# Beyond Automation: The Impact of Robotaxi Services on Ride-Hailing Consumer Behavior

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## Abstract

Robotaxi technology, an innovative advancement within the realm of ride-hailing services, is undergoing regional deployments across different countries, and yet its influence on consumer behavior remains largely unexplored. Our identification strategy exploits the quasi-random allocation of robotaxi services to consumers when they request robotaxi services and employs a difference-in-differences (DID) model to estimate the causal impact of robotaxi usage on consumers' ride-hailing behavior. Our findings reveal a significant 23.2% increase in a consumer's total weekly rides after experiencing the robotaxi service on the focal platform. Our further analysis indicates that robotaxi services do not cannibalize a consumer's demand for regular rides but instead lead to a positive spillover effect on the consumer's demand for regular ride-hailing services in robotaxi-accessible areas. This increased demand is observed not only among multi-homing consumers, potentially switching from other platforms, but also among single-homing consumers, likely due to a category expansion effect. Moreover, we find that multi-homing consumers experience a more pronounced increase in demand in robotaxi-accessible areas but significantly reduce their usage of the focal platform in inaccessible areas. These findings can be explained by the evidence of multi-homing consumers' shifts in platform preference across regions. These differential impacts on single-homing and multi-homing consumers highlight the nuanced implications of robotaxi, as an AI-powered innovative service, for consumer demand and preferences in the presence of platform competition.

**Keywords:** Robotaxi, AI-Powered Automation, Multi-homing, Consumer Demand, Spillover Effect

## 1. Introduction

AI-powered automation is revolutionizing various sectors, including healthcare (Yip et al. 2023), finance (Chaboud et al. 2014), and ride-hailing (Noh et al. 2023), with the advent of robotaxi services standing out as a prominent example. In cities across the United States and China, companies like Waymo and Baidu have launched robotaxi fleets, offering innovative autonomous ride-hailing services to the public. Similarly, Tesla has entered the robotaxi market with its ambitious *Cybercab* project, unveiled in October 2024 and slated for production by 2026, positioning itself as a key player in autonomous ride-hailing.[1] According to a study by *MarketsandMarkets* research, the robotaxi market is projected to reach USD 45.7 billion by 2030.[2]

This surge in automation mirrors a broader trend across industries, fueling debates about the "march of the machines" (Warwick 2004) and the potential implications for human employment—whether AI will displace jobs entirely or transform their nature, for better or worse (Acemoglu and Restrepo 2018, Brynjolfsson et al. 2018, Autor et al. 2024). Despite the rapid adoption of robots and algorithms in consumer–firm interactions and intense debate about their impact on the labor market, there is still a significant gap in understanding how such innovations influence consumer behavior (Granulo et al. 2019, Mende et al. 2019). This issue is critical, as demand-side behavior plays a pivotal role in shaping firms' decisions to deploy automation, beyond the traditional supply-side considerations of cost savings and productivity gains, which typically assume demand-side behavior remains unchanged.

Focusing on robotaxis as an example, the impact of such automation on consumer behavior on ride-hailing platforms remains largely unexplored. On the one hand, robotaxis might not spark significant interest from consumers or merely replace a portion of the services currently served by human drivers, resulting in a negligible effect on a consumer's overall demand. On the other hand, as a novel and appealing innovation, robotaxis could serve as a differentiating factor in the market (Arrow 1972), potentially generating new demand by appealing to certain consumer segments, particularly those navigating across

[1] https://www.theverge.com/2024/10/10/24265530/tesla-robotaxi-elon-musk-features-range-price-release-date
[2] https://www.marketsandmarkets.com/Market-Reports/robo-taxi-market-132098403.html

multiple platforms, thus increasing those consumers' demand. Moreover, as a platform gradually introduces robotaxis from one area to another, the availability of such innovative services in selected areas may influence a consumer's preference for the focal platform differently in areas with and without access to such services, especially in the presence of competition from other platforms.

This mixed impact highlights a practically important question and at the same time a significant void in the existing literature, which has yet to fully address these complexities. First, while recent marketing research has begun to explore consumer acceptance of innovative services provided by machines, it primarily focuses on consumer preference or choice between human and machine services (Luo et al. 2019), providing limited insights into consumer demand when both options are available. Second, existing research using field data primarily examines low-stakes consumer purchase decisions, such as AI serving as a customer service agent for tasks like ordering food or providing recommendations (Mende et al. 2019, Longoni and Cian 2022), with scant attention to high-stakes decision-making contexts. The few studies that look at autonomous vehicle (AV) services often rely on theoretical modeling (Castro and Frazelle 2024) or hypothetical scenario-based questions (Leung et al. 2018), leaving a gap in understanding real-world consumer behavior in such high-stakes situations. Specifically, there is a lack of insight into how such innovative offerings influence consumers' overall consumption patterns, as well as their continued use of regular services that are not directly related to these new options. Third, previous research has not examined how automation-based innovations may influence consumer preferences in areas with disparate accessibility to such services, particularly in environments characterized by platform competition and varying levels of consumer loyalty.

Motivated by these considerations, we aim to address the following research questions:

*1) How does the adoption of robotaxi services on a platform affect a consumer's overall consumption of ride-hailing services on the platform?*

*2) How does the adoption of robotaxi services on a platform affect a consumer's consumption of its regular ride-hailing services that do not involve or request robotaxi options?*

*3) How do the above effects differ across areas with and without access to robotaxi services?*

To answer these questions, we obtained a proprietary dataset from a prominent ride-hailing platform in Asia that was the first ride-hailing platform to introduce robotaxi services in the region we study. The dataset provides granular, consumer-level data and includes detailed characteristics of both robotaxi and regular rides. Our study utilizes a difference-in-differences (DID) approach, leveraging the introduction of robotaxi services to assess their impact on consumer behavior on ride-hailing platforms. We employ a quasi-natural experiment, wherein for consumers who have requested both robotaxi and regular services, the assignment to a robotaxi or regular vehicle is randomly determined by real-time availability rather than by the consumers' preferences or characteristics.

We find interesting results regarding the impact of robotaxi services on ride-hailing consumer behavior. First, we observe a significant 23.2% increase in total weekly rides among consumers who experienced robotaxi services, indicating that such innovative offerings stimulate additional demand rather than merely redistributing demand from regular ride-hailing services to robotaxis. Second, intriguingly, even when considering only regular rides from requests that do not include robotaxi, there is a 10.2% increase. This suggests that robotaxi services have a positive spillover effect on consumer demand for regular rides rather than a cannibalization effect. Third, while the robotaxi experience significantly increases consumers' regular rides in robotaxi-accessible areas, it decreases their rides in inaccessible areas.

Thanks to the exceptional granularity and comprehensiveness of our proprietary data, which includes rides booked both directly through the platform and via a dominant ride-hailing aggregator, we can match consumer identities across both platforms to identify multi-homing consumers. This enables us to explore the mechanisms underlying the observed treatment effect on consumer behavior following the robotaxi introduction. Specifically, we investigate whether this effect is primarily attributable to a shift in platform preference among multi-homing consumers by differentiating between single-homing and multi-homing consumers and analyzing their orders across different platforms.

Our findings indicate that the treatment effect of the robotaxi rollout extends beyond a mere uniform shift in platform preference among multi-homing consumers. Specifically, our results reveal two distinct types of effects that jointly drive the observed treatment effects. First, we offer suggestive evidence of a category expansion effect, where single-homing consumers show an increased frequency of regular rides in accessible areas, as demonstrated by their temporal and spatial expansion in ride-hailing consumption. Second, the platform preference shift observed among multi-homing consumers appears to be highly dependent on the availability of innovative services. They experience a larger increase in rides in accessible areas but a decrease in inaccessible areas, suggesting stronger platform preference in the former and a diminished preference in the latter. This nuanced shift is further supported by their increased usage of the platform's own app over a dominant ride-hailing aggregator to request regular rides in robotaxi-accessible areas, coupled with a significant decrease in its usage in other areas.

Our findings have important practical implications and highlight the dual impacts—both benefits and risks—associated with introducing innovative services amidst platform competition. On the one hand, these innovative services enhance overall consumer consumption on the platform by motivating both single-homing and multi-homing consumers to increase their usage of ride-hailing services (both innovative and regular services) in areas where these innovations are accessible. On the other hand, the staggered rollout of these services can lead to reduced preferences among multi-homing consumers in areas where the services remain unavailable, potentially diminishing their usage of the platform in these regions. Platform owners must therefore be mindful of the implications associated with the phased introduction of innovative services and strategically manage their consumer communications to sustain their competitive position in the broader market.

This research contributes to related literature on AI and automation, AV services, and digital platforms in several ways. First, it advances the literature on the impact of AI and automation, which has primarily focused on supply-side effects such as labor displacement and productivity gains (Brynjolfsson and Mitchell 2017, Acemoglu and Restrepo 2018, Autor et al. 2024), by shifting the focus to demand-side effects. While some prior research has explored consumers' acceptance of AI-provided customer service or recommendations in comparison to those provided by humans (Luo et al. 2019, Longoni and Cian 2022), we expand this body of work by examining consumer behavior in settings where both AI-driven services (e.g., robotaxi services) and human-provided services (e.g., human-operated ride-hailing services) are available simultaneously. Additionally, we analyze the spillover effects of introducing AI-driven services on the demand for regular human-provided services.

Second, we contribute to the emerging literature on AVs, which has predominantly relied on small-scale surveys or theoretical models to evaluate consumer perceptions and adoption (Lokhandwala and Cai 2018, Dai et al. 2021, Yin et al. 2023), with limited understanding of real-world consumer behavior in high-stakes contexts such as robotaxi usage. Drawing on a large-scale sample of actual consumers, our study advances this research by providing empirical evidence on the impact of robotaxi services on consumer consumption behavior in real-world environments.

Third, our study contributes to the digital platforms literature by empirically documenting the spatial spillover effects of the phased introduction of innovative robotaxi services, highlighting their differential impact on single-homing and multi-homing consumers. While prior studies have examined innovative services as replacements for existing ones to achieve differentiation (Johnson et al. 2006, Hauser et al. 2006, Xu et al. 2014), the literature has largely overlooked scenarios involving staggered rollouts of innovative services alongside existing offerings. Our study bridges a critical gap by quantifying the spillover effects of platforms' staggered innovative offerings, such as robotaxi services, on the consumption of regular ride-hailing services in regions where innovative services have not yet been introduced. Furthermore, we demonstrate that such spatial spillover effects differ between single-homing and multi-homing consumers, offering suggestive evidence of the potential mechanisms driving these variations. Our results can shed light on platforms' rollout strategies for new technological innovations in general, particularly in contexts where multi-homing is prevalent.

## 2. Literature Review

### 2.1. Artificial Intelligence (AI) and Automation

Our research first builds upon existing literature on AI and automation technology, which has examined the potential for automation to replace or augment human labor (e.g., Autor 2015, Brynjolfsson and Mitchell 2017). Acemoglu and Restrepo (2018) reveal that while automation can reduce employment and wages, creating new tasks in which labor has a comparative advantage can counteract these effects, leading to a balanced growth path and long-term economic stability. Hui et al. (2023) document that generative AI significantly decreases the short-term employment and earnings of freelancers in online labor markets, implying a notable job replacement effect. While these studies provide valuable insights into the supply-side impact of automation technology, they do not study its effect on consumer demand.

While recent marketing research has started to examine the effect of automation technology on consumer demand, it has primarily focused on comparing consumer acceptance of services provided by automated machines versus humans. Luo et al. (2019) find that consumers demonstrate a reduced willingness to purchase products when they become aware that customer service is provided by machines. Mende et al. (2019) observe that the presence of service robots can increase consumer discomfort, which in turn leads to an increase in compensatory consumption as consumers seek to alleviate their unease. Longoni and Cian (2022) investigate how people choose between recommendations from AI and humans. They find that for practical or utilitarian recommendations, consumers tend to prefer AI, whereas for recommendations related to enjoyment or pleasure, consumers often favor human advice. Leung et al. (2018) also show that automation is often resisted when identity motives play a significant role, as people prefer attributing identity-relevant outcomes to themselves rather than automated processes.

Despite the abundant literature documenting consumers' purchase decisions in scenarios where services are provided exclusively by either humans or machines,[3] there is a void in understanding consumer behavior when both machine and human services are available concurrently. Advancing this stream of literature, we investigate the impact of offering robotaxi as an additional service option and examine how this influences a consumer's overall ride-hailing demand, as well as the spillover effect on regular rides provided by human drivers.

### 2.2. Autonomous Vehicle (AV) Services

Our study also ties into the emerging literature on AVs, which generally follows three primary research

[3] All the aforementioned studies used a between-subject design, assigning respondents to scenarios with either human-provided or AI-provided services, but none offered the option to choose both.

directions. The first direction explores consumers' perceptions, evaluations, and adoption of AVs, often through surveys. The second direction investigates the broader societal impacts of AVs by leveraging public aggregate-level data or simulations. And the third direction examines how the introduction of AVs impacts the efficiency and fleet size of ride-hailing platforms and AV ride service companies, mostly using game-theoretical models or simulations.

