When Uber Eats its own business, and its competitors' too:

Platform diversification and cross-platform cannibalization

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Abstract

How does a platform firm's diversification influence its existing business? We conjecture that a diversifying platform firm faces a unique challenge in allocating complementors' resources between businesses due to its lack of ownership over them. At the same time, the potential synergy from serving multiple businesses in a diversifying platform firm can divert ownership-free complementors away from competing platform firms. We analyze changes in the rideshare business in Manhattan, New York City, after Uber launched Uber Eats in the city. We find that the launch of Uber Eats was associated with a reduction in trip numbers for both Uber and Lyft. However, both effects were weakened during rush hours, when the opportunity costs of resource reallocation to Uber Eats were higher for the rideshare drivers. [<=125 words]

Keywords: platform, diversification, resources, complementor, rideshare

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1. INTRODUCTION

Since the turn of the century, platforms have become the nexus of technological and economic exchanges in an increasing number of industries (Adner et al., 2019; Kapoor & Agarwal, 2017; Kuan & Lee, 2020; Masucci et al., 2020; Seamans & Zhu, 2014). More recently, several platform firms have broadened their scope by diversifying into new businesses that share platform infrastructure, users or complementors with their primary business.[1] For instance, Amazon, originally an e-commerce platform, has diversified into e-reader, digital streaming, and cloud computing services. Uber, which started as a rideshare platform, has diversified into food delivery, grocery delivery, and freight businesses. However, the platform literature has mostly focused on platform activities within a single industry and paid less attention to platform expansions across industries. Such focus may be justified if diversification by platform firms is similar to that by traditional firms in terms of theories and predictions. Accordingly, it becomes imperative to explore unique features of platform firms that may shape the consequences of diversification differently (Ahuja & Novelli, 2017; Kretschmer et al., 2022; McIntyre et al., 2021; Rietveld & Schilling, 2021).

A small number of studies have identified a few benefits for a diversifying platform firm, such as economies of scope from leveraging platform firms' resources (e.g., platform technologies or user base) (Cennamo, 2021; Eisenmann et al., 2011; Gawer, 2021). Nevertheless, the role of complementors (and their resources) in such diversification moves has often been neglected. Because a platform firm relies on complementors to create value (Baldwin, 2020;

[1]We define platforms as products, services, or technologies that facilitate transactions between complementors and users (Gawer & Cusumano, 2014). Organizations that operate and provide platforms to users and complementors are referred to as "platform owners" (Wen & Zhu, 2019), "platform providers" (Eisenmann et al., 2009), "platform regulators" (Boudreau & Hagiu, 2009) or "platform sponsors" (Rietveld & Schilling, 2021). For simplicity, we refer to these organizations as "platform firms" throughout the paper.

Gawer & Cusumano, 2002), complementors can have a significant influence on a platform firm's diversification performance. Reliance on complementors deprives the platform firm of its control rights over complementors and their resources (Hagiu & Wright, 2019; Jacobides et al., 2018). Without the control rights, a diversifying platform firm faces a unique challenge in allocating complementors' resources between businesses: Complementors may allocate their resources between businesses based on their private interests rather than the platform firm's goal of overall value creation (Cennamo & Santaló, 2019; Gu & Zhu, 2021; Wang & Miller, 2020).[2] In addition, the lack of control rights makes it difficult for platform firms to forbid complementors from sharing resources across platform firms, which may generate a direct spillover effect across competing platforms following diversification moves. Therefore, understanding complementors' resource allocation decisions within and across platform firms is critical in studying platform diversification.

Against this background, we first examine how a platform firm's diversification into a new business will influence its existing business through resource allocation. For a non-platform firm, diversification can either benefit its existing business through synergy arising from resource sharing (Panzar & Willig, 1981; Teece, 1980) or hurt its existing business due to cannibalization arising from resource reallocation to the new business (Schoar, 2002; Wu, 2013). We argue that for a platform firm, the cannibalization effect may dominate the synergetic benefit for its existing business. In particular, the lack of control over complementors makes it harder to prevent complementors from allocating resources away from their existing business to the new business. The new business provides an opportunity for complementors to achieve economies of

[2]For example, news media have reported that some rideshare or food delivery drivers intentionally decline ride/delivery requests or turn off their apps to create artificial price surges and raise pay rates. These drivers act collectively by grouping offline or creating an online forum (e.g., #DeclineNow) (Ford, 2021; Sweeney, 2019).

scope by amortizing the costs of acquiring complementor-specific resources across the existing and new businesses.[3] The potential synergy may incentivize complementors to reallocate some of their resources to the new business. If a significant number of complementors in the existing business shift their resources to the new business, the existing business could experience a reduction in volume.

A related question is how a platform firm's expansion into a new business will influence its competitors in the existing business. For a non-platform diversifying firm, the synergistic benefits from resource sharing will enhance its competitiveness at the cost of its competitors in the existing business, whereas the cannibalization effect arising from resource reallocation will damage its competitiveness to the benefit of its competitors in the existing business. For a platform firm, diversification may cause a more direct impact on its competitors due to the movement of complementors between platforms. Specifically, the new business of a diversifying platform firm may divert complementors from a competing platform firm in the existing business. Similar to complementors on the diversifying platform firm, complementors on the competing platform firm may reallocate their resources to the new business because of a potential synergy from allocating resources between the existing and new businesses. At the same time, operating on both the new business of the diversifying platform firm and the existing business of the competing platform firm results in multi-homing costs (Cennamo et al., 2018; Eisenmann, 2007). When the multi-homing costs are too high, the complementors may shift their

[3]Complementor-specific resources refer to a complementor's resources that can be combined with platform-specific resources to produce complements (Chung et al., 2022; Corts & Lederman, 2009). Examples of complementor-specific resources include software developers' programming skills and investments in writing software for multiple game consoles or smartphone operating systems or rideshare drivers' vehicles, driving skills, and time.

resources away from the competing platform firm to the diversifying platform firm. In turn, this can cause a reduction in the competing platform firm's business volume.

