these subsamples, the estimated coefficients on the Treat*Post variable remain negative and directionally consistent with the main results, with several estimates reaching statistical significance at the 5% level. These findings reinforce the robustness of our conclusions against sample selection concerns.

6.4 Alternative Specifications

To test the robustness of our findings, we re-estimate the baseline model using alternative measures of carbon emissions as the dependent variable. Specifically, we replace the logged total CO_2 emissions with three variants: the raw level of

CO_2 emissions in tons, CO_2 emissions per unit of GDP, and CO_2 emissions per capita. Across all these alternative specifications, the estimated coefficients on the Treat*Post variable remain consistently negative and statistically significant. These results confirm that the observed emission-reducing effect of platform economy Treat*Post is not driven by a specific measurement choice, thereby reinforcing the reliability and robustness of our main conclusion.

By employing placebo tests, subsample analysis, and alternative dependent variables, we verify that the observed negative relationship between the platform economy and urban carbon emissions is robust across multiple dimensions, ruling out concerns of model misspecification or sample bias.

7 Heterogeneity Analysis

Past studies suggest contextual factors shape sharing economy sustainability. For example, Zhang and Wang (2021) note ride-hailing's CO_2 benefits vary by urban transit infrastructure. Urban form (Li et al., 2025) and digital platform governance (Cohen, 2017) further moderate effectiveness[3][4][8].

To better understand the differentiated impacts of the platform economy on carbon emissions, we perform subgroup regressions based on two dimensions: regional development level and industrial structure (secondary sector share). We complement the empirical findings with theoretical reasoning to explain the observed heterogeneity.

7.1 Regional Development Level

In economically advanced cities, the sharing economy benefits from more supportive institutions, better infrastructure, and higher user acceptance. These conditions enable platforms to maximize their efficiency gains. Well-established public transit, digital infrastructure, and stronger environmental awareness further amplify the emission-reducing impact. Our results show that Treat*Post has a significantly negative coefficient of -0.0063 in developed regions, while it is insignificant in less developed areas. This highlights the critical synergy between platform capacity and local governance systems.

In economically advanced cities, where institutional capacity and infrastructure are typically stronger, the emission-reducing effects of the platform economy are more pronounced. Specifically, regression estimates show that in developed regions, the coefficient for platform Treat*Post is -0.0063 and statistically significant, indicating a robust negative association between platform expansion and carbon emissions. In contrast, in less-developed regions, the coefficient is only 0.0013 and statistically insignificant, suggesting limited or no measurable effect. This pattern highlights that platform-driven environmental benefits are more effectively realized in regions with higher levels of economic development, thereby supporting Hypothesis 2 (H2).

7.2 Industrial Structure

Cities with lower shares of the secondary sector and higher shares of the tertiary sector tend to have carbon emissions stemming more from transportation and consumption-related activities. These are precisely the sectors most directly impacted by platform-based resource reallocation. As such, platform Treat*Post has stronger marginal effects on emissions in these cities.

Empirical results confirm this pattern: in cities with a lower secondary industry share, Treat*Post has a significantly negative coefficient of −0.0125 ($p < 0.01$), whereas it is insignificant in high-industry cities. This suggests that the carbon-reduction benefits of the platform economy are more pronounced in service-oriented cities, reflecting a higher degree of compatibility between platform functions and urban industrial composition.

The heterogeneity analysis by industrial structure further confirms that the carbon-reduction benefits of platform Treat*Post are contingent on local economic composition. In cities with a higher share of the secondary industry (i.e., more industrialized), the coefficient on platform Treat*Post is −0.0024 and statistically insignificant, indicating no clear environmental impact. However, in cities where industrial activity is less dominant and the service sector plays a greater role, the coefficient is significantly negative at −0.0125 ($p < 0.01$). This suggests that platform-based efficiencies are better leveraged in service-oriented economies, aligning with Hypothesis 3 (H3) that anticipates stronger environmental gains in less industrialized urban contexts.

These heterogeneous effects highlight that the sharing economy delivers stronger environmental benefits in cities with stronger governance and more service-oriented economies. This underscores the need for place-based policy interventions to enhance institutional readiness, infrastructure, and regulatory frameworks that support both platform development and emission reduction.

8 Conclusion

Using monthly panel data for 292 Chinese cities from 2015 to 2017, this study exploits the staggered Treat*Post of platform economy services as a quasi-natural experiment and employs a high-dimensional fixed effects (HDFE) model to evaluate their impact on urban carbon emissions. We obtain the following main findings:

First, platform Treat*Post significantly reduces urban carbon emissions by an average of 0.61%, confirming the sharing economy's environmental co-benefits;

Second, such effects are more pronounced in economically developed and service-oriented cities, revealing marked heterogeneity;

Third, mechanism analysis identifies two key pathways: traffic efficiency improvement and governance co-evolution;
Finally, robustness checks—placebo tests, subsample analysis, and variable replacements—all validate the stability of the results.

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