In the first research strand, Dai et al. (2021) survey 383 experienced robotaxi consumers to assess factors such as attitudes toward use, perceived ease of use, and perceived usefulness, all of which influence continuous use intentions. Based on 485 valid survey responses, Yin et al. (2023) investigate the impact of introducing robotaxis in certain cities on consumer preferences and attitudes by comparing consumers in cities with robotaxi services to those in cities without such services. Their findings reveal no significant differences in willingness to pay for travel and waiting time between the two groups. However, they do observe that the presence of robotaxis influences psychological factors like trust and hedonic motivations.

The second research strand examines the traffic and environmental impacts of AVs, considering both positive and negative implications. On the one hand, Lokhandwala and Cai (2018) demonstrate that robotaxis in New York City could significantly reduce carbon emissions while maintaining service levels. Complementing this, Li et al. (2023) conduct a systematic review of studies on the efficacy of urban traffic control strategies in mixed traffic environments involving regular, connected, and automated vehicles, finding that advanced traffic control can alleviate congestion and enhance safety. On the other hand, Wang et al. (2024) highlight a negative externality of AVs on public traffic conditions, noting an increase in traffic accidents among non-AVs based on city-level data. This phenomenon is attributable to disruptions caused by AVs and increased risk-taking behaviors by other drivers, who anticipate AV-integrated traffic conditions as safer and more accommodating.

The third research direction, closely related to our study, explores how AVs impact the efficiency and fleet size of ride-hailing platforms. Lokhandwala and Cai (2018) use an agent-based model to analyze the performance of ride-hailing platforms incorporating both traditional taxis and robotaxis in New York City. Their simulation results indicate that robotaxis could reduce fleet size by more than 50%. Noh et al. (2023)

model the dynamic competition between AV ride services and traditional ride-hailing companies. They find that traditional ride-hailing firms often outperform AV firms in the market when customers are willing to wait, achieving lower customer delays, higher prices, greater market share, and higher profits—even when facing higher costs. Castro and Frazelle (2024) explore strategic interactions between human drivers and AVs within ride-hailing platforms. Their model results suggest that higher wages for human drivers could paradoxically lead to fewer available rides for them, reducing human-driver participation while expanding the AV fleet.

The studies examining the impact of AVs in the ride-hailing context often rely on hypothetical scenario-based questions or game-theoretical model assumptions, leaving a gap in understanding real-world consumer behavior in high-stakes situations, such as taking robotaxis. Our research addresses this gap by providing empirical evidence on the impact of robotaxi services on consumer behavior in a real-world setting, drawing on a large-scale sample and capturing both direct and spillover effects across different types of consumers.

**2.3. Digital Platforms**

Our research also contributes to the literature on digital platforms, particularly in the area of platform competition. In the dynamic world of digital marketplaces, platform competition is intense, especially when multi-homing is prevalent on one or both sides of the platforms (Li and Zhu 2021). Prior research identifies two general types of competition strategies: pricing and differentiation strategies (McIntyre and Srinivasan 2017).

The first body of research focuses on pricing strategies, such as setting lower prices for consumers to penetrate the market or subsidizing complementors (such as Uber drivers or app developers) to leverage cross-side network effects (i.e., the “seesaw principle”) (e.g., Dou and Wu 2021, Zhang et al. 2022). Bakos and Halaburda (2020) further show that the common strategic advice to subsidize one side to maximize platform profits can be ineffective when both sides multi-home.

Our study is most related to the second body of research focusing on differentiation strategies, which platforms use to build a distinct platform identity (Cennamo 2021) and reduce substitutability by improving service quality or variety, such as offering innovative services. Chang and Sokol (2022) study the competition between hotels and Airbnb. They suggest that low-quality hotels primarily compete with Airbnb by lowering prices, while high-quality hotels respond by enhancing their investment in service quality to differentiate themselves. Farronato et al. (2024) find that, following a platform merger, the increase in platform dominance leads to a reduction in platform differentiation, which outweighs the positive effects of elevated network effects and harms a subset of consumers. These studies underscore the critical role of differentiation strategies in shaping platform competition outcomes.

We examine innovative offerings as a platform differentiation strategy. Although not studied empirically in the context of platform competition, such offerings have been shown to bolster brand equity and loyalty, as evidenced by survey-based studies in consumer behavior research (Johnson et al. 2006, Xu et al. 2014, Hauser et al. 2006). For instance, Johnson et al. (2006) demonstrate that tech-innovative offerings enhance consumers' affective commitment to maintaining a relationship with the brand and brand equity, which, in turn, increase perceived value and foster stronger brand loyalty. Building on this, Xu et al. (2014) find that information and communication technology (ICT) service innovations, particularly through service leadership and customization-personalization, enhance brand equity and boost customer loyalty. The role of innovations in improving brand equity and loyalty is further supported by Wu (2014) and Yao et al. (2019). Hauser et al.'s review (2006) also notes that consumers with higher innovativeness, i.e., a higher propensity to adopt new products, tend to respond more positively to innovation.

Together, these consumer behavior studies highlight the potential of innovation offerings that a platform can leverage as a strategy to differentiate and enhance competitive advantage. However, the impact of such offerings on consumer behavior in the context of platform competition has not been empirically examined, particularly the implications of platforms' staggered rollout of innovative offerings alongside pre-existing options. The phased introduction of innovation raises important questions about potential spillover effects in regions where innovative services are not yet available. These effects could be positive, driven by factors such as enhanced brand equity, or negative, due to unmet expectations stemming from the unavailability of the innovation. These dynamics remain largely underexplored in the literature.

Our research advances this stream of literature by examining the impact of a platform's phased introduction of innovative services, specifically robotaxi services, on consumer behavior across regions with varying levels of service availability.

Furthermore, the phenomenon of multi-homing plays a crucial role in shaping platform competition. While existing research has examined its implications for competition and market dynamics, relatively little attention has been given to the role of innovative offerings. Landsman and Stremersch (2011) find that platform owners are incentivized to deter multi-homing, as it can reduce their market shares and sales. Li and Zhu (2021) highlight the challenges associated with such a strategy. They note that deterring multi-homing on one side of a platform's market (e.g., merchants) can unintentionally increase multi-homing (e.g., consumers) on the other side, potentially giving competitors an advantage. In addition, Tian et al. (2022) demonstrate that managing multi-homing becomes increasingly critical as platform compatibility improves, which can lower barriers to multi-homing and intensify competition among platforms. Our study contributes to the multi-homing perspective in the digital platforms literature by investigating the role of innovative offerings in shaping single-homing and multi-homing consumer behavior differently, along with the associated implications for platform competition.

## 3. Research Context and Data

We obtained our data from a leading Asian ride-hailing platform. The focal platform has its services covering over 140 cities, boasting over 800,000 registered drivers and exceeding 250 million registered consumers. Our dataset includes detailed consumer demographics and ride-hailing activities, such as ride searches and completed rides.

In May 2022, the platform introduced the robotaxi service in a district of a major Chinese city without any pre-announcement, becoming the first ride-hailing platform to offer such a service in the region.[4] Prior to this launch, consumers only had access to regular (human-driven) ride-hailing services. The launch of

[4] This case is similar to Uber's integration of Waymo's AV service within its app. A key distinction is that, while Waymo consumers can also book rides through Waymo's own app, the robotaxi service is integrated directly into the focal ride-hailing platform, without a separate app dedicated to the robotaxi service.

the robotaxi service provided consumers with an additional option, priced in line with mainstream regular services similar to Uber X or Didi's Kuaiche. After the launch, when using the platform's app within the designated district, consumers have the option to request regular ride-hailing services, robotaxi services, or both simultaneously. If both options were chosen, a robotaxi or human-driven car would be assigned quasi-randomly by the platform, which prioritizes platform-wide matching efficiency without considering consumers' preferences, ride histories, or characteristics.

To casually estimate the treatment effect of robotaxi services, our identification strategy exploits quasi-random variation in the actual allocation of robotaxi services when consumers requested both robotaxi and regular services simultaneously in the district where the robotaxi service was launched. For these consumers, who are all interested in robotaxi services, the likelihood of robotaxi fulfillment is exogenous. Such exogeneity allows us to employ the DID model to estimate the impact of robotaxi service usage on their ride consumption. Specifically, this study focuses on consumers who were active both before and after the introduction of robotaxi services and have requested both robotaxi and regular services simultaneously.[5] We categorize these consumers into two groups: 1) the treatment group, including 5,813 consumers who have had at least one robotaxi ride within the study period, and 2) the control group, consisting of 9,407 consumers who, despite requesting robotaxi services, have not received them.

Compared to prior studies exploiting variation in self-selected treatment status (Xu et al. 2017, Narang and Shankar 2019, Son et al. 2023), our study focuses on the quasi-random variation in realized treatment status, which is beyond consumers' control and thus exogenous to consumer characteristics, thereby mitigating the potential self-selection bias.[6] To address the concern about the potential violation of the Stable Unit Treatment Value Assumption (SUTVA) (Rubin 1990), we also conducted robustness checks

[5] Note that we require consumers attempting to be treated to have requested both robotaxi and regular services simultaneously in all of their ride-hailing requests prior to receiving the treatment. However, once treated (i.e., after experiencing a robotaxi ride), we no longer require them to choose regular services simultaneously when requesting robotaxi service, as their service choices at that time may be influenced by the treatment effect.
[6] It is worth noting that any changes in supply would affect the treatment and control groups in the same way, given our identification approach, thus mitigating the concern that supply-side factors might compromise the validity of our findings.

using a group of consumers who have never requested robotaxi services in the designated district (Section 7.1), as well as consumers in another comparable district (Section 7.2) as an alternative control group.

Our observation window includes four months before and four months after the rollout of the robotaxi service, as illustrated in Figure 1. We analyze consumers' ride-hailing activity at the weekly level, focusing on a consumer's total number of rides completed on the platform per week, including rides requested with and without the robotaxi option. Additionally, since the consumers in our sample also travel to other districts where robotaxi service is unavailable, we also examine changes in their rides in robotaxi accessible and inaccessible areas separately.

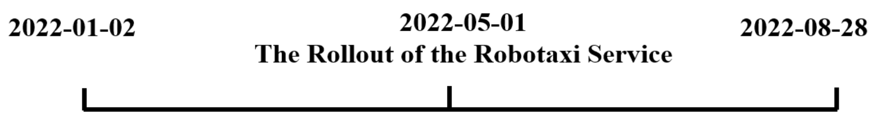


**Figure 1. Observation Window of the Research Context**

The definitions and descriptive statistics of key variables are reported in Table 1.

**Table 1. Definitions and Descriptive Statistics of Variables**

| Variable | Description | Obs | Mean | SD | Min | Max |
|---|---|---|---|---|---|---|
| Dependent variable | | | | | | |
| All Areas | | | | | | |
| *Total Rides* | The number of rides completed by a consumer each week | 513,433 | 0.78 | 1.97 | 0 | 36 |
| *Regular Rides* | The number of rides completed by a consumer each week, considering only those ride requests where the robotaxi option was *not* selected | 513,433 | 0.70 | 1.88 | 0 | 36 |
| Accessible Areas | | | | | | |
| *Total Rides* | The number of rides completed by a consumer each week in robotaxi-accessible areas | 513,433 | 0.25 | 0.90 | 0 | 30 |
| *Regular Rides* | The number of rides completed by a consumer each week in robotaxi-accessible areas, considering only those ride requests where the robotaxi option was *not* selected | 513,433 | 0.17 | 0.72 | 0 | 22 |
| Inaccessible Areas | | | | | | |
| *Total Rides* | The number of rides completed by a consumer each week in robotaxi-inaccessible areas | 513,433 | 0.53 | 1.66 | 0 | 36 |
| Focal variable | | | | | | |
| *Treatment* | A dummy variable that equals 1 for a consumer in the treatment group | 513,433 | 0.38 | 0.49 | 0 | 1 |
| *After* | A dummy variable that equals 1 since the rollout of the robotaxi service | 513,433 | 0.53 | 0.50 | 0 | 1 |

## 4. Empirical Model

Following prior studies (Xu et al. 2017, Narang and Shankar 2019, Son et al. 2023), we employ a DID model with consumer-level and week-level fixed effects to estimate the treatment effect of robotaxi services, as specified below:

$$y_{it} = \beta_0 + \beta_1 Treatment_i \times After_t + \alpha_i + \gamma_t + \varepsilon_{it} \tag{1}$$

where $y_{it}$ represents the total number of rides completed by consumer $i$ in week $t$. $Treatment_i$ and $After_t$ are defined in Table 1. $\alpha_i$ denotes consumer-level fixed effects, capturing unobserved consumer heterogeneity. $\gamma_t$ denotes week-level fixed effects, which account for the effect of time-varying factors (e.g., seasonality and exogenous temporal shocks). Note that the main effects of $Treatment_i$ and $After_t$ are unidentifiable, as they are subsumed by $\alpha_i$ and $\gamma_t$, respectively. $\varepsilon_{it}$ is the idiosyncratic error term clustered at the consumer level to allow the errors within a consumer to be correlated.