Resource allocation depends on not only the expected return from the target use but also the opportunity costs related to alternative uses (Levinthal & Wu, 2010; Lieberman et al., 2017). Therefore, we explore how demand conditions in the existing business will influence complementors' decision to reallocate their resources and consequently both the within- and cross-platform spillover effects of platform diversification on the existing business. Prior studies have argued that demand conditions in different segments affect opportunity costs for firm resources and, consequently, diversification decisions or performance (Anand & Singh, 1997; Chandler, 1969). Consistently, we argue that the opportunity cost for reallocating resources from a high-demand submarket in the existing business is higher than from low-demand submarkets.[4] Therefore, complementors on both the diversifying and competing platform firms will be less likely to reallocate their resources away from high-demand submarkets in the existing business to the new business, weakening the spillover effects within and across platform firms.

We empirically test these predictions using both quantitative and qualitative data. Quantitatively, we use trip-level rideshare data in Manhattan, New York City (NYC) to examine how Uber's and Lyft's rideshare trip numbers changed after Uber's diversification into the food delivery industry through the launch of Uber Eats in March 2016. The launch of Uber Eats created an exogenous shock for rideshare drivers, which enables us to employ a continuous difference-in-differences (DID) model. Specifically, using as treatments the proportion of restaurants that joined Uber Eats in each geographic zone in Manhattan, we compare the trip

[4]We use submarkets to refer to individual markets in different time periods, geographic areas, or product segments.

numbers of Uber and Lyft before and after the launch of Uber Eats (i.e., between October 2015 and October 2016) to identify both within- and cross-platform spillover effects. We further exploit heterogeneity in the two spillover effects against demand differences throughout the day (e.g., rush hours vs. non-rush hours). To supplement the quantitative data, we collected qualitative data through semi-structured interviews with rideshare drivers, food delivery bike couriers, and restaurant owners that joined Uber Eats when the service was launched in Manhattan.

We found that, overall, an increase in the proportion of restaurants that joined Uber Eats in a geographic zone was associated with a reduction in trip numbers for both Uber and Lyft in the same zone. A one percent increase in local restaurants that joined Uber Eats was associated with 2.1% fewer Uber trips and 6.8% fewer Lyft trips. However, these negative impacts were weakened during rush hours, a high-demand submarket for rideshare drivers. A one percent increase in local restaurants that joined Uber Eats was associated with only 0.5% fewer Uber trip numbers and 5.1% fewer Lyft trip numbers during rush hours. These results hold when we employ different DID models (e.g., a binary treatment effect model or models with different control groups), as well as zone, week, day-of-the-week, and hour-fixed effects. To rule out alternative demand- and supply-side explanations, we conducted several additional analyses, such as DID models using taxi trips as dependent variables, Triple-differences models based on the heterogeneity in population demographics, and DID models using the launch of DoorDash in Brooklyn, NYC.

Our study contributes to several strands of literature. First, it extends the research on platform scope by connecting it to the diversification literature. Existing research on platform scope has focused on platform firms' vertical scope decisions, such as decisions to enter complementors’ businesses (Gawer & Henderson, 2007; Li & Agarwal, 2017; Zhu & Liu, 2018). Only a small body of research investigates platform firms’ horizontal diversification strategies (Cennamo, 2021; Eisenmann et al., 2011; Gawer, 2021). The effect of diversification on platform firms’ existing business segments has been rarely examined. Even less attention has been paid to its impact on complementors. Given that a large number of complementors serve as the driving force in the platform economy, it is crucial to understand how complementors respond to platform diversification. Our study fills in the gap by showing that platform diversification could reduce complementor activities in the existing business for both the diversifying and competing platform firms, thereby cannibalizing the existing business for both firms.

Second, we enrich the diversification literature by investigating the effect of diversification on business segments when resources are highly fluid and difficult to contract or control. Several studies on non-platform diversification argue that profit-maximizing decisions at the corporate level can have a negative impact at the business level, thereby highlighting the tradeoff between corporate-level and business-level profits (Gomes & Livdan, 2004; Maksimovic & Phillips, 2002; Wu, 2013). Within platform firms, we find that profit-maximizing decisions at the complementor level can have a negative effect at the business level, thereby highlighting the tradeoff between complementor-level and business-level profits.

Third, we contribute to the resource-based view (RBV) of the firm by enriching the importance of resource ownership. While the role of resources has been a central concern in the theory of the firm, “strategy scholars have spent little time considering how RBV’s precepts apply to platform (firms)” (Eisenmann et al., 2011, p. 1282). Similarly, Jacobides et al. (2018, p. 2270) stress that: “RBV mostly concern themselves with owned resources. … If firms gain from others participating in an ecosystem, but cannot fully control them, what does that imply for how they attain advantage?" Prior platform studies have argued that, by forfeiting ownership of particular resources, a platform firm can retain flexible access to diverse knowledge, thereby accelerating product innovation and harnessing network effects (Alexy et al., 2018; Boudreau, 2010; Parker & Van Alstyne, 2018). In contrast, our findings suggest a potential limit to leveraging unowned resources: A diversifying platform firm might cannibalize its own businesses due to the free movement of complementors between its businesses. In addition, a competing platform firm might lose its complementors to a diversifying platform firm. Through such analysis, we highlight some common themes between the two strands of literature on platforms and RBV, thereby answering the call for stronger connections with mainstream theories (Gawer, 2021, p. 13; Rietveld & Schilling, 2021, p. 1547).

Finally, the paper offers some managerial implications for platform firms. The small number of existing studies on platform diversification has mainly focused on the benefits to the platform firms. Our study suggests that managers should also be aware of the hidden costs of platform diversification, especially to their existing business in low-demand submarkets. Moreover, platform firms are often influenced by "interactions that do not happen at firm's boundaries" (Boudreau & Hagiu, 2009, p. 187). Our study illuminates one of these interactions (through the movements of complementors) and sheds light on why managers should be aware of the platform diversification decisions not only by their own firm but also by competing firms.

2. RELATED LITERATURE

Diversification has long been a central concern in the field of strategy, yet it has received relatively little attention from platform scholars. Studies on platform scope have mostly examined platform activities within a single industry, such as platform firms' vertical scope decisions (i.e., expansion into complementors' businesses) (Gawer & Henderson, 2007; Li &

Agarwal, 2017; Zhu & Liu, 2018). While some studies examine complementors' (within-industry) diversification strategies and their consequences (e.g., Tanriverdi & Lee, 2008), diversification by platform firms has been understudied.