A key identifying assumption underlying the DID model is the parallel trends assumption (e.g., Autor 2003, Angrist and Pischke 2009, Burtch et al. 2018). To test the parallel trends assumption in the pre-treatment period (e.g., Autor 2003, Angrist and Pischke 2009, Burtch et al. 2018), we present the results of a dynamic DID specification through a lead and lag analysis. This is achieved by replacing the $After_t$ dummy in Equation (1) with dummies representing the chronological distance in weeks from the treatment time, resulting in Equation (2):

$$\begin{aligned} y_{it} = \beta_0 &+ \beta_1\, Treatment_i \times D_{it}^{-10} + \beta_2\, Treatment_i \times D_{it}^{-9} + \cdots + \beta_{19}\, Treatment_i \times D_{it}^{+9} + \\ &\beta_{20}\, Treatment_i \times D_{it}^{+10} + \alpha_i + \gamma_t + \varepsilon_{it} \end{aligned} \tag{2}$$

where $D_{it}^{-\tau}(D_{it}^{\tau})$ equals 1 for consumer $i$ in the $\tau$-th week before (after) the treatment ($\tau \in [-10, 10]$). Following the extant literature (Autor 2003, Burtch et al. 2018), we designate the relative time dummy ($D_{it}^{-1}$) as the omitted baseline. We expect that the coefficients for pre-treatment relative time dummies will not significantly deviate from zero, thereby supporting the validity of the parallel trends assumption.

# 5. Results

## 5.1. Parallel Trend Test

As the parallel trends assumption is a prerequisite for DID estimation, we begin by testing this assumption. As illustrated in Figure 2, all lead coefficients are not significantly different from zero, suggesting that the treatment and control groups follow a parallel trend before the robotaxi introduction. This increases our confidence in the validity of our DID design. Following the launch of robotaxi services, consumers in the treatment group completed significantly more rides than those in the control group over time, demonstrating a sustained positive impact of robotaxi services on ride-hailing consumption, unlikely attributable to a mere novelty effect.

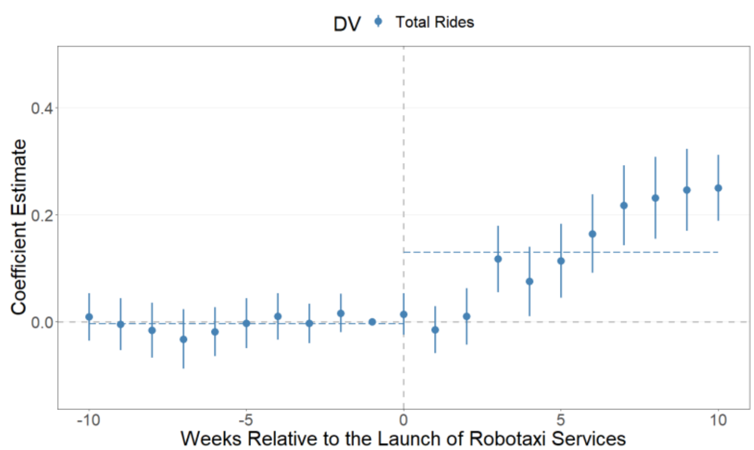


**Figure 2. Parallel Trend Test**

Notes: a) The dashed vertical grey line denotes the week in which the platform officially launched the robotaxi service (May 2022). b) The colored dash horizontal line denotes the average of lead and lag coefficients. c) Error bars represent 95% confidence intervals.

## 5.2. Main Results on Ride-Hailing

The results of our DID estimation are summarized in Table 2. As presented in Column 1, consumers who have experienced robotaxi services see a 23.2% increase in their total weekly rides (calculated as 0.175/0.753, where the coefficient is divided by the average number of completed rides in the control group). To investigate whether this increase is driven solely by consumers' direct attempts to use robotaxi services, we further decompose their rides into those requesting the robotaxi option and those without requesting it. We then focus on the latter to estimate the spillover effect of the robotaxi rollout on the demand exclusively designated for regular ride-hailing services. The analysis reported in Column 2 reveals that the robotaxi treatment not only boosts rides involving the robotaxi option but also leads to a significant 10.2% rise in *rides from requests that did not include robotaxis* (referred to as "*regular rides*") (calculated as 0.071/0.694). This increase accounts for roughly 40.6% of the overall rise in rides (calculated as 0.071/0.175, considering that rides in the control groups are exclusively regular rides). Our findings suggest that the robotaxi experience does not cannibalize consumer demand for regular rides; instead, it has a complementary spillover effect that boosts regular ride-hailing consumption.[7] Results are highly consistent when using consumers' weekly expenditure as the alternative dependent variable (see Appendix A).

**Table 2. Impact of Robotaxi Services on Consumers' Ride-Hailing Consumption**

| Dep. Var. | Number of Completed Rides | |
|---|---|---|
| | Total Rides | Regular Rides |
| | (1) | (2) |
| After × Treatment | 0.175*** | 0.071*** |
| | (0.019) | (0.017) |
| Consumer FE | Yes | Yes |
| Time FE | Yes | Yes |
| Observations | 513,433 | 513,433 |
| Number of Consumers | 15,220 | 15,220 |
| R-squared | 0.425 | 0.439 |

Notes: a) Robust standard errors clustered at the consumer level. b) * $p$<0.1, ** $p$<0.05, *** $p$<0.01.

### 5.3. Heterogeneous Treatment Effect: Robotaxi-Accessible vs. Inaccessible Areas

Having examined how the robotaxi experience affects a consumer's overall rides and regular rides alone, we now investigate how this impact varies across different areas. Specifically, we assess whether the treatment effects differ between areas with and without access to these services, shedding light on how the availability of the innovative robotaxi service influences consumers' ride-hailing consumption. Intriguingly, in Table 3, we observe a significant uptick in both total and regular rides within robotaxi-accessible areas (Columns 1 and 2), contrasted with a significant decrease in (regular) rides outside these areas (Column 3). This heterogeneous treatment effect (HTE) between accessible and inaccessible areas, along with the positive spillover effect on regular rides alone, again suggests that our observed impact is

[7] We cannot perform a meaningful DID analysis on rides that specifically include the robotaxi option in their requests, as such rides only became available after the robotaxi service was launched.

not merely a "novelty effect."

**Table 3. HTE on by Robotaxi-Accessible vs. Inaccessible Areas**

| Dep. Var. | Number of Completed Rides | | |
|---|---|---|---|
| Area | Accessible Areas | | Inaccessible Areas |
| | Total Rides (1) | Regular Rides (2) | Total (Regular) Rides (3) |
| After × Treatment | 0.209*** (0.010) | 0.105*** (0.008) | -0.033** (0.015) |
| Consumer FE | Yes | Yes | Yes |
| Time FE | Yes | Yes | Yes |
| Observations | 513,433 | 513,433 | 513,433 |
| Number of Consumers | 15,220 | 15,220 | 15,220 |
| R-squared | 0.260 | 0.269 | 0.470 |

Notes: a) Robust standard errors clustered at the consumer level. b) * $p$<0.1, ** $p$<0.05, *** $p$<0.01.

Moreover, the starkly contrasting effects observed in accessible and inaccessible areas suggest that different mechanisms may be at play, highlighting the potential complexity of the factors driving these positive and negative spillover effects. In particular, these effects likely result from a shift in consumer preferences for the ride-hailing category, the platform, or both. We will present additional analyses in Section 6 to investigate the potential mechanisms underlying these positive and negative spillover effects.

## 6. Suggestive Evidence for Potential Underlying Mechanisms

Our main results suggest that the robotaxi treatment has a positive spillover effect on consumers' regular rides (where they did not request robotaxis) in robotaxi-accessible areas and a negative spillover effect in inaccessible areas. Two potential mechanisms may contribute to these spillover effects.

First is the category expansion effect. Prior research in promotion contexts has found that advertising or platform recommendations can lead to increased consumption of related products or services in the same category (e.g., Liu et al. 2015, Li and Agarwal 2017, Liang et al. 2019). While such an effect has not been examined in the context of introducing an innovative offering (e.g., robotaxi), the robotaxi rollout can trigger a similar category expansion effect, resulting in a broader shift in consumer preferences toward the ride-hailing category as a whole, leading to increased usage.

Another potential mechanism could be a shift in consumer preferences specifically toward the platform offering innovative services. Prior consumer behavior literature has found a positive impact of innovative offerings on brand equity and consumer loyalty (e.g., Johnson et al. 2006, Xu et al. 2014, Wu 2014). By differentiating the platform through innovation, robotaxis have the potential to strengthen consumer loyalty and preference. Correspondingly, the availability of robotaxis might influence consumers' preference for the focal platform, thereby impacting their ride-hailing consumption on this platform. However, this positive spillover effect may depend on the geographic availability of robotaxis and could weaken—or even reverse—in areas where they are not accessible, a possibility that warrants further empirical investigation.

To deepen our understanding, we begin by identifying and differentiating between single-homing and multi-homing consumers in Section 6.1 by leveraging the exceptional granularity and comprehensiveness of our proprietary dataset. This is followed by the HTE analysis in Section 6.2. Typically, single-homing consumers' consumption is based primarily on preferences for ride-hailing services, while multi-homing consumers' consumption on the focal platform is influenced by their preferences for both this service category and the platform. Disentangling their behaviors informs how robotaxi services reshape consumer preferences. Following this, we examine the validity of these proposed mechanisms in Sections 6.3 and 6.4, respectively.

**6.1. Identification of Single-Homing and Multi-Homing Consumers**

Notably, our data captures all ride-hailing services fulfilled by the focal platform, which can be requested through two main channels: the platform's own app or Gaode, a dominant ride-hailing aggregator in China. Gaode embeds its aggregate ride-hailing request services within its widely used mapping and navigation app (i.e., Gaode Maps). Through Gaode, consumers can simultaneously request ride-hailing services from most major ride-hailing platforms in China, including our focal platform. The platform assigned to fulfill the ride request is automatically decided by Gaode based on the estimated price and waiting time. The robotaxi service can only be requested on the platform's own app.

Building on existing platform studies (Li and Zhu 2021, Farronato et al. 2024) and recognizing the potential differences in consumption patterns between consumers who use Gaode for multi-homing and those who never use it, we managed to cross-reference consumers' ride requests made via both platforms before the rollout of robotaxis, using their mobile phone numbers.[8] We then categorized them into three groups: 1) multi-homing consumers, who ordered rides from the focal platform via both its app and the aggregator; 2) single-homing consumers, who appeared to order rides from the focal platform only via its app; and 3) an unknown group, whose multi-homing behavior could not be determined due to limitations in data matching. Given the high uncertainty among consumers in the unknown group, we exclude this group when examining how robotaxi usage affects single-homing and multi-homing consumers differently.[9] It is worth noting that our classification method yields a conservative sample of multi-homing consumers due to constraints in data matching and may over-identify single-homing consumers as some of them might use other ride-hailing aggregator services not captured by our data sources. This presents challenges in discerning variations in consumer behavior between single-homing and multi-homing consumers, thus making our estimated HTE in Section 6.2 a conservative estimate of the actual difference in effects.

### 6.2. Heterogeneous Treatment Effect: Single-Homing vs. Multi-Homing Consumers

To examine the heterogeneity in the treatment effect of robotaxi services across single-homing and multi-homing consumers, we interact $Treatment_i \times After_t$ with the consumer-level moderator $Multihoming_i$, which indicates whether consumer $i$ is in the multi-homing group, in Equation (4) below:

$$y_{it} = \beta_0 + \beta_1 Treatment_i \times After_t + \beta_2 Treatment_i \times After_t \times Multihoming_i$$
$$+\alpha_i + \gamma_t + \theta_{it} + \varepsilon_{it} \tag{4}$$

Similar to Section 5.4, considering the potential differential time trends across consumer subgroups,

[8] Due to the sensitivity of the mobile phone data, the consumer matching process was conducted by the focal platform's employees using all ride data prior to the rollout of robotaxis, which is not limited to the observation window of our analysis. Because only the first four and last four digits of the mobile phone numbers are provided by the aggregator, the employees first compare ride orders from the platform's own app and the aggregator by matching mobile phone numbers that share the same first four and last four digits. If a consumer's mobile number from requests made via the platform's app does not have any matches in the aggregator's data, they are classified as *single-homing*. For cases where mobile numbers appear in both datasets, accounts are identified as belonging to the same individual if (1) their mobile numbers share the same first and last four digits, and (2) they have at least one pair of corresponding ride requests across platforms that occur nearly simultaneously with identical origins and destinations; otherwise, accounts are classified into an *unknown* group.

[9] Results are highly consistent when the unknown group is included as a separate group in our analysis (see Appendix B).

we allow the week-level fixed effects to vary across single-homing and multi-homing consumers by interacting calendar week dummies with two subgroup dummies, captured by $\theta_{it}$, thereby subsuming the interaction term $After_t \times Multihoming_i$.

The HTE results reported in Table 4 reveal three key observations. First, there are no significant differences in the treatment effect on total rides between single-homing and multi-homing consumers. However, notable heterogeneity emerges when analyzing rides in different areas. Second, the treatment effect on rides within robotaxi-accessible areas is positive for both consumer types, with a more pronounced effect observed among multi-homing consumers. For single-homing consumers, the positive effect underscores an enhancement in their general preference for ride-hailing services, supporting a category expansion effect. Additionally, the larger increase in rides among multi-homing consumers implies that robotaxi services not only boost their general preference for ride-hailing but also enhance their preference for the focal platform in accessible areas, supporting an additional platform preference shift.

**Table 4. HTE on Single-homing vs. Multi-homing Consumers**

| Dep. Var. | Number of Completed Rides | | | | |
|---|---|---|---|---|---|
| Area | All Areas | | Accessible Areas | | Inaccessible Areas |
| | Total Rides | Regular Rides | Total Rides | Regular Rides | Total Rides |
| | (1) | (2) | (3) | (4) | (5) |
| After × Treatment | 0.155*** | 0.076*** | 0.159*** | 0.080*** | -0.004 |
| | (0.029) | (0.027) | (0.014) | (0.011) | (0.024) |
| After × Treatment × Multihoming | -0.042 | -0.073 | 0.097*** | 0.066** | -0.139** |
| | (0.068) | (0.064) | (0.037) | (0.029) | (0.055) |
| Consumer FE | Yes | Yes | Yes | Yes | Yes |
| Time FE for Singlehoming Group | Yes | Yes | Yes | Yes | Yes |
| Time FE for Multihoming Group | Yes | Yes | Yes | Yes | Yes |
| Observations | 249,881 | 249,881 | 249,881 | 249,881 | 249,881 |
| Number of Consumers | 7,433 | 7,433 | 7,433 | 7,433 | 7,433 |
| R-squared | 0.449 | 0.464 | 0.252 | 0.261 | 0.490 |

Notes: a) Robust standard errors clustered at the consumer level. b) In this analysis, we have excluded the unknown group whose multi-homing behavior is undetermined, resulting in a reduced sample size compared to Table 2. Results are highly consistent when the unknown group is included (see Appendix B). c) Results are highly consistent if we control for overall time FE instead of subgroup-specific time trends (captured by Time FE for the singlehoming group and Time FE for the multihoming group). d) * $p$<0.1, ** $p$<0.05, *** $p$<0.01.

Finally, the treatment effect on single-homing consumers for rides outside the district is insignificant in contrast to a significantly negative effect on multi-homing consumers (coefficient = -0.143, $p$-value < 0.01). This implies that while the absence of robotaxi services does not affect consumers' overall preference for ride-hailing, it considerably reduces multi-homing consumers' preference for the specific platform in inaccessible areas. Specifically, for consumers who have used robotaxi services, such services can become a "*phantom decoy*" (an attractive but unavailable option) (Farquhar and Anthony 1993) in those inaccessible areas. Its unavailability can evoke a sense of perceived loss, akin to the *endowment effect* (Trueblood and Pettibone 2017), which may result in a decreased preference for the specific platform compared to other platforms with consistent offerings across areas.

### 6.3. Category Expansion among Consumers

To assess whether and to what extent consumers expand their ride-hailing category consumption, we consider two types of expansion: *temporal expansion* (increasing usage across more days) and *spatial expansion* (using ride-hailing services in more locations). First, regarding temporal expansion, we use the number of days per week on which a consumer uses ride-hailing services provided by the focal platform as the dependent variable and rerun the DID model. The results in Table 5 indicate that the robotaxi experience significantly increases the number of ride-hailing usage days per week for single-homing consumers, but only in accessible areas. This finding supports the proposed category expansion effect on their ride-hailing consumption in accessible areas.

**Table 5. HTE on Consumption Days among Single-homing vs. Multi-homing Consumers**

| Dep. Var. | Number of Days with Ride-hailing Consumption per Week | | | | |
|---|---|---|---|---|---|
| Area | All Areas | | Accessible Areas | | Inaccessible Areas |
| | Total Rides | Regular Rides | Total Rides | Regular Rides | Total Rides |
| | (1) | (2) | (3) | (4) | (5) |
| After × Treatment | 0.095*** | 0.052*** | 0.106*** | 0.061*** | -0.011 |
| | (0.016) | (0.015) | (0.010) | (0.008) | (0.013) |
| After × Treatment × Multihoming | 0.013 | -0.008 | 0.076*** | 0.055*** | -0.063** |
| | (0.038) | (0.036) | (0.025) | (0.021) | (0.029) |
| Consumer FE | Yes | Yes | Yes | Yes | Yes |
| Time FE for Singlehoming Group | Yes | Yes | Yes | Yes | Yes |
| Time FE for Multihoming Group | Yes | Yes | Yes | Yes | Yes |
| Observations | 249,881 | 249,881 | 249,881 | 249,881 | 249,881 |
| Number of Consumers | 7,433 | 7,433 | 7,433 | 7,433 | 7,433 |
| R-squared | 0.442 | 0.457 | 0.274 | 0.281 | 0.488 |

Notes: a) In this analysis, we have excluded the unknown group whose multi-homing behavior is undetermined, resulting in a reduced sample size compared to Table 2. Results are highly consistent when the unknown group is included. b) Results are highly consistent if we control for overall time FE instead of subgroup-specific time trends (captured by Time FE for the singlehoming group and Time FE for the multihoming group). c) Robust standard errors clustered at the consumer level. d) * $p<0.1$, ** $p<0.05$, *** $p<0.01$.

Compared to single-homing consumers, the positive treatment effect on usage days is larger in accessible areas but turns significantly negative in inaccessible areas among multi-homing consumers (coefficient = -0.074, $p$-value < 0.01). This is likely driven by the additional effect of platform preference shift among multi-homing consumers, which will be further examined in the next subsection.

Second, with respect to spatial expansion, we conduct a similar analysis using the number of distinct pick-up hexagons (the platform's unit for indexing equal-sized areas)[10] per week in which a consumer uses ride-hailing services provided by the platform as the dependent variable. As delineated in Table 6, we consistently find that the robotaxi experience significantly expands single-homing consumers' ride-hailing consumption spatially within accessible areas, further supporting the proposed category expansion effect. Moreover, the HTE analysis regarding multi-homing consumers also indicates a similar platform preference switching pattern, as observed in Table 5.

**Table 6. HTE on Location Diversity among Single-homing vs. Multi-homing Consumers**

| Dep. Var. | Number of Distinct Departure Hexagons per Week | | | | |
|---|---|---|---|---|---|
| Area | All Areas | | Accessible Areas | | Inaccessible Areas |
| | Total Rides<br>(1) | Regular Rides<br>(2) | Total Rides<br>(3) | Regular Rides<br>(4) | Total Rides<br>(5) |
| After × Treatment | 0.084*** | 0.054*** | 0.072*** | 0.042*** | 0.012 |
| | (0.015) | (0.014) | (0.007) | (0.006) | (0.013) |
| After × Treatment × Multihoming | -0.011 | -0.026 | 0.061*** | 0.046*** | -0.072** |
| | (0.034) | (0.033) | (0.016) | (0.014) | (0.029) |
| Consumer FE | Yes | Yes | Yes | Yes | Yes |
| Time FE for Singlehoming Group | Yes | Yes | Yes | Yes | Yes |
| Time FE for Multihoming Group | Yes | Yes | Yes | Yes | Yes |
| Observations | 249,881 | 249,881 | 249,881 | 249,881 | 249,881 |
| Number of Consumers | 7,433 | 7,433 | 7,433 | 7,433 | 7,433 |
| R-squared | 0.398 | 0.414 | 0.204 | 0.211 | 0.446 |

Notes: a) In this analysis, we have excluded the unknown group whose multi-homing behavior is undetermined, resulting in a reduced sample size compared to Table 2. Results are highly consistent when the unknown group is included. b) Results are highly consistent if we control for overall time FE instead of subgroup-specific time trends (captured by Time FE for the singlehoming group and Time FE for the multihoming group). c) Robust standard errors clustered at the consumer level. d) * $p$<0.1, ** $p$<0.05, *** $p$<0.01.

### 6.4. Platform Preference Shift among Multi-homing Consumers

To provide more direct evidence of the shift in platform preference among multi-homing consumers,

[10] Mirroring Uber's approach, this platform employs a hexagonal hierarchical spatial indexing system and divides cities into equally sized hexagons. Since most rides occur within the city to which the robotaxi-accessible areas belong, we focus solely on considering and measuring their distinct pick-up hexagons within that specific city and estimate the treatment effect accordingly.

we examine the treatment effect on their platform selection when requesting ride-hailing services. As outlined in Section 6.1, multi-homing consumers can request services from the focal platform either directly via the platform's app or through the aggregator, which then sends ride requests to multiple platforms simultaneously. Since ride requests through the aggregator are not designated to be fulfilled by the focal platform and reflect a less committed relationship with the platform brand, we use the ratio of regular ride requests via the platform's own app to the total regular ride requests across both platforms as a proxy for consumers' preference for the focal platform.

The results in Table 7 reveal distinct patterns in multi-homing consumers' ride-hailing behavior across different areas: the proportion of regular ride requests via the platform's own app increases in accessible areas (Column 2) and decreases in other areas (Column 3). This aligns with our earlier findings that introducing innovative services in certain areas can shift multi-homing consumers' preferences towards the focal platform in those areas, whereas their unavailability in other areas may lead to reduced platform preference compared to other platforms.

**Table 7. Treatment Effect on Ratio of Rides via the Platform's Own App**

| Dep. Var. | % of Ride Requests via Its Own App | | |
|---|---|---|---|
| Area | All Areas<br>(1) | Accessible Areas<br>(2) | Inaccessible Areas<br>(3) |
| After × Treatment | -0.006 | 0.062*** | -0.045*** |
| | (0.012) | (0.021) | (0.011) |
| Consumer FE | Yes | Yes | Yes |
| Time FE | Yes | Yes | Yes |
| Observations | 30,195 | 13,930 | 24,647 |
| Number of Consumers | 2,008 | 2,008 | 2,008 |
| R-squared | 0.552 | 0.642 | 0.681 |

Notes: a) The analysis is conducted on the multi-homing consumers only. b) Robust standard errors clustered at the consumer level. c) Observations are removed for a consumer in a week with no requests. d) * $p$<0.1, ** $p$<0.05, *** $p$<0.01.

Collectively, our findings indicate that the observed treatment effects across different regions and among single-homing versus multi-homing consumers may be jointly influenced by both the category expansion effect and the platform preference shift effect. The positive spillover observed in regular ride-hailing services within robotaxi-accessible areas, particularly among single-homing consumers, likely stems from a category expansion effect, supporting an increased preference for the ride-hailing category as a whole. In contrast, for multi-homing consumers, the heightened positive spillover in accessible areas, coupled with the negative spillover in inaccessible areas, suggests a shift in platform preference. Specifically, there is an increased platform preference in areas with greater accessibility to robotaxis and a decreased preference in areas lacking such accessibility.

## 7. Robustness Checks

We conduct a series of robustness checks to validate the reliability of our findings, as summarized in Table 8.

**Table 8. Summary of Robustness Checks**

| Robustness Check | Objective | Section |
|---|---|---|
| *Alternative Treatment and Control Groups* | | |
| Alternative control group of consumers without robotaxi requests | Alleviating the concern of potential "contamination" in the control group | 7.1 |
| Alternative control group from a district without robotaxi services | Alleviating the concern of potential violation of SUTVA | 7.2 |
| Expanding treatment group by including those consumers who have exclusively requested robotaxi services before being first served by a robotaxi | Evaluating the generalizability to a broader consumer base interested in robotaxi services | Appendix C |
| *Alternative DID Designs* | | |
| Staggered DID design (based on the timing of consumers' first robotaxi experience) | Evaluating the robustness of observed treatment effects to an alternative DID design | 7.3 |
| HTE-robust staggered DID design | Alleviating the concern of potential bias in staggered DID estimates with two-way fixed effects | 7.4 |
| Falsification test using non-treated observations | Safeguarding against spurious causality | 7.5 |
| *Other Robustness Checks* | | |
| Placebo test with random treatment assignment | Safeguarding against spurious causality | 7.6 |
| Log-transformation of dependent variables | Demonstrating result robustness to alternative model specification | Appendix D |
| Alternative dependent variable | Demonstrating result robustness to alternative measure | Appendix A |

First, we test the robustness of our results to alternative treatment and control group definitions. This includes using two different control groups: those who have never requested robotaxi services (see Section

7.1) and those from a comparable district without robotaxi services (see Section 7.2). Additionally, we refine the treatment group to further include consumers who have exclusively requested robotaxi services before their first experience with a robotaxi (see Appendix C).

Second, we perform several robustness checks with alternative DID designs to address concerns about spurious causality. We first apply a staggered DID approach, using the timing of consumers' first robotaxi experience as the treatment time (see Section 7.3), rather than relying on a static DID design. We then demonstrate that our DID estimates remain robust to potential biases associated with the two-way-fixed-effect (TWFE) staggered DID design (see Section 7.4). To further validate that the effects are driven by the actual treatment, we conduct two sets of falsification tests (see Section 7.5).

Furthermore, we conduct additional robustness checks to further validate our findings, including a placebo test (see Section 7.6), the use of log-transformation to dependent variables (see Appendix D), and analysis with an alternative dependent variable (see Appendix A). In all the robustness checks, the results remain highly consistent.

### 7.1. An Alternative Control Group of Consumers without Robotaxi Requests

While the DID design in our main analysis, which leverages the quasi-random variation in the treatment assignment from the platform's car dispatch algorithm, effectively mitigates self-selection concerns, there remains a potential concern about "contamination" in the control group. Specifically, this concern arises if consumers in the control group, who requested but were not served by robotaxis, might still be indirectly affected by the treatment.

To alleviate this concern, we employ an alternative control group comprising consumers who have never requested robotaxi services. To better align the treatment and control groups, we retain consumers who began using the platform prior to the introduction of robotaxi services and had requested at least one (regular) ride in the accessible area after the introduction of robotaxi services. To further strengthen the comparability between the two groups, we apply the Coarsened Exact Matching (CEM) method (Blackwell et al. 2009) for one-to-one matching without replacement. This process results in 5,252 matched pairs of treated and control consumers. Appendix E details the covariates used in the matching process, along with balance check results, which indicate that the matched sample is balanced across all covariates.