A limited number of studies on platform diversification are mostly theoretical and focus on their expansion strategies (Cennamo, 2021; Eisenmann et al., 2011; Gawer, 2021). These studies have identified several benefits that a diversifying platform firm can enjoy from leveraging platform firms' resources (e.g., platform technologies or installed user base). For instance, Eisenmann et al. (2011) show that by bundling different platform functionalities (i.e., platform envelopment), a platform firm can enter adjacent businesses and achieve supply-side and demand-side economies of scope from leveraging platform-specific resources and user base. However, the role of complementors (and their resources) in such diversification strategies has often been neglected. Consequently, several studies have pointed out that "to what degree … diversification strategies of platform (firms) are similar to or different from those of traditional firms" (Kretschmer et al., 2022, p. 419) is not clear, thereby emphasizing the need to explore unique features of platform firms' diversification (Ahuja & Novelli, 2017; Rietveld & Schilling, 2021).

3. THEORETICAL DEVELOPMENT

A key feature of platform firms is their reliance on complementors (Gawer & Cusumano, 2002)(C. Y. Baldwin, 2020; Gawer & Cusumano, 2002). Unlike a non-platform firm, a platform firm does not own all the critical resources it needs to create value; rather, it relies on its complementors' resources to provide a variety of products and services (i.e., complements) to users without fully acquiring essential resources (Baldwin & Woodard, 2009). For example, Airbnb, the largest accommodation provider, does not own any real estate, and Uber, the largest rideshare company, does not own a single vehicle (Goodwin, 2015). At the same time, it deprives the platform firm of the authority over complementors and direct control over their resources (Hagiu & Wright, 2019; Jacobides et al., 2018). This is in stark contrast to hierarchical non-platform firms, where firms have decision rights over employees based on long-term contracts and asset ownership (Hart & Moore, 1990; Williamson, 1985). Complementors have private interests that may go against the overall goal of platform firms, similar to employees in non-platform firms (Cennamo & Santaló, 2019; March, 1994; Simon, 1947). However, unlike employees in non-platform firms, complementors retain control and ownership over their resources and do not delegate decision rights to platform firms (Gawer, 2021; Kretschmer et al., 2022). This allows complementors to achieve a broader span of control in resource utilization than employees in non-platform firms and to choose activities based on their own interests (Gu & Zhu, 2021; Wang & Miller, 2020). Overlooking such reliance on complementors may result in a misguided understanding of platform diversification in general and an under-appreciation of the potential spillover effects between business segments both within and across platform firms.

3.1. Within-platform spillover effect

Existing studies suggest that a (non-platform) firm's diversification can result in two countervailing effects on its existing business. On the one hand, the existing business might benefit from the economies of scope that arise from resource sharing across businesses (Panzar & Willig, 1981; Teece, 1980). On the other hand, the existing business might be damaged from resources being allocated away to the new business (Roberts & McEvily, 2005; Schoar, 2002; Wu, 2013). In both cases, diversification into a new business requires (non-platform) firms to share or reallocate (owned) resources from existing businesses (Helfat & Eisenhardt, 2004; Penrose, 1959). Absent the control rights over complementors (and their resources), a diversifying platform firm cannot force or forbid complementors from allocating their resources between businesses. Therefore, the impact of platform diversification on the existing business will in part depend on the (opportunistic) allocation of complementors' resources.

Complementors often invest in complementor-specific resources and combine them with platform-specific resources to produce differentiated complements (Cennamo et al., 2018; Gawer & Cusumano, 2014). Because complementors tend to face capacity constraints (Burtch et al., 2018; Tae et al., 2020), they may allocate complementor-specific resources to their most profitable use by adjusting their portfolio of complements (Koo & Eesley, 2021; Rietveld et al., 2021). A platform firm's expansion into a new business creates an opportunity for complementors in the existing business to re-optimize their resource reallocation. In particular, allocating some resources to the new business may allow the complementors to achieve economies of scope by amortizing the costs of acquiring complementor-specific resources across the existing and new businesses. Resources are often accumulated over time (Dierickx & Cool, 1989) and require significant investments (Gawer & Henderson, 2007; Zhu & Liu, 2018). Operating in multiple businesses allows complementors to amortize such investments and increase joint profits across businesses. The potential within-platform synergy will incentivize complementors to reallocate some of their resources to the new business. If a significant number of complementors reallocate their resources to the new business, the existing business could experience a reduction in the level of complementor activities.[5]

[5]It is noteworthy that our predictions are about the level of complementor activities within platforms, not about platform's financial performance. Because platform firms often cross-subsidize complementors or users to harness network effects (Caillaud & Jullien, 2003; Rochet & Tirole, 2003), financial performance has not been a main concern to platform firms. While complementor activity and platform performance is likely to be correlated (e.g., Boudreau, 2012), future studies may build on recent studies that focus on profitability (Koo & Eesley, 2021; Tae et al., 2020) to examine the effect of platform diversification on financial performance.

Hypothesis 1 (H1). *A platform firm's diversification into a new business reduces complementor activities in the existing business (within-platform spillover effect).*

3.2. Cross-platform spillover effect

Studies on non-platform firms suggest that a diversifying firm might experience a change in its competitive advantages in the existing business, thereby indirectly influencing its competitors' performance. The synergistic benefits from resource sharing will enhance its competitiveness at the cost of its competitors in the existing business, whereas the cannibalization effect arising from resource reallocation will damage its competitiveness to the benefit of its competitors in the existing business. For a platform firm, diversification may cause a more direct impact on its competitors. The lack of control over complementors impairs platform firms' ability to forbid complementors from switching between platforms. The more fluid movement of complementors (compared to employees) across platform firms undermines the boundary between platform firms and creates a potential spillover effect of one firm's diversification move on another.

When a platform firm diversifies, the potential within-platform synergy may attract complementors on competing platform firms. However, complementors that attempt to share resources between the new business of the diversifying platform firm and competing platform firms can face high multi-homing costs (Cennamo et al., 2018; Chen et al., 2022; Eisenmann, 2007). In order to maintain coherence and support interoperability, a typical platform requires its participants to follow platform-specific rules, such as technology standards, interfaces, procedures, policies, and contracts (Baldwin & Clark, 2000; Boudreau & Hagiu, 2009). To operate on multiple platforms, complementors need to tailor their products or services to platform-specific interfaces and architectures (Anderson et al., 2014; Cennamo et al., 2018). The costs of adjusting complements to different platforms are often immense and recurring. When the multi-homing costs across platform firms are sufficiently high, it might offset the growth and profit opportunity in the new business. Consequently, complementors on competing platform firms that wish to pursue opportunities on the diversifying platform firm may need to withdraw their resources from competing platforms to lower the multi-homing costs. If a significant number of complementors withdraw their resources from the competing platform firm, the competing platform firm could experience a reduction in complementor activities.