The results, presented in Tables 9 and 10, consistently indicate a positive spillover effect on regular rides in robotaxi-accessible areas for both single-homing and multi-homing consumers and a negative spillover effect for multi-homing consumers only in inaccessible areas (coefficient = -0.113, $p$-value < 0.05).

**Table 9. Impact of Robotaxi Services on Consumers' Ride-Hailing Consumption (Using Consumers Never Requesting Robotaxi as Control)**

| Dep. Var. | Number of Completed Rides | | | | |
|---|---|---|---|---|---|
| Area | All Areas | | Accessible Areas | | Inaccessible Areas |
| | Total Rides (1) | Regular Rides (2) | Total Rides (3) | Regular Rides (4) | Total (Regular) Rides (5) |
| After × Treatment | 0.227*** | 0.017 | 0.271*** | 0.061*** | -0.043*** |
| | (0.020) | (0.019) | (0.011) | (0.009) | (0.015) |
| Consumer FE | Yes | Yes | Yes | Yes | Yes |
| Time FE | Yes | Yes | Yes | Yes | Yes |
| Observations | 355,702 | 355,702 | 355,702 | 355,702 | 355,702 |
| Number of Consumers | 10,504 | 10,504 | 10,504 | 10,504 | 10,504 |
| R-squared | 0.357 | 0.365 | 0.259 | 0.259 | 0.401 |

Notes: a) Robust standard errors clustered at the consumer level. b) * $p$<0.1, ** $p$<0.05, *** $p$<0.01.

**Table 10. HTE on Single-homing vs. Multi-homing Consumers (Using Consumers Never Requesting Robotaxi as Control)**

| Dep. Var. | Number of Completed Rides | | | | |
|---|---|---|---|---|---|
| Area | All Areas | | Accessible Areas | | Inaccessible Areas |
| | Total Rides (1) | Regular Rides (2) | Total Rides (3) | Regular Rides (4) | Total Rides (5) |
| After × Treatment | 0.214*** | 0.048* | 0.208*** | 0.042*** | 0.006 |
| | (0.029) | (0.027) | (0.016) | (0.013) | (0.023) |
| After × Treatment × Multihoming | 0.015 | -0.059 | 0.134*** | 0.059* | -0.119** |
| | (0.072) | (0.066) | (0.042) | (0.034) | (0.053) |
| Consumer FE | Yes | Yes | Yes | Yes | Yes |
| Time FE for Singlehoming Group | Yes | Yes | Yes | Yes | Yes |
| Time FE for Multihoming Group | Yes | Yes | Yes | Yes | Yes |
| Observations | 167,195 | 167,195 | 167,195 | 167,195 | 167,195 |
| Number of Consumers | 4,944 | 4,944 | 4,944 | 4,944 | 4,944 |
| R-squared | 0.353 | 0.360 | 0.247 | 0.243 | 0.391 |

Notes: a) Robust standard errors clustered at the consumer level. b) In this analysis, we have excluded the unknown group whose multi-homing behavior is undetermined, resulting in a reduced sample size compared to Table 9. Results are highly consistent when the unknown group is included. c) Results are highly consistent if we control for overall time FE instead of subgroup-specific time trends (captured by Time FE for the singlehoming group and Time FE for the multihoming group). d) * $p$<0.1, ** $p$<0.05, *** $p$<0.01.

### 7.2. An Alternative Control Group from a Different District

To address potential violations of SUTVA among treatment and control consumers in the same robotaxi-accessible district, we utilize an alternative control group comprising consumers from a counterfactual district that is highly comparable to the robotaxi-accessible district in terms of population and economic characteristics.[11] This alternative district is carefully selected from a different city in the same province.[12]

**Table 11. Impact of Robotaxi Services on Consumers' Ride-Hailing Consumption (An Alternative Control Group from a Different District)**

| Dep. Var. | Number of Completed Rides | | | | |
|---|---|---|---|---|---|
| Area | All Areas | | Accessible Areas | | Inaccessible Areas |
| | Total Rides (1) | Regular Rides (2) | Total Rides (3) | Regular Rides (4) | Total (Regular) Rides (5) |
| After × Treatment | 0.321*** | 0.112*** | 0.342*** | 0.132*** | -0.021 |
| | (0.019) | (0.018) | (0.010) | (0.008) | (0.015) |
| Consumer FE | Yes | Yes | Yes | Yes | Yes |
| Time FE | Yes | Yes | Yes | Yes | Yes |
| Observations | 379,948 | 379,948 | 379,948 | 379,948 | 379,948 |
| Number of Consumers | 11,132 | 11,132 | 11,132 | 11,132 | 11,132 |
| R-squared | 0.361 | 0.369 | 0.238 | 0.228 | 0.404 |

Notes: a) In the control group, "accessible" and "inaccessible" areas are defined as the counterfactual district and all areas outside of this district, respectively. b) Although the overall spillover effect on consumers' regular rides in inaccessible areas is not significantly negative, we consistently observe a significant negative spillover effect among multi-homing consumers in Table 13. As the proportion of multi-homing consumers may vary across districts, the overall spatial spillover effect could differ accordingly. c) Robust standard errors clustered at the consumer level. d) * $p<0.1$, ** $p<0.05$, *** $p<0.01$.

**Table 12. HTE on Single-homing vs. Multi-homing Consumers (An Alternative Control Group from a Different District)**

| Dep. Var. | Number of Completed Rides | | | | |
|---|---|---|---|---|---|
| Area | All Areas | | Accessible Areas | | Inaccessible Areas |
| | Total Rides (1) | Regular Rides (2) | Total Rides (3) | Regular Rides (4) | Total Rides (5) |
| After × Treatment | 0.243*** | 0.079*** | 0.237*** | 0.073*** | 0.006 |
| | (0.027) | (0.025) | (0.015) | (0.012) | (0.021) |
| After × Treatment × Multihoming | 0.079** | 0.012 | 0.129*** | 0.062*** | -0.050* |
| | (0.037) | (0.035) | (0.021) | (0.016) | (0.030) |
| Consumer FE | Yes | Yes | Yes | Yes | Yes |
| Time FE for Singlehoming Group | Yes | Yes | Yes | Yes | Yes |
| Time FE for Multihoming Group | Yes | Yes | Yes | Yes | Yes |
| Observations | 320,360 | 167,195 | 167,195 | 167,195 | 167,195 |
| Number of Consumers | 9,398 | 9,398 | 9,398 | 9,398 | 9,398 |
| R-squared | 0.354 | 0.363 | 0.235 | 0.230 | 0.398 |

Notes: a) In the control group, "accessible" and "inaccessible" areas are defined as the counterfactual district and all areas outside of this district, respectively. b) In this analysis, we have excluded the unknown group whose multi-homing behavior is undetermined, resulting in a reduced sample size compared to Table 11. Results are highly consistent when the unknown group is included. c) Results are highly consistent if we control for overall time FE instead of subgroup-specific time trends (captured by Time FE for the singlehoming group and Time FE for the multihoming group). d) Robust standard errors clustered at the consumer level. e) * $p<0.1$, ** $p<0.05$, *** $p<0.01$.

[11] Similar to Section 7.1, we align the treatment and control groups by retaining consumers who begun using the platform before the introduction of robotaxi services and had requested at least one (regular) ride in their respective districts after May 2022. Additionally, we exclude all consumers in the counterfactual district who had taken any rides in the focal district where the robotaxi service was rolled out.

[12] Based on the most recent Census and government reports relevant to our observation period, the focal district and the counterfactual district have similar population sizes and comparable GDP figures.

To ensure that the treatment and control groups are comparable, we also apply the CEM method for one-to-one matching, similar to our approach in Section 7.1, and obtain 5,566 pairs of matched treated and control consumers. Detailed balance check results are reported in Appendix F, confirming that the matched sample is highly comparable across all covariates. The results in Tables 11-12 confirm the robustness of our main results.

### 7.3. Cohort-based Staggered DID Design

In addition to the static DID design, we implement a cohort-based staggered DID design. Specifically, each consumer in the treatment group is matched with a control group cohort who has similar characteristics, comparable prior ride-hailing behavior, and requested robotaxi services in the same week, with the treated consumer fulfilled by the robotaxi service and the matched control cohort receiving regular ride-hailing services. This process results in 4,433 matched pairs of treated and control consumers. The balance checks detailed in Appendix G verify the comparability of the matched sample across all covariates.

In the staggered DID model, we define the treatment time as the actual timing of each treated consumer's first experience with robotaxi rides. Table 13 presents consistent evidence of the overall positive treatment effect on consumers' total ride-hailing consumption, along with the differential spillover effects in accessible and inaccessible areas, reinforcing confidence in our findings. Additionally, Table 14 corroborates these results by demonstrating a similar HTE pattern.

**Table 13. Impact of Robotaxi Services on Consumers' Ride-Hailing Consumption (Staggered DID)**

| Dep. Var. | Number of Completed Rides | | | | |
|---|---|---|---|---|---|
| Area | All Areas | | Accessible Areas | | Inaccessible Areas |
| | Total Rides<br>(1) | Regular Rides<br>(2) | Total Rides<br>(3) | Regular Rides<br>(4) | Total (Regular) Rides<br>(5) |
| Treated | 0.250***<br>(0.026) | 0.105***<br>(0.022) | 0.290***<br>(0.017) | 0.146***<br>(0.012) | -0.041**<br>(0.017) |
| Consumer FE | Yes | Yes | Yes | Yes | Yes |
| Time FE | Yes | Yes | Yes | Yes | Yes |
| Observations | 299,369 | 299,369 | 299,369 | 299,369 | 299,369 |
| Number of Consumers | 8,866 | 8,866 | 8,866 | 8,866 | 8,866 |
| R-squared | 0.331 | 0.316 | 0.265 | 0.189 | 0.350 |

Notes: a) Robust standard errors clustered at the consumer level. b) * $p$<0.1, ** $p$<0.05, *** $p$<0.01.

**Table 14. HTE on Single-homing vs. Multi-homing Consumers (Staggered DID)**

| Dep. Var. | Number of Completed Rides | | | | |
|---|---|---|---|---|---|
| Area | All Areas | | Accessible Areas | | Inaccessible Areas |
| | Total Rides | Regular Rides | Total Rides | Regular Rides | Total Rides |
| | (1) | (2) | (3) | (4) | (5) |
| Treated | 0.226*** | 0.106*** | 0.233*** | 0.113*** | -0.007 |
| | (0.038) | (0.033) | (0.023) | (0.016) | (0.026) |
| Treated × Multihoming | -0.036 | -0.071 | 0.142** | 0.108** | -0.178** |
| | (0.114) | (0.103) | (0.070) | (0.055) | (0.083) |
| Consumer FE | Yes | Yes | Yes | Yes | Yes |
| Time FE for Singlehoming Group | Yes | Yes | Yes | Yes | Yes |
| Time FE for Multihoming Group | Yes | Yes | Yes | Yes | Yes |
| Observations | 140,344 | 140,344 | 140,344 | 140,344 | 140,344 |
| Number of Consumers | 4,166 | 4,166 | 4,166 | 4,166 | 4,166 |
| R-squared | 0.342 | 0.330 | 0.258 | 0.176 | 0.358 |

Notes: a) Robust standard errors clustered at the consumer level. b) In this analysis, we have excluded the unknown group whose multi-homing behavior is undetermined, resulting in a reduced sample size compared to Table 13. Results are highly consistent when the unknown group is included. c) Results are highly consistent if we control for overall time FE instead of subgroup-specific time trends (captured by Time FE for the singlehoming group and Time FE for the multihoming group). d) * $p$<0.1, ** $p$<0.05, *** $p$<0.01.

### 7.4. HTE-robust Staggered DID Design

In the above cohort-based staggered DID setting, the TWFE DID estimator is a weighted average of three types of DID comparisons (Goodman-Bacon 2021): (1) treated vs. never-treated, (2) earlier-treated vs. later-treated, and (3) later-treated vs. earlier-treated. The third type becomes problematic if there exists significant heterogeneity in treatment effects over time or across cohorts (Borusyak et al. 2021, Callaway and Sant'Anna 2021). Through decomposition, we find that a large portion (77.8%) of the estimated treatment effects arises from treated versus never-treated comparisons, while the proportion of potentially problematic third-type DID comparisons is relatively low, at only 5.4%.

Despite this small proportion, we apply the BJS estimator (Borusyak et al. 2021) to the cohort-based matched sample from Section 7.3 to address this potential concern. To provide an estimator robust to HTE across time periods and cohorts, this method uses pre-treatment observations to impute the counterfactual outcomes for treated units. This avoids the negative weight issue, thereby reducing bias. As shown in Table 15, the treatment effects estimated using the BJS estimator align with our main findings, indicating that our findings are robust to TWFE-related biases in staggered DID models.

**Table 15. Impact of Robotaxi Services on Consumers' Ride-Hailing Consumption Using the HTE-Robust Staggered DID Estimator**

| Dep. Var. | Number of Completed Rides | | | | |
|---|---|---|---|---|---|
| Area | All Areas | | Accessible Areas | | Inaccessible Areas |
| | Total Rides (1) | Regular Rides (2) | Total Rides (3) | Regular Rides (4) | Total (Regular) Rides (5) |
| Treated | 0.339*** | 0.116*** | 0.377*** | 0.154*** | -0.037** |
| | (0.025) | (0.021) | (0.018) | (0.013) | (0.015) |
| Consumer FE | Yes | Yes | Yes | Yes | Yes |
| Time FE | Yes | Yes | Yes | Yes | Yes |
| Observations | 299,369 | 299,369 | 299,369 | 299,369 | 299,369 |
| Number of Consumers | 8,866 | 8,866 | 8,866 | 8,866 | 8,866 |

Notes: a) Robust standard errors clustered at the consumer level. b) * *p*<0.1, ** *p*<0.05, *** *p*<0.01.

### 7.5. Falsification Test Using Non-Treated Observations

Our primary identification strategy uses the introduction timing of robotaxi services as the treatment timing, providing a conservative estimate of the treatment effect of actual robotaxi service adoption on ride-hailing consumer behavior. To further validate that the effects are driven by the actual treatment, we conduct two sets of falsification tests. First, we exclude observations of treated consumers after their actual treatment timing. The results, presented in Table 16, Columns 1-3, show no significant effects on their regular rides, both in accessible and inaccessible areas, confirming that the observed effects are indeed driven by the actual treatment. Second, we exclude observations of all consumers in our sample after their first request for robotaxi services. The results, shown in Table 16, Columns 4-6, also indicate no significant effects on their regular rides in both accessible and inaccessible areas. This further strengthens our confidence that the results are driven by the robotaxi treatment.

**Table 16. Impact of Robotaxi Services on Consumers' Ride-Hailing Consumption**

| Dep. Var. | Number of Completed Regular Rides | | | | | |
|---|---|---|---|---|---|---|
| Observation Window | Before the Actual Treatment | | | Before the First Robotaxi Request | | |
| Area | All Areas (1) | Accessible Areas (2) | Inaccessible Areas (3) | All Areas (4) | Accessible Areas (5) | Inaccessible Areas (6) |
| After × Treatment | -0.019 | 0.005 | -0.024 | -0.008 | 0.009 | -0.017 |
| | (0.016) | (0.006) | (0.014) | (0.016) | (0.006) | (0.015) |
| Consumer FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Time FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 458,074 | 458,074 | 458,074 | 339,594 | 339,594 | 339,594 |
| Number of Consumers | 15,220 | 15,220 | 15,220 | 15,220 | 15,220 | 15,220 |
| R-squared | 0.453 | 0.267 | 0.481 | 0.481 | 0.301 | 0.507 |

Notes: a) Robust standard errors clustered at the consumer level. b) * *p*<0.1, ** *p*<0.05, *** *p*<0.01.

### 7.6. Placebo Test

Following the existing literature (Abadie et al. 2015, Burtch et al. 2018), we conduct a placebo test by randomly reassigning consumers into the treatment and control groups, and subsequently re-run our DID models with this new randomized treatment variable to assess placebo effects. We repeat this permutation procedure 1,000 times and capture the distribution of placebo effects. We then compare the observed treatment effect of the robotaxi service from our main results with the distribution of placebo effects to determine its significance.

As shown in Table 17, the mean of placebo effects is close to zero, and the probability of observing a treatment effect of a similar magnitude in our main analysis by chance is less than 0.2%. This indicates that our results are very unlikely to be driven by a spurious causal relationship.

**Table 17. Results of the Placebo Test**

| Dep. Var. | Number of Completed Rides | | | | |
|---|---|---|---|---|---|
| | All Areas | | Accessible Areas | | Inaccessible Areas |
| | Total Rides (1) | Regular Rides (2) | Total Rides (3) | Regular Rides (4) | Total (Regular) Rides (5) |
| $\mu$ of placebo effects | 0.001 | -0.000 | 0.000 | -0.000 | 0.000 |
| $\sigma$ of placebo effects | 0.018 | 0.016 | 0.009 | 0.007 | 0.014 |
| Actual treatment effect | 0.175*** | 0.071*** | 0.209*** | 0.105*** | -0.033** |
| Replications | 1,000 | 1,000 | 1,000 | 1,000 | 1,000 |
| $z$-score | -9.657 | -4.394 | -22.782 | -15.562 | 2.381 |
| $p$-value | $p < 0.001$ | $p < 0.001$ | $p < 0.001$ | $p < 0.001$ | $p = 0.015$ |

### 7.7. Additional Robustness Checks

We conduct additional robustness checks to further validate our findings. First, we consider an alternative treatment group by including consumers who exclusively requested robotaxi services in our sample to enhance the generalizability of our findings to a broader group of consumers interested in robotaxi services. We then rerun our analysis, finding that the results remain consistent, as reported in Appendix C. Second, we apply a log transformation to the dependent variables to address potential skewness and ensure that our results hold under alternative specifications. Detailed results can be found in Appendix D. Third, we perform analyses using an alternative dependent variable to demonstrate the robustness of our findings. Results are available in Appendix A. Results from all these robustness checks remain consistent, reinforcing the validity of our main findings.

## 8. Discussion and Conclusion

The impact of introducing automation-driven innovative technologies on consumer demand has been a relatively unexplored area in the existing literature on AI and automation. In this paper, we investigate one such emerging technology—robotaxi—which is expected to become a core component of ride-hailing services[13] and is currently being experimentally introduced in various cities by pioneering companies.[14]

Leveraging the quasi-random allocation of robotaxi services to consumers when they request robotaxi services, we employ a DID model to estimate the causal impact of robotaxi experience on consumers' ride-hailing consumption behavior. Our analysis reveals that the robotaxi experience can significantly increase a consumer's total weekly rides on the platform by 23.2%. Notably, this growth in demand is not accompanied by cannibalization of the consumer's regular ride-hailing usage. Instead, we observe a positive spillover effect on regular ride-hailing services in robotaxi-accessible areas. This demand growth and spillover effect are evident among both multi-homing and single-homing consumers, suggesting a possible category expansion effect. We further find that multi-homing consumers experience a more pronounced increase in demand in robotaxi-accessible areas but significantly reduce their usage of the focal platform in inaccessible areas. This pattern aligns with their shift in platform preference, evidenced by their greater reliance on the focal platform's own app (as opposed to an aggregator) for regular ride requests in robotaxi-accessible areas, and a decreased preference in inaccessible areas. These findings highlight the differential impacts of robotaxi, as an automation-driven innovative service on single-homing and multi-homing consumers across regions, which contributes to a deeper understanding of the broader potential of automation to reshape consumer preferences and platform competition.

Our study underscores the often-overlooked potential impact of automation innovations on consumer demand. Existing literature has predominantly focused on the supply-side effects of automation (e.g., Autor

[13] https://www.bloomberg.com/news/articles/2024-11-17/trump-team-said-to-want-to-ease-us-rules-for-self-driving-cars
[14] https://waymo.com/blog/2024/09/waymo-and-uber-expand-partnership/ and https://techcrunch.com/2024/11/06/lyft-partners-with-may-mobility-mobileye-to-bring-autonomous-vehicles-to-the-app/

2015, Acemoglu and Restrepo 2018, Brynjolfsson and Mitchell 2017), such as cost savings, productivity gains, job displacement, and wage inequality, typically assuming that the demand-side behavior remains unaffected. Under this assumption, services enabled by automation are generally expected to cannibalize those traditionally provided by human workers. Our findings challenge this expectation, demonstrating that automation, in the form of robotaxis, may not only avoid cannibalization but also lead to an expansion in a consumer's demand.

Our study suggests significant managerial implications for technology companies offering innovative services such as robotaxis. For one thing, introducing innovative services may not necessarily cannibalize the demand for existing services but can increase consumer preference for the product category, thereby imposing a positive spillover effect and boosting overall demand. Our study context mirrors the scenario where Uber partners with Waymo to offer robotaxi services to consumers of the Uber app. As a pioneer in rolling out robotaxi services into a mainstream ride-hailing platform, Uber's strategy could potentially boost consumers' consumption across all ride-hailing services, including regular rides. Moreover, our findings reveal that during the four-month post-treatment period, consumers exhibit a tendency to develop habitual consumption patterns, expanding their ride-hailing usage across both temporal and spatial dimensions. These insights offer valuable guidance for platform growth strategies, suggesting that platforms can drive sustained consumer engagement and increase consumption by leveraging in-house innovations or by forming partnerships with innovative startups to introduce novel offerings.

For another, innovative services can attract multi-homing consumers by serving as a differentiating factor in competition with other platforms, thereby enhancing their preference for the focal platform. However, for markets where a large proportion of consumers are multi-homing, staggered deployment of innovative services in certain areas may backfire in regions without access to these services. Companies must therefore strategically manage the expansion and communication of their service rollout to retain consumer preference and mitigate unintended negative spillover effects to underserved areas. Our findings thus provide valuable insights for ride-hailing platforms as well as other stakeholders navigating the evolving landscape of AI-driven services.

Our study is not without limitations. First, we assess the impact of the robotaxi service on consumer ride-hailing consumption and find that the treatment effect can last up to four months post-treatment, which, along with the heterogenous spillover effects, alleviate concerns about a "novelty effect." However, this period may be insufficient to capture the long-term impact on consumer retention and changes in commuting habits. Future research looking into the long-term impact would be valuable if such data is available. Second, we have done our best to cross-reference consumer identities across the partner platform's own app and a leading ride-hailing aggregator with the most granular data available (i.e., partially masked mobile phone numbers and ride requests). However, our measurement of single-homing and multi-homing variables is not perfect, leaving a group of consumers unclassified. Moreover, our analysis is limited to multi-homing behaviors between the platform's own app and a leading aggregator, which could make our estimated HTE a conservative estimate of the actual difference in effects. While our results are robust to the inclusion of the unknown group in the analysis, future research could further explore the potential differential treatment effects among consumers with varying types of multi-homing behaviors. Third, while our data can reveal the treatment effect of the robotaxi service on consumers' actual ride-hailing consumption behavior, we can only provide suggestive evidence for the proposed mechanisms behind the observed impact, as with most studies based on archival data. Future studies could consider leveraging different methodologies, such as surveys or interviews, and richer data to further explore how this innovative service influences consumers' perceptions of various commuting options (e.g., regular ride-hailing, robotaxis, buses) and their attitudes toward the platform, particularly when the availability of robotaxis varies. Fourth, we acknowledge that the size of the treatment effects of robotaxis may vary depending on their supply. In our study, the supply of robotaxis was constrained and remained relatively stable over time, limiting our ability to examine the potential moderating effect of robotaxi availability. Our findings suggest that robotaxis could have a positive spillover effect on demand for regular rides in areas where robotaxis are accessible, while potentially causing unintended negative effects in areas without access. Although the effect size may vary, we believe that the observed patterns of category expansion and platform preference shift likely transcend our specific context. Future studies should continue to investigate how the supply of robotaxis influences different aspects of treatment effects on consumer demand for various ride-hailing options across different areas.

Overall, we hope that our study serves as a pioneering effort that inspires further research into the broader and exciting economic and social implications of robotaxis and AVs broadly. Our findings can also assist practitioners in making more informed decisions and refining their strategies for innovative offerings powered by AI.

## References


Abadie, A., Diamond, A., & Hainmueller, J. (2015). Comparative politics and the synthetic control method. *American Journal of Political Science*, 59(2), 495-510.

Acemoglu, D., & Restrepo, P. (2018). The race between man and machine: Implications of technology for growth, factor shares, and employment. *American Economic Review*, *108*(6), 1488-1542.

Angrist, J. D., & Pischke, J. S. (2009). *Mostly harmless econometrics: An empiricist's companion*. Princeton University Press.

Arrow, K. J. (1972). Economic welfare and the allocation of resources for invention. In *Macmillan Education UK*, 219-236.

Autor, D. H. (2003). Outsourcing at will: The contribution of unjust dismissal doctrine to the growth of employment outsourcing. *Journal of Labor Economics*, *21*(1), 1–42.

Autor, D. H. (2015). Why are there still so many jobs? The history and future of workplace automation. *Journal of Economic Perspectives*, *29*(3), 3-30.

Autor, D., Chin, C., Salomons, A., & Seegmiller, B. (2024). New frontiers: The origins and content of new work, 1940–2018. *The Quarterly Journal of Economics*, *qjae008*.

Bakos, Y., & Halaburda, H. (2020). Platform competition with multihoming on both sides: Subsidize or not? *Management Science*, *66*(12), 5599-5607.

Blackwell, M., Iacus, S., King, G., & Porro, G. (2009). CEM: Coarsened exact matching in Stata. *The Stata Journal*, *9*(4), 524-546.

Borusyak, K., Hull, P., & Jaravel, X. (2022). Quasi-experimental shift-share research designs. *The Review of Economic Studies*, 89(1), 181-213.

Brynjolfsson, E., & Mitchell, T. (2017). What can machine learning do? Workforce implications. *Science*, *358*(6370), 1530-1534.

Brynjolfsson, E., Mitchell, T., & Rock, D. (2018, May). What can machines learn and what does it mean for occupations and the economy?. In *AEA Papers and Proceedings*, *108*, 43-47.

Burtch, G., Carnahan, S., & Greenwood, B. N. (2018). Can you gig it? An empirical examination of the gig economy and entrepreneurial activity. *Management science*, 64(12), 5497-5520.