Hypothesis 2 (H2). *A platform firm's diversification into a new business reduces complementor activities on competing platform firms in the existing business (cross-platform spillover effect).*

3.3. Demand conditions of the existing business

Resource allocation depends on not only the expected return from the target use but also the opportunity costs related to alternative uses (Levinthal & Wu, 2010; Sakhartov & Folta, 2015).[6] When a platform firm diversifies, complementors in its existing business will compare the expected return from continuing to operate in the existing business and reallocating their resources to the new business.

Prior studies suggest that demand conditions in different businesses can affect opportunity costs for firm resources, thereby influencing allocation decisions and performance (Anand & Singh, 1997; Chandler, 1969). Specifically, firms face a higher opportunity cost for withdrawing resources from a high-demand submarket in the existing business than from a low-demand submarket (Chang, 1996; Wu, 2013). Following the same logic, we argue that, for both

[6] We mainly focus on resource allocation, which is similar to but broader than resource redeployment. While resource redeployment implies permanently withdrawing resources from one business and reallocating them to another business (Helfat & Eisenhardt, 2004; Lieberman et al., 2017; Sakhartov & Folta, 2014), our context involves resources constantly being allocated back and forth without fully exiting from one activity (Levinthal, 2017; Levinthal & Wu, 2010).

the diversifying and competing platform firms, complementors in the existing business will be less likely to withdraw resources from the high-demand submarkets. Therefore, both the within- and cross-platform spillover effects will be weaker in high-demand submarkets than in low-demand submarkets of the existing business.

Hypothesis 3 (H3). *Both within- and cross-platform spillover effects are weaker in high-demand submarkets than in low-demand submarkets.*

4. EMPIRICAL DESIGN

The empirical context of the study is the rideshare market in New York City. NYC has experienced explosive growth in the rideshare services since the entry of Uber in 2011 and Lyft in 2014 and has become the second-largest rideshare market in the U.S. after San Francisco (Akhtar & Kiersz, 2019). As of 2016, rideshare services in NYC provided about 91 million trips, with Uber supplying the largest share (77%), followed by Lyft (13%). In March 2016, Uber launched Uber Eats, a food delivery platform, in several U.S. cities, including NYC (Uber, 2016). In NYC, Uber Eats was only available in Manhattan at first but expanded to most areas by December 2016 (Covert & Fickenscher, 2016). By October 2016, about 4.5 percent of the restaurants located in Manhattan (495 out of 10,880) joined Uber Eats.

This is an appropriate setting for our study for several reasons. First, Uber's entry into the food delivery business (and restaurants' decisions to join Uber Eats) created an exogenous localized shock to rideshare drivers (complementors in Uber's existing business). Our reading of news articles suggests anecdotally that the launch of Uber Eats was not based on the availability of Uber drivers within each geographic zone for two reasons. First, Uber Eats focused on recruiting popular restaurants to attract users (Uber, 2016). Second, the difficulty of vehicle parking in Manhattan forced Uber Eats to focus on recruiting bike couriers rather than vehicle drivers.[7] Our interviews with Uber drivers in Manhattan confirmed that Uber Eats did not provide any incentives to Uber drivers for joining Uber Eats. In addition, our interviews with three restaurant owners who joined Uber Eats by October 2016 revealed that the restaurants' decisions to join Uber Eats were not based on the availability of Uber drivers near their restaurants.[8] For instance, an owner of an Asian restaurant in Manhattan stated:

> "(When an Uber Eats salesman visit the restaurant) I had no idea how many Uber drivers were out there. … I just wanted to get more money and thought Uber Eats could be a good opportunity."

Figure 1 visualizes the percentages of restaurants that joined Uber Eats for each geographic zone in Manhattan. The proportion of restaurants that joined Uber Eats exhibited a large variation across 69 geographic zones in Manhattan. Consequently, the launch of Uber Eats could have heterogeneous impacts on rideshare drivers depending on their active zones. Using as treatments the proportion of restaurants that joined Uber Eats in each geographic zone, we can adopt a continuous DID estimation to identify within- and cross-platform spillover effects. Second, detailed rideshare trip records allow us to identify submarkets with different levels of demand in the rideshare business (e.g., rush hours vs. non-rush hours) and to investigate heterogeneity in the effect of Uber's diversification across these submarkets. Lastly, NYC provides trip-level data for both rideshare and taxi businesses, which enables us to use non-platform taxi trips as a control group to account for unobserved location- or time-specific factors.

[7]Uber Eats recruited about 600 bike couriers when it launched its service in Manhattan (Novellino, 2016).
[8]Three restaurant owners also confirmed that Uber Eats did not give any incentives or perks in joining Uber Eats.

Insert Figure 1 here

4.1. Data and sample

We drew on data from multiple sources. First, we collected anonymized trip-level data from NYC Taxi and Limousine Commission (TLC), the agency responsible for licensing rideshare vehicles and taxis in NYC. The initial data included about 1.3 billion trip records provided by rideshare services and Yellow Taxi from 2015 to 2019, with information on pick-up times and locations. Information on locations was given as one of 263 taxi zones in NYC.[9] Second, we obtained from ReferenceUSA a list of all restaurants operating in NYC during 2015 and 2016. Third, we merged the restaurant list with a proprietary dataset that contains information scraped from all major food delivery platforms (i.e., DoorDash, Grubhub, Postmates, and Uber Eats) to identify restaurants that have joined each of these platforms. We matched the data sets by restaurant name and address. Ambiguous matches were further verified manually via web searches. Finally, we obtained population demographics information on NYC from the American Community Survey.