Callaway, B., & Sant'Anna, P. H. (2021). Difference-in-differences with multiple time periods. *Journal of Econometrics*, 225(2), 200-230.

Castro, F., & Frazelle, A. (2024). Getting out of your own way: Introducing autonomous vehicles on a ride-hailing platform. *Production and Operations Management*.

Cennamo, C. (2021). Competing in digital markets: A platform-based perspective. *Academy of Management Perspectives*, *35*(2), 265-291.

Chaboud, A. P., Chiquoine, B., Hjalmarsson, E., & Vega, C. (2014). Rise of the machines: Algorithmic trading in the foreign exchange market. *The Journal of Finance*, *69*(5), 2045-2084.

Chang, H. H., & Sokol, D. D. (2022). How incumbents respond to competition from innovative disruptors in the sharing economy—The impact of Airbnb on hotel performance. *Strategic Management Journal*, *43*(3), 425-446.

Dai, J., Li, R., Liu, Z., & Lin, S. (2021). Impacts of the introduction of autonomous taxi on travel behaviors of the experienced user: Evidence from a one-year paid taxi service in Guangzhou, China. *Transportation Research Part C: Emerging Technologies*, *130*, 103311.

Dou, Y., & Wu, D. J. (2021). Platform competition under network effects: Piggybacking and optimal subsidization. *Information Systems Research*, *32*(3), 820-835.

Farquhar, P. H., & Pratkanis, A. R. (1993). Decision structuring with phantom alternatives. *Management Science*, *39*(10), 1214-1226.

Farronato, C., Fong, J., & Fradkin, A. (2024). Dog eat dog: Balancing network effects and differentiation in a digital platform merger. *Management Science*, *70*(1), 464-483.

Granulo, A., Fuchs, C., & Puntoni, S. (2019). Psychological reactions to human versus robotic job replacement. *Nature Human Behaviour*, *3*(10), 1062-1069.

Goodman-Bacon, A. (2021). Difference-in-differences with variation in treatment timing. *Journal of Econometrics*, 225(2), 254-277.

Gowrisankaran, G., Joiner, K., & Léger, P. T. (2023). Physician practice style and healthcare costs: Evidence from emergency departments. *Management Science*, *69*(6), 3202-3219.

Hauser, J., Tellis, G. J., & Griffin, A. (2006). Research on innovation: A review and agenda for marketing science. *Marketing Science*, *25*(6), 687-717.

Hui, X., Reshef, O., & Zhou, L. (2023). The short-term effects of generative artificial intelligence on employment: Evidence from an online labor market. Available at SSRN 4527336.

Johnson, M. D., Herrmann, A., & Huber, F. (2006). The evolution of loyalty intentions. *Journal of Marketing*, *70*(2), 122-132.

Landsman, Vardit, Stefan Stremersch. 2011. Multihoming in two-sided markets: An empirical inquiry in the video game console industry. *Journal of Marketing*, 75(6) 39–54.

Leung, E., Paolacci, G., & Puntoni, S. (2018). Man versus machine: Resisting automation in identity-based consumer behavior. *Journal of Marketing Research*, *55*(6), 818-831.

Li, H., & Zhu, F. (2021). Information transparency, multihoming, and platform competition: A natural experiment in the daily deals market. *Management Science*, *67*(7), 4384-4407.

Li, J., Yu, C., Shen, Z., Su, Z., & Ma, W. (2023). A survey on urban traffic control under mixed traffic environment with connected automated vehicles. *Transportation Research Part C: Emerging Technologies*, *154*, 104258.

Li, Z., & Agarwal, A. (2017). Platform integration and demand spillovers in complementary markets: Evidence from Facebook's integration of Instagram. *Management Science*, *63*(10), 3438-3458.

Liang, C., Shi, Z., & Raghu, T. S. (2019). The spillover of spotlight: Platform recommendation in the mobile app market. *Information Systems Research*, *30*(4), 1296-1318.

Liu, Q., Steenburgh, T. J., & Gupta, S. (2015). The cross attributes flexible substitution logit: Uncovering category expansion and share impacts of marketing instruments. *Marketing Science*, *34*(1), 144-159.

Lokhandwala, M., & Cai, H. (2018). Dynamic ride sharing using traditional taxis and shared autonomous taxis: A case study of NYC. *Transportation Research Part C: Emerging Technologies*, *97*, 45-60.

Longoni, C., & Cian, L. (2022). Artificial intelligence in utilitarian vs. hedonic contexts: The "word-of-machine" effect. *Journal of Marketing*, *86*(1), 91-108.

Luo, X., Tong, S., Fang, Z., & Qu, Z. (2019). Frontiers: Machines vs. humans: The impact of artificial intelligence chatbot disclosure on customer purchases. *Marketing Science*, *38*(6), 937-947.

McIntyre, D. P., & Srinivasan, A. (2017). Networks, platforms, and strategy: Emerging views and next steps. *Strategic Management Journal*, *38*(1), 141-160.

Mende, M., Scott, M. L., Van Doorn, J., Grewal, D., & Shanks, I. (2019). Service robots rising: How humanoid robots influence service experiences and elicit compensatory consumer responses. *Journal of Marketing Research*, *56*(4), 535-556.

Narang, U., & Shankar, V. (2019). Mobile app introduction and online and offline purchases and product returns. *Marketing Science*, *38*(5), 756-772.

Noh, D., Tunca, T. I., & Xu, Y. (2023). Evolution of ride services: From ride hailing to autonomous vehicles. Available at SSRN 3903493.

Rubin, D. B. (1990). Formal mode of statistical inference for causal effects. *Journal of Statistical Planning and Inference*, *25*(3), 279-292.

Son, Y., Oh, W., & Im, I. (2023). The voice of commerce: How smart speakers reshape digital content consumption and preferences. *MIS Quarterly*, *47*(2).

Tian, J., Zhao, X., & Xue, L. (2022). Platform Compatibility and Developer Multihoming: A Trade-off Perspective. *Management Information Systems Quarterly*, 46(3), 1661-1690.

Trueblood, J. S., & Pettibone, J. C. (2017). The phantom decoy effect in perceptual decision making. *Journal of Behavioral Decision Making*, *30*(2), 157-167.

Wang, X., Zhang, Y., & Zheng, J. (2024). Beyond the value for AI adopters: Analyzing the impacts of autonomous vehicle testing on traffic conditions in California. Available at SSRN: https://ssrn.com/abstract=4775378.

Warwick, K. (2004). March of the machines: The breakthrough in artificial intelligence. *University of Illinois Press*.

Wu, C. W. (2014). The study of service innovation for digiservice on loyalty. *Journal of Business Research*, *67*(5), 819-824.

Xu, K., Chan, J., Ghose, A., & Han, S. P. (2017). Battle of the channels: The impact of tablets on digital commerce. *Management Science*, *63*(5), 1469-1492.

Xu, X., Thong, J. Y., & Venkatesh, V. (2014). Effects of ICT service innovation and complementary strategies on brand equity and customer loyalty in a consumer technology market. *Information Systems Research*, *25*(4), 710-729.

Yao, Q., Huang, L., & Li, M. (2019). The effects of tech and non-tech innovation on brand equity in China: The role of institutional environments. *PloS One*, 14(5), e0215634.

Yin, H., Cherchi, E., & Nettle, D. (2023). Living in a city where automated taxis are operating and using them: Does this affect consumers' preferences?. *Transportation Research Record*, *2677*(7), 627-638.

Yip, M., Salcudean, S., Goldberg, K., Althoefer, K., Menciassi, A., Opfermann, J. D., ... & Lee, I. C. (2023). Artificial intelligence meets medical robotics. *Science*, *381*(6654), 141-146.

Zhang, C., Chen, J., & Raghunathan, S. (2022). Two-sided platform competition in a sharing economy. *Management Science*, *68*(12), 8909-8932.

# Supplementary Online Appendices

## Appendix A. Alternative Dependent Variable

Our findings remain consistent when we use an alternative dependent variable, i.e., consumers' total expenditure, as detailed in Tables A1 and A2.

**Table A1. Impact of Robotaxi Services on Consumers' Ride-Hailing Consumption (DV: Weekly Expenditure)**

| Dep. Var. | Weekly Expenditure | | | | |
|---|---|---|---|---|---|
| Area | All Areas | | Accessible Areas | | Inaccessible Areas |
| | Total Rides<br>(1) | Regular Rides<br>(2) | Total Rides<br>(3) | Regular Rides<br>(4) | Total (Regular) Rides<br>(5) |
| After × Treatment | 2.761***<br>(0.455) | 1.487***<br>(0.431) | 3.379***<br>(0.206) | 1.849***<br>(0.168) | -0.618*<br>(0.363) |
| Consumer FE | Yes | Yes | Yes | Yes | Yes |
| Time FE | Yes | Yes | Yes | Yes | Yes |
| Observations | 513,433 | 513,433 | 513,433 | 513,433 | 513,433 |
| Number of Consumers | 15,220 | 15,220 | 15,220 | 15,220 | 15,220 |
| R-squared | 0.393 | 0.401 | 0.231 | 0.229 | 0.427 |

Notes: a) Robust standard errors clustered at the consumer level. b) * $p$<0.1, ** $p$<0.05, *** $p$<0.01.

**Table A2. HTE on Single-homing vs. Multi-homing Consumers (DV: Weekly Expenditure)**

| Dep. Var. | Weekly Expenditure | | | | |
|---|---|---|---|---|---|
| Area | All Areas | | Accessible Areas | | Inaccessible Areas |
| | Total Rides<br>(1) | Regular Rides<br>(2) | Total Rides<br>(3) | Regular Rides<br>(4) | Total Rides<br>(5) |
| After × Treatment | 2.436***<br>(0.754) | 1.224*<br>(0.723) | 2.635***<br>(0.307) | 1.423***<br>(0.252) | -0.199<br>(0.626) |
| After × Treatment × Multihoming | -2.167<br>(1.643) | 0.039<br>(1.557) | 1.534**<br>(0.701) | 1.142**<br>(0.574) | -3.701***<br>(1.369) |
| Consumer FE | Yes | Yes | Yes | Yes | Yes |
| Time FE for Singlehoming Group | Yes | Yes | Yes | Yes | Yes |
| Time FE for Multihoming Group | Yes | Yes | Yes | Yes | Yes |
| Observations | 249,881 | 249,881 | 249,881 | 249,881 | 249,881 |
| Number of Consumers | 7,433 | 7,433 | 7,433 | 7,433 | 7,433 |
| R-squared | 0.424 | 0.434 | 0.234 | 0.233 | 0.454 |

Notes: a) Robust standard errors clustered at the consumer level. b) In this analysis, we have excluded the unknown group whose multi-homing behavior is undetermined, resulting in a reduced sample size compared to Table A1. Results are highly consistent when the unknown group is included. c) Results are highly consistent if we control for overall time FE instead of subgroup-specific time trends (captured by Time FE for the singlehoming group and Time FE for the multihoming group). d) * $p$<0.1, ** $p$<0.05, *** $p$<0.01.

## Appendix B. Including Consumers with Unidentifiable Multi-Homing Behavior in the HTE Analysis

In the analysis presented in Table 5 (Section 6.2), we excluded consumers with undetermined multi-homing status. To assess robustness, we reran the model including these unknown groups. As shown in Table B1, the results remain consistent, indicating that the inclusion of an additional consumer subgroup does not impact the overall findings.

**Table B1. HTE on Single-homing vs. Multi-homing Consumers (Including the Unknown Group)**

| Dep. Var. | Number of Completed Rides | | | | |
|---|---|---|---|---|---|
| Area | All Areas | | Accessible Areas | | Inaccessible Areas |
| | Total Rides | Regular Rides | Total Rides | Regular Rides | Total Rides |
| | (1) | (2) | (3) | (4) | (5) |
| After × Treatment | 0.155*** | 0.076*** | 0.159*** | 0.080*** | -0.004 |
| | (0.029) | (0.027) | (0.014) | (0.011) | (0.024) |
| After × Treatment × Multihoming | -0.042 | -0.073 | 0.097*** | 0.066** | -0.139** |
| | (0.068) | (0.064) | (0.037) | (0.029) | (0.055) |
| After × Treatment × Unknown | 0.015 | -0.022 | 0.056*** | 0.019 | -0.042 |
| | (0.038) | (0.036) | (0.020) | (0.016) | (0.031) |
| Consumer FE | Yes | Yes | Yes | Yes | Yes |
| Time FE for Singlehoming Group | Yes | Yes | Yes | Yes | Yes |
| Time FE for Multihoming Group | Yes | Yes | Yes | Yes | Yes |
| Time FE for Unknown Group | Yes | Yes | Yes | Yes | Yes |
| Observations | 513,433 | 513,433 | 513,433 | 513,433 | 513,433 |
| Number of Consumers | 15,220 | 15,220 | 15,220 | 15,220 | 15,220 |
| R-squared | 0.428 | 0.442 | 0.263 | 0.271 | 0.472 |

Notes: a) Robust standard errors clustered at the consumer level. b) Results are highly consistent if we control for overall time FE instead of subgroup-specific time trends (captured by Time FE for the singlehoming group, Time FE for the multihoming group, and Time FE for the unknown group). c) * $p$<0.1, ** $p$<0.05, *** $p$<0.01.