Given the availability of data, we chose our sample period to be from October 2015 to October 2016. Specifically, we compared the trip volume of rideshare services in the same zone, same hour, same day-of-the-week, and same week of the year between October 2015 and October 2016 (i.e., before and after the launch of Uber Eats).[10] To minimize location- and time-

[9]TLC has divided NYC into 263 taxi zones, with 69 zones located in Manhattan. Detailed maps for the 263 taxi zones specified by TLC are shown in Appendix Figure A1.
[10]To compare the same day-of-the-week, date *t* in 2016 is matched to date (*t+2*) in 2015. For example, to estimate Uber trip number on October 1st, 2016 (Saturday), we controlled for its trip number on October 3rd, 2015 (Saturday). Accordingly, we compare rideshare trips during October 1st–28th, 2016 to Oct 3rd – 30th, 2015.

sensitive patterns in the rideshare business, we performed our analyses at the hour-day-zone level. Because demand and supply for transportation could differ between weekdays and weekends, we follow prior studies (e.g., Forbes & Lederman, 2010; Prince & Simon, 2009) to exclude weekends. We also excluded three island zones in Manhattan where no rideshare trips nor restaurants were observed during our sample period.[11] Our final sample contains over 61,000 observations across 960 (=40×24) day-hours and 66 geographic zones in Manhattan.

To supplement our quantitative data, we collected qualitative data through semi-structured interviews with rideshare drivers, Uber Eats bike courier, and restaurant owners that joined Uber Eats at the launch of Uber Eats in NYC.[12] The interviews confirmed our predictions that: the launch of Uber Eats acted as an exogenous shock to rideshare drivers, there exist significant multi-homing costs from operating on multiple platforms (i.e., coordinating schedules between platforms), and drivers constantly reallocate their resources (i.e., driving time) between rideshare and food delivery businesses.

4.2. Variables

Our main dependent variable is the number of trips, Y_{jiht}, that was reported on platform *i* (Uber or Lyft), in zone *j*, during the h^{th} hour of day *t*. Because trip numbers exhibited a large variation across different zones and during different periods, we log-transformed the dependent variable to reduce value dispersion. Consequently, the estimated coefficients reflect percentage changes in the dependent variable after Uber launched Uber Eats in Manhattan.

[11] These are Zone 103 (Liberty Island), Zone 104 (Ellis Island), and Zone 105 (Governor's Island).
[12] These include interviews with seven rideshare drivers, one Uber Eats bike couriers, and three restaurant owners in Manhattan, NYC that joined Uber Eats by October 2016.

Our main independent variable, UE_j, represents the proportion of restaurants that joined Uber Eats in zone *j* by October 2016.[13]

Our second independent variable, R_h, is a binary variable that equals one for rush hours (7–10 am and 5–8 pm), and zero otherwise. To confirm our categorization of rush hours, we constructed a heat map using the hourly trip number of Uber and Lyft in NYC during 2015 (Figure 2). The heat maps show that both Uber and Lyft provided high trip numbers during rush hours (7–10 am and 5–8 pm), suggesting that rush hours are high-demand submarkets. Our categorization aligns with the high-demand periods of the rideshare market specified in existing studies (Bialik et al., 2015; NYC TLC and Department of Transportation, 2019).

Insert Figure 2 here

It is possible that our heat maps capture a relative shortage of driver supply rather than low demand during non-rush hours. To further validate our distinction of submarkets, we compared our heat map of trip numbers with the heat map of surge pricing in prior studies (Cohen et al., 2016). Surge pricing is the pricing algorithm that increases the prices of rides during periods of excessive demand relative to driver supply. If non-rush hours were high-demand submarkets with few drivers, those periods should be subjected to surge pricing. In contrast, the heat map of surge pricing showed that non-rush hours did not experience price surges while rush hours experienced high levels of surge pricing. Therefore, we believe that our categorization captures different demand conditions across submarkets. Our control variables

[13]We used proportions, rather than numbers, of restaurants that joined Uber Eats because the number of restaurants in each zone differs significantly. Our results hold when we used the number of restaurants that joined Uber Eats.

(X_{jt}) include the total number of restaurants to account for unobservable geographic variations in restaurant demand.

Table 1 provides summary statistics at the hour-day-zone level. Similar to Figure 1, it reveals substantial heterogeneity in the proportion of restaurants that operate on food delivery platforms. On average, 4 percent of restaurants per zone joined Uber Eats, but the proportion varies significantly from 0 to 12.27 percent. In the rideshare business, Uber provided 74 trips per hour and zone while Lyft provided 8 trips.

Insert Table 1 here

4.3. Specification

We employed a continuous DID estimation with treatments being the proportion of restaurants that joined Uber Eats in each zone. Among 66 zones in Manhattan, 54 zones had at least one restaurant that joined Uber Eats (treatment group), whereas 12 zones did not have any restaurants on Uber Eats (control group). Figure 3 compares the monthly Uber trip volumes between treated and control groups, normalized by the trip volumes during March 2016 (when Uber Eats was launched). It shows that, compared to Uber trips in the control group, Uber trips in the treated group exhibited a lower growth rate.

Insert Figure 3 here

We first estimated the effect of Uber's diversification on rideshare trip numbers using the following specification:

$$Y_{ijht} = \beta_0 + \beta_1 Post_t UE_j + \beta_2 X_{jt} + \alpha_j + \gamma_t + \delta_h + \tau_t + \varepsilon_{ijht}, \quad (1)$$

where $Y_{ijht}, UE_j,$ and X_{jt} are as defined earlier. $Post_t$ is a binary variable taking the value of 1 for year 2016 and 0 for year 2015. All regressions include zone (α_j), day-of-the-week (γ_t), hour (δ_h), and week (τ_t) fixed effects. Standard errors are clustered at the zone level to account for correlation among trip numbers within the same zone.

To test H1 (within-platform spillover effect), we used (log) Uber trip number as the dependent variable. H1 predicts $\beta_1 < 0$. To test H2 (cross-platform spillover effect), we used (log) Lyft trip number as the dependent variable. H2 predicts $\beta_1 < 0$.

Next, to explore whether the effects of Uber's diversification differ with demand conditions in submarkets, we employed a triple differences model by adding R_h through an interaction term, shown in equation (2):

$$Y_{ijht} = \beta_0 + \beta_1 Post_t UE_j + \beta_2 Post_t UE_j R_h + \beta_3 X_{jt} + \alpha_j + \gamma_t + \delta_h + \tau_t + \varepsilon_{ijht}, \quad (2)$$

In equation (2), our control variable (X_{jht}) includes other two-way interaction terms (i.e., $Post_t R_h$, $UE_j R_h$) as well as the total number of restaurants. For both Uber and Lyft trip numbers, H3 predicts $\beta_2 > 0$.

5. RESULTS

5.1. Within-platform spillover effect

Table 2 compares the within-zone changes of Uber trip numbers in zones where at least one restaurant joined Uber Eats with changes in zones where no restaurants joined Uber Eats. Column 1 estimates the baseline model. The coefficient shows that overall, for every one percent of restaurants that joined Uber Eats in a specific zone, trips provided by Uber drivers in the zone decreased by 2.12 percent (p = .001) compared to zones where no restaurants joined Uber Eats. This supports H1. Based on Uber's Manhattan trip volume during 2016 (41,973,334 trips) and the average proportion of restaurants that joined Uber Eats (4%), we can infer that, on a yearly basis, the launch of Uber Eats reduced Uber's trip number in Manhattan by about 3,359,339 trips (=41,973,334×0.0212×4).

Insert Table 2 here

5.2. Cross-platform spillover effect

Table 3 compares the within-zone changes of Lyft trip numbers in zones where at least one restaurant joined Uber Eats with changes in zones where no restaurants joined Uber Eats. The coefficient in Column 1 shows that, overall, for every one percent of restaurants that joined Uber Eats in a specific zone, trips provided by Lyft drivers in the zone decreased by 6.43 percent (p = .002) compared to zones where Uber Eats did not enter. This supports H2. Using a similar method as in Section 5.1., we estimate that the launch of Uber Eats reduced Lyft's trip number in Manhattan by about 1,337,594 trips (=5,200,600×0.0643×4).

Insert Table 3 here

These effects are larger for Lyft than for Uber in percentage terms (-6.43% vs. -2.12%, Table 2), albeit smaller for Lyft than for Uber in absolute trip numbers (1,337,594 vs. 3,359,339). The larger percentage decline in Lyft trip numbers implies that, for rideshare drivers, the benefits from multi-homing on both Uber and Lyft platforms may be smaller than the synergy from operating in both the rideshare and food delivery businesses within Uber. Complementors (i.e., drivers) can enjoy synergies across businesses within the same platform firm from sharing platform-specific resources (Baldwin & Woodard, 2009; Chung et al., 2022). For instance, drivers can take orders from Uber and Uber Eats simultaneously using a single app. The Uber app connects drivers to both rideshare passengers and food delivery orders based on drivers' locations and distances to destinations, which would maximize drivers' earnings per hour. In contrast, Lyft dispatches rideshare trips to drivers solely based on demand for its rideshare business. To avoid getting rideshare requests from Lyft (and having to reject them) while working on food delivery requests from Uber Eats, drivers have to log off the Lyft app to work on Uber Eats.[14] Coordination costs arising from joint scheduling and adjustments are known to limit firms' activity scope (Marschak & Radner, 1972; Zhou, 2011). Similarly, the increased workloads from coordinating schedules across Uber Eats and Lyft could force drivers to exit from the platform that offers less synergy (i.e., Lyft). Our interviews with several rideshare drivers confirmed our arguments. For instance, a rideshare driver who has been working on multiple rideshare and food delivery platforms stated:

> "Acceptance rate is important for us, as high rate gives us trips with a better fare. … (to maintain the acceptance rate) we need to turn off one app while serving a trip from another app. Though I've been working for years now, I sometimes still forget to do so."

[14]While drivers can log in to both Lyft and Uber Eats apps and decline incoming requests while working on one, both Lyft and Uber penalize drivers for declining requests. Drivers may get fewer trips dispatched or get deactivated, which forbids them from logging in to the apps.

5.3. Demand conditions in the existing business segment

We first examine the heterogeneous effects of Uber Eats on Uber trip numbers. Column 2 in Table 2 compares the effects between rush and non-rush hours. It shows that, while the launch of Uber Eats had a negative effect on Uber trip numbers during both rush and non-rush hours, the effect was weaker during rush hours (-2.57 + 1.87 = -0.7%, $p < .001$) than non-rush hours (-2.57%, $p = .001$).

Column 5 in Table 2 separates the effects on trip numbers during morning rush hours and evening rush hours. Coefficients show that the cannibalization effect was the weakest during morning rush hours. In fact, the coefficients suggest that Uber trip numbers even increased in zones where Uber Eats entered (-2.57 + 2.71 = 0.14%, $p < .001$). This suggests the possibility of a reverse flow of drivers: Drivers who newly join Uber Eats (the food delivery business) may temporarily switch to Uber (the rideshare business) during high-demand periods to utilize their excess resources.

Next, we explore the heterogeneous effects of Uber Eats on Lyft trip numbers. Column 2 in Table 3 shows a similar result to the effect on Uber trip numbers: While the launch of Uber Eats had a negative effect on Lyft trip numbers during both rush and non-rush hours, the decline in Lyft trip numbers was weaker during rush hours (-6.92 + 2.08 = -4.84%, $p = .021$) than non-rush hours (-6.92%, $p = .001$).

Column 5 in Table 3 separates the effects on trip numbers during morning rush hours and evening rush hours. It shows that the launch of Uber Eats had the strongest effect on Lyft trip numbers during non-rush hours (a drop of about 6.92%, $p = 0.001$) and the smallest effect during morning rush hours (a drop of about 3.42%, $p = 0.013$). The coefficient for evening rush hours, while still negative, is not statistically significant (a drop of about 6.32%, $p = 0.437$).

5.4. Alternative explanations

Our DID models enable us to control for unobservable time-variant factors that affected both the treated and control groups. However, there might be unobservable time-variant factors that influenced only the treated group (but not the control group), which could confound our results. We illustrate such time-variant factors and our solutions to rule out the alternative explanations.

5.4.1. Unobservable time-variant factors from the demand side

The rideshare trip numbers in the treated group might have been influenced by the change in the demand side. For example, the launch of Uber Eats may incentivize diners who used to go to restaurants to order food deliveries instead. That is, the relative reduction in rideshare trips in the treated group might be caused by a reduction in users who used to visit restaurants in the treated group with rideshare services or taxis. While several rideshare drivers stated that they did not experience significant changes in trips that ended near restaurants, we conducted the following analyses to account for such factors.