## Appendix C. Incorporating Consumers Exclusively Requesting Robotaxi Services

Our main analysis focuses on consumers who request both robotaxi and regular services to leverage the quai-random assignment in addressing the self-selection concern. To assess the generalizability of our findings to a broader group of consumers interested in robotaxi services, we conduct a supplementary analysis by expanding the treatment group to include not only those who have always requested robotaxi and regular services simultaneously before their first robotaxi experience, but also those who have exclusively requested robotaxi services prior to their first robotaxi experience. This approach results in a sample of 6,483 treated consumers and 9,407 control consumers. The results, presented in Tables C1-C2, are consistent with our main results. The treatment effect on multi-homing consumers remains significantly negative in inaccessible areas (coefficient = -0.142, $p$-value < 0.05).

**Table C1. Impact of Robotaxi Services on Consumers' Ride-Hailing Consumption (Including Exclusive Robotaxi Requesters)**

| Dep. Var. | Number of Completed Rides | | | | |
|---|---|---|---|---|---|
| Area | All Areas | | Accessible Areas | | Inaccessible Areas |
| | Total Rides<br>(1) | Regular Rides<br>(2) | Total Rides<br>(3) | Regular Rides<br>(4) | Total (Regular) Rides<br>(5) |
| After × Treatment | 0.178***<br>(0.018) | 0.043**<br>(0.017) | 0.214***<br>(0.010) | 0.079***<br>(0.008) | -0.036**<br>(0.014) |
| Consumer FE | Yes | Yes | Yes | Yes | Yes |
| Time FE | Yes | Yes | Yes | Yes | Yes |
| Observations | 534,735 | 534,735 | 534,735 | 534,735 | 534,735 |
| Number of Consumers | 15,890 | 15,890 | 15,890 | 15,890 | 15,890 |
| R-squared | 0.423 | 0.436 | 0.288 | 0.285 | 0.468 |

Notes: a) Robust standard errors clustered at the consumer level. b) * $p$<0.1, ** $p$<0.05, *** $p$<0.01.

**Table C2. HTE on Single-homing vs. Multi-homing Consumers (Including Exclusive Robotaxi Requesters)**

| Dep. Var. | Number of Completed Rides | | | | |
|---|---|---|---|---|---|
| Area | All Areas | | Accessible Areas | | Inaccessible Areas |
| | Total Rides | Regular Rides | Total Rides | Regular Rides | Total Rides |
| | (1) | (2) | (3) | (4) | (5) |
| After × Treatment | 0.135*** | 0.037 | 0.150*** | 0.052*** | -0.015 |
| | (0.028) | (0.027) | (0.014) | (0.012) | (0.023) |
| After × Treatment × Multihoming | -0.012 | -0.054 | 0.115*** | 0.072** | -0.127** |
| | (0.067) | (0.063) | (0.035) | (0.029) | (0.054) |
| Consumer FE | Yes | Yes | Yes | Yes | Yes |
| Time FE for Singlehoming Group | Yes | Yes | Yes | Yes | Yes |
| Time FE for Multihoming Group | Yes | Yes | Yes | Yes | Yes |
| Observations | 260,409 | 260,409 | 260,409 | 260,409 | 260,409 |
| Number of Consumers | 7,768 | 7,768 | 7,768 | 7,768 | 7,768 |
| R-squared | 0.448 | 0.462 | 0.294 | 0.299 | 0.488 |

Notes: a) Robust standard errors clustered at the consumer level. b) In this analysis, we have excluded the unknown group whose multi-homing behavior is undetermined, resulting in a reduced sample size compared to Table C1. Results are highly consistent when the unknown group is included. c) Results are highly consistent if we control for overall time FE instead of subgroup-specific time trends (captured by Time FE for the singlehoming group and Time FE for the multihoming group). d) * $p<0.1$, ** $p<0.05$, *** $p<0.01$.

## Appendix D. Log-transformation of Dependent Variables

In the main analysis, we do not log-transform the dependent variables to ensure that the estimated treatment effect on rides across all areas equals the sum of the estimated treatment effects on rides in robotaxi-accessible and inaccessible areas. To demonstrate the robustness of the results, we also apply a log transformation to the dependent variables and report the findings. As reported in Tables D1-D2, the results remain consistent with our main analysis. The treatment effect on multi-homing consumers remains significantly negative in inaccessible areas (coefficient = -0.028, $p$-value < 0.05).

**Table D1. Impact of Robotaxi Services on Consumers' Ride-Hailing Consumption (Log-transformation to Dependent Variables)**

| Dep. Var. | Number of Completed Rides | | | | |
|---|---|---|---|---|---|
| Area | All Areas | | Accessible Areas | | Inaccessible Areas |
| | Total Rides<br>(1) | Regular Rides<br>(2) | Total Rides<br>(3) | Regular Rides<br>(4) | Total (Regular) Rides<br>(5) |
| After × Treatment | 0.061***<br>(0.005) | 0.031***<br>(0.005) | 0.075***<br>(0.004) | 0.043***<br>(0.003) | -0.005<br>(0.004) |
| Consumer FE | Yes | Yes | Yes | Yes | Yes |
| Time FE | Yes | Yes | Yes | Yes | Yes |
| Observations | 513,433 | 513,433 | 513,433 | 513,433 | 513,433 |
| Number of Consumers | 15,220 | 15,220 | 15,220 | 15,220 | 15,220 |
| R-squared | 0.405 | 0.419 | 0.256 | 0.259 | 0.459 |

Notes: a) Robust standard errors clustered at the consumer level. b) * $p$<0.1, ** $p$<0.05, *** $p$<0.01.

**Table D2. HTE on Single-homing vs. Multi-homing Consumers (Log-transformation to Dependent Variables)**

| Dep. Var. | Number of Completed Rides | | | | |
|---|---|---|---|---|---|
| Area | All Areas | | Accessible Areas | | Inaccessible Areas |
| | Total Rides<br>(1) | Regular Rides<br>(2) | Total Rides<br>(3) | Regular Rides<br>(4) | Total Rides<br>(5) |
| After × Treatment | 0.050***<br>(0.008) | 0.030***<br>(0.008) | 0.056***<br>(0.005) | 0.033***<br>(0.004) | 0.002<br>(0.007) |
| After × Treatment × Multihoming | -0.0001<br>(0.018) | -0.011<br>(0.018) | 0.035***<br>(0.012) | 0.025**<br>(0.011) | -0.030**<br>(0.015) |
| Consumer FE | Yes | Yes | Yes | Yes | Yes |
| Time FE for Singlehoming Group | Yes | Yes | Yes | Yes | Yes |
| Time FE for Multihoming Group | Yes | Yes | Yes | Yes | Yes |
| Observations | 249,881 | 249,881 | 249,881 | 249,881 | 249,881 |
| Number of Consumers | 7,433 | 7,433 | 7,433 | 7,433 | 7,433 |
| R-squared | 0.435 | 0.452 | 0.250 | 0.259 | 0.485 |

Notes: a) Robust standard errors clustered at the consumer level. b) In this analysis, we have excluded the unknown group whose multi-homing behavior is undetermined, resulting in a reduced sample size compared to Table D1. Results are highly consistent when the unknown group is included. c) Results are highly consistent if we control for overall time FE instead of subgroup-specific time trends (captured by Time FE for the singlehoming group and Time FE for the multihoming group). d) * $p$<0.1, ** $p$<0.05, *** $p$<0.01.

## Appendix E. Balance Checks of the Matched Sample in Section 7.1

In Section 7.1, we use a sample of consumers who have never requested robotaxi services as an alternative control group and apply the Coarsened Exact Matching (CEM) method for one-to-one matching to the treatment group. Table E1 presents the covariate statistics for the treatment and control groups after matching. The means of all the variables show no significant differences between the two groups, suggesting that the matching is successful and results in balanced groups.

**Table E1. Balance Check for the Matched Sample in Section 7.1**

| Variable | Definition | Mean of Treatment Group (SD) | Mean of Control Group (SD) | t-Statistic (*p*-value) |
|---|---|---|---|---|
| *Age* | A consumer's age | 28.358<br>(3.699) | 28.364<br>(3.702) | 0.084<br>(0.933) |
| *Multihoming* | A dummy variable that equals 1 if a consumer is in the multi-homing group | 0.297<br>(0.457) | 0.297<br>(0.457) | 0.000<br>(1.000) |
| *Unknown* | A dummy variable that equals 1 if a consumer's multi-homing behavior is unknown | 0.529<br>(0.499) | 0.529<br>(0.499) | 0.000<br>(1.000) |
| *Prior_Weekly_Total_Rides* | A consumer's average weekly number of total rides prior to the introduction of the robotaxi service | 0.422<br>(0.847) | 0.432<br>(0.849) | 0.608<br>(0.543) |
| *Prior_Weekly_Acc_Rides* | A consumer's average weekly number of rides in accessible areas prior to the introduction of the robotaxi service | 0.128<br>(0.344) | 0.136<br>(0.344) | 1.274<br>(0.203) |
| *Prior_Weekly_InAcc_Rides* | A consumer's average weekly number of rides in inaccessible areas prior to the introduction of the robotaxi service | 0.294<br>(0.764) | 0.296<br>(0.767) | 0.101<br>(0.919) |

## Appendix F. Balance Checks of the Matched Sample in Section 7.2

In Section 7.2, we use a sample of consumers from a different district as an alternative control group and perform one-to-one matching with the treatment group, using the CEM method, without replacement. Table F1 reveals that the means of all the variables do not differ significantly between the treatment and control groups. This indicates that the matched treatment and control consumers are highly comparable.

**Table F1. Balance Check for the Matched Sample in Section 7.2**

| Variable | Definition | Mean of Treatment Group (SD) | Mean of Control Group (SD) | t-Statistic ($p$-value) |
|---|---|---|---|---|
| *Age* | A consumer's age | 28.295<br>(4.000) | 28.312<br>(3.956) | 0.226<br>(0.821) |
| *Multihoming* | A dummy variable that equals 1 if a consumer is in the multi-homing group | 0.321<br>(0.467) | 0.321<br>(0.467) | 0.000<br>(1.000) |
| *Unknown* | A dummy variable that equals 1 if a consumer's multi-homing behavior is unknown | 0.515<br>(0.500) | 0.515<br>(0.500) | 0.000<br>(1.000) |
| *Prior_Weekly_Total_Rides* | A consumer's average weekly number of total rides prior to the introduction of the robotaxi service | 0.427<br>(0.876) | 0.427<br>(0.873) | 0.021<br>(0.983) |
| *Prior_Weekly_Acc_Rides* | A consumer's average weekly number of rides in accessible areas prior to the introduction of the robotaxi service | 0.100<br>(0.256) | 0.099<br>(0.256) | -0.301<br>(0.763) |
| *Prior_Weekly_InAcc_Rides* | A consumer's average weekly number of rides in inaccessible areas prior to the introduction of the robotaxi service | 0.326<br>(0.836) | 0.328<br>(0.832) | 0.115<br>(0.909) |

Notes: a) For the control group, "accessible areas" are defined as the counterfactual district, while "inaccessible areas" refer to all regions outside of this district.

## Appendix G. Cohort-Based Matching in the Staggered DID Analysis

While it is impossible to randomly assign robotaxis to consumers to identify the impact of the robotaxi experience on consumers' ride-hailing behavior, given that these are high-stakes decisions that cannot be directly imposed by platforms, we leverage the quasi-random assignment of robotaxis to consumers who request both robotaxis and human-driven cars simultaneously to estimate the treatment effect. To further minimize the differences between the two groups, we focus only on the treatment and control users who requested both robotaxis and human-driven cars within the same week and match them based on their demographics and prior ride-hailing behavior. Specifically, we employ the CEM method to perform one-to-one matching without replacement between the control and treatment groups, leveraging the quasi-random variation in the assignment of robotaxis among consumers attempting to use them within a given week. When doing so, we require that consumers in both the treatment and control groups have made at least one robotaxi request during the cohort's treatment week. As shown in Table G1, the distribution of all key covariates is well-balanced between the treatment and control groups.

**Table G1. Balance Check for the Matched Sample in Section 7.3**

| Variable | Definition | Mean of Treatment Group (SD) | Mean of Control Group (SD) | t-Statistic (*p*-value) |
|---|---|---|---|---|
| *Age* | A consumer's age | 27.842<br>(3.082) | 27.582<br>(3.065) | 0.149<br>(0.882) |
| *Multihoming* | A dummy variable that equals 1 if a consumer is in the multi-homing group | 0.218<br>(0.413) | 0.218<br>(0.413) | 0<br>(1.000) |
| *Unknown* | A dummy variable that equals 1 if a consumer's multi-homing behavior is unknown | 0.530<br>(0.499) | 0.530<br>(0.499) | 0<br>(1.000) |
| *Prior_Weekly_Total_Rides* | A consumer's average weekly number of total rides prior to the introduction of the robotaxi service | 0.308<br>(0.613) | 0.306<br>(0.610) | -0.206<br>(0.837) |
| *Prior_Weekly_Access_Rides* | A consumer's average weekly number of rides in accessible areas prior to the introduction of the robotaxi service | 0.064<br>(0.140) | 0.062<br>(0.139) | -0.656<br>(0.512) |
| *Prior_Weekly_Inaccess_Rides* | A consumer's average weekly number of rides in inaccessible areas prior to the introduction of the robotaxi service | 0.241<br>(0.602) | 0.241<br>(0.598) | 0.047<br>(0.963) |