First, we compare taxi trip volumes between the treated and control groups (Figure 4). If users took either taxis or rideshare services to visit restaurants in the treated group, we would see a relative reduction in taxi trips for the treated group after the launch of Uber Eats. Taxi trip volumes are normalized by the trip volumes during March 2016. Unlike Figure 3, taxi trip volumes in the treated and control groups exhibit a similar trend before and after the launch of Uber Eats, suggesting that our results were not driven by the reduction in rideshare users.

Insert Figure 4 here

To further rule out the alternative explanation from the demand side, we replicate the models in Table 2 but instead estimate the effect of the launch of Uber Eats on taxi trip numbers. Results are presented in Table 4. The coefficients of the independent variable (Post × UE restaurants) are all negative but insignificant, suggesting that taxi trips in the treated zones did not change significantly compared to taxi trips in the control zones after the launch of Uber Eats.

Insert Table 4 here

It is possible that users who frequently use Uber and Uber Eats might exhibit different demographics from those that typically use taxis. For instance, the younger population is more familiar with smartphones and thus more likely to use Uber than taxis. In such cases, zones with younger populations would exhibit a larger reduction in rideshare trips compared to zones with older populations. To account for such factors, we employ a triple differences model by adding Age_j through an interaction term, shown in equation (3):

$$Y_{ijht} = \beta_0 + \beta_1 Post_t UE_j + \beta_2 Post_t UE_j Age_j + \beta_3 X_{jht} + \alpha_j + \gamma_t + \delta_h + \tau_t + \varepsilon_{ijht}, \qquad (3)$$

where $Y_{ijht}, Post_t, UE_i,$ and X_{jht} are as defined earlier in Section 4.2. Age_j represents the median population age in zone j during 2015.[15] All regressions include zone (α_j), day-of-the-week (γ_t), hour (δ_h), and week (τ_t) fixed effects. Standard errors are clustered at the zone level to account for correlation among trip numbers within the same zone. Results are shown in Table 5. Columns 2 and 4 show that, while the launch of Uber Eats had negative effects on both Uber and Lyft trip numbers, the negative effects were not stronger for zones with younger population

[15]Zones in Manhattan exhibited a significant variation in median population age. In 2015, the average value was 38.67, with the minimum value of 30.39 and the maximum value of 55.

age. We re-estimate equation (3) using a binary variable of median population age, where the variable equals one if the median age in a given zone was above 38.67 in 2015, and 0 otherwise (Appendix Table A1). Our result holds. Therefore, we can infer that our main result is not driven by the change in rideshare users' behaviors but by the movement of rideshare drivers.

Insert Table 5 here

5.4.2. Unobservable time-variant factors from competing food delivery platforms

The rideshare trip numbers in the treated group might have been influenced by the change in competing food delivery platforms (i.e., DoorDash, Grubhub, Postmates). While all competing food delivery platforms were launched before our sample period started (October 2015), more restaurants might have joined those food delivery platforms, which could have attracted rideshare drivers.

To account for such factors, we replicate the DID models in Tables 2 and 3 but instead use the proportion of restaurants that joined Uber Eats by October 2016 but *not* competing food delivery platforms as treatments. Results are presented in Table 6. Columns 2 and 4 show that, for every one percent of restaurants that joined Uber Eats (but not competing food delivery platforms) in a specific zone, trips provided by Uber and Lyft drivers in the zone decreased by about 2.68 and 11.17 percent, respectively. The result suggests that the reduction in rideshare trip numbers was not driven by the increased presence of competing food delivery platforms.

Insert Table 6 here

To further confirm that food delivery platforms did not divert drivers away from rideshare platforms, we estimate how rideshare trip numbers were affected by the launch of DoorDash, a competing food delivery platform. In NYC, DoorDash started its service in April 2015, initially serving Brooklyn only (Bromwich, 2015).[16] Specifically, we employ a DID model that compares the trip numbers of Uber and Lyft between Brooklyn and other boroughs (i.e., The Bronx, Manhattan, Queens, and Staten Island) before and after the launch of DoorDash (i.e., between March and May 2015). Columns 1 and 3 in Table 7 show that both Uber and Lyft trip numbers did not decrease in Brooklyn after the launch of DoorDash compared to other boroughs, suggesting that the launch of DoorDash did not divert drivers away from the rideshare business. The result also indicates that our findings were not driven by the change in rideshare users who used to visit restaurants, supplementing Section 5.4.1.

Insert Table 7 here

5.5. Robustness checks

We ran a battery of supplementary tests to check the robustness of our results. These additional analyses are shown in the Appendix. First, continuous DID models assume a linear relationship between the treatment level and the dependent variable, putting less weight on treatment groups with a low treatment level. This could have underestimated the effect of Uber Eats on zones where the portion of restaurants that joined Uber Eats was low. To estimate the average effect on all zones where Uber Eats entered, we re-estimated the DID models using a binary treatment effect (i.e., whether a given zone has at least one restaurant that joined Uber

[16]DoorDash expanded its service to Manhattan by June 2015 and to most areas of NYC by September 2017 (Bromwich, 2015; Pak, 2017).

Eats or not) (Appendix Table A2). The coefficients in Columns 1 and 3 indicate that, on average, trips provided by Uber and Lyft decreased by 20.2 percent (p = 0.001) and 43.9 percent (p = 0.042), respectively, in zones where Uber Eats was available compared to trips in zones where Uber Eats was not available. Columns 2 and 4 show that the negative effect was weakened during rush hours: Trips provided by Uber and Lyft decreased only by about 12.9 percent (p = 103) and 26.8 percent (p = 0.041), respectively, during rush hours.

Second, one potential weakness of our approach is that there could be a potential violation of the Stable Unit Treatment Value Assumption (SUTVA) (Rubin, 1980), where the outcome in the control group is affected by the treatment. In our context, rideshare drivers that work in zones where no restaurants joined Uber Eats (control group) might move to zones where at least one restaurant joined Uber Eats (treatment group) to work on the Uber Eats platform, causing rideshare trip numbers in the control group to decrease. This might bias our result downward, making it more difficult to find support for our hypothesis. Thus, our coefficient estimates should be interpreted as the lower bound of the true effect size.

That said, to address this bias, we use a DID model that compares trip numbers of Uber and Lyft between Manhattan and boroughs outside Manhattan (i.e., The Bronx, Brooklyn, Queens, and Staten Island) (Appendix Table A3). Because drivers' movement between Manhattan and outer boroughs is more costly and difficult than the movement between zones in Manhattan, we predict that the bias from the potential violation of SUTVA would be partially mitigated. Our results show that rideshare trip numbers in Manhattan (where Uber Eats entered) declined significantly compared to trip numbers in outer boroughs (where Uber Eats did not enter at the time).

Third, there might be unobservable time trends between October 2015 and October 2016 that could confound our results. We re-estimate our models using a different time window. Specifically, we compare four weeks before and after the launch of Uber Eats (February 23rd-April 19th, 2016) (Appendix Table A4). Because Uber Eats was available in the core area (below 100th street) when first launched in Manhattan (Uber, 2016), we use zones located in the core area as the treated group and other zones as the control group.

Lastly, we re-estimate our models using trips that were made during weekends, when high-demand submarkets were late-night periods (Sat 9 pm–Sun 3 am, Figure 1) (Appendix Table A5). Our results generally hold.

6. DISCUSSION AND CONCLUSION

The main objective of this study was to explore how diversification by a platform firm affects its existing business and that of its competitors. Using a unique dataset on the rideshare and food delivery businesses in NYC, we analyzed changes in rideshare trip numbers after Uber launched Uber Eats in Manhattan, NYC. We found that Uber's expansion into the food delivery business reduced rideshare trip numbers for both Uber and Lyft. In addition, the negative effect of Uber Eats on Uber and Lyft was stronger during non-rush hours than rush hours.

The key theoretical contribution of the study is to bridge the two streams of literature on platform scope and diversification, respectively. We examine the understudied phenomenon of platform diversification and reveal that it could have negative effects on the existing business segment of both a focal platform and competing platforms. In addition, we enrich the diversification literature by exploring the effect of diversification on existing business segments when resources are not owned nor contracted by firms and, therefore, highly fluid. We find that resource allocation decisions by complementors to maximize their profit can damage the platform firm's existing business segment, thereby highlighting the tradeoff between complementor-level and business-level profit.

Furthermore, we add to a rich body of research on RBV by enriching the concept of resource ownership to clarify the connection between resources and the scope of platform firms that has puzzled strategy scholars (Jacobides et al., 2018; Kretschmer et al., 2022). In doing so, we echo prior arguments for the importance of both platform-specific and complementor-specific resources for platform firms (Baldwin & Woodard, 2009; Cennamo et al., 2018) and extend recent efforts to distinguish these resources (Chung et al., 2022).

The findings of the paper are subject to a couple of caveats that create opportunities for future studies. First, we focus on the effects of one platform firm's diversification (i.e., Uber's entry into the food delivery business). Analyzing millions of trips within a single platform firm allowed us to eliminate unobserved heterogeneity across platform firms and to extract detailed data on complementor activities within a single platform firm. However, prior studies on non-platform diversification suggest that diversifying firms may be systematically different from others (Campa & Kedia, 2002; Villalonga, 2004), which may imply boundary conditions for our findings. Specifically, Uber had enough drivers to maintain its dominance in the rideshare business even after losing some of them to the food delivery business. For smaller platform firms, losing complementors to the new business might deprive them of a "critical mass" of complementors necessary to attract customers, ultimately driving these firms out of business (Arthur, 1989; Caillaud & Jullien, 2003). Future studies can investigate how the effects of platform diversification vary with the size or market share of platform firms.

Second, due to data availability, we have limited the sample period to be from six months before Uber Eats' launch to six months after. This short time period, along with the DID design, enables us to control for unobservable time-specific factors and identify the causal effect in a more tightly controlled external environment. Our results might change over a longer time period. In particular, as more restaurants join Uber Eats, more drivers may enter the food delivery business, which may increase competition among food delivery drivers and result in a reverse flow of drivers into the rideshare business. Future research can examine both the short-term and long-term impacts of platform diversification on complementor activities.

One intriguing question our results raise is the spillover effect of platform diversification on competitors in the new rather than existing business. The launch of Uber Eats can influence not only competing platform firms in the rideshare business (e.g., Lyft) but also those in the food delivery business (e.g., DoorDash, Grubhub, or Postmates). Intuitively, there could be two countervailing effects. On the one hand, a diversifying platform firm may divert complementors (i.e., food delivery drivers) away from competing platform firms in its new business, thereby weakening their market power. On the other hand, it can bring in more complementors from its existing business and enlarge the potential pool of complementors in the new business. Future studies can explore such dynamics when data become available.

In sum, despite the limitations, this paper highlights the unique challenge that a diversifying platform firm faces in managing complementor resources across submarkets, business segments, and platform firms. We hope it provides a theoretical and empirical basis for future studies of platform diversification.

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FIGURE 1 Percentages of restaurants that joined Uber Eats within each zone in Manhattan

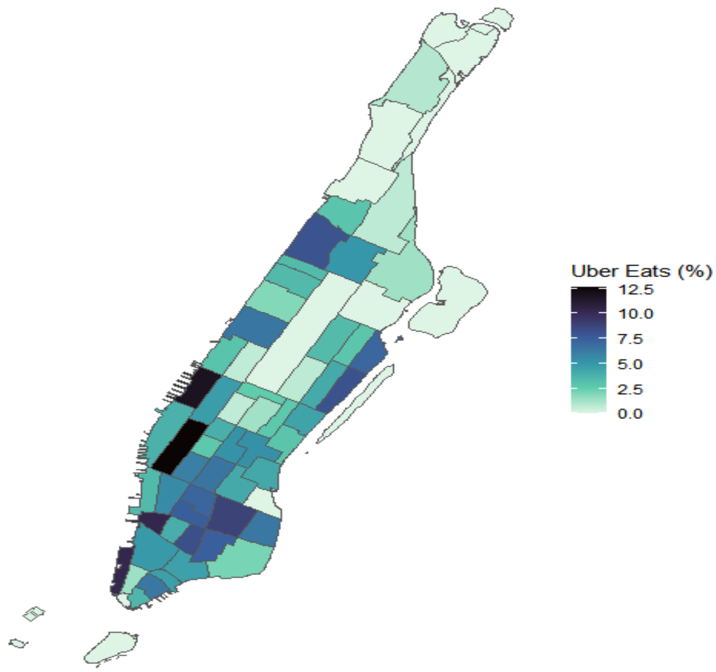


FIGURE 2 Heat map of trip volume during 2015 by the hour of the week for Uber (left) and Lyft (right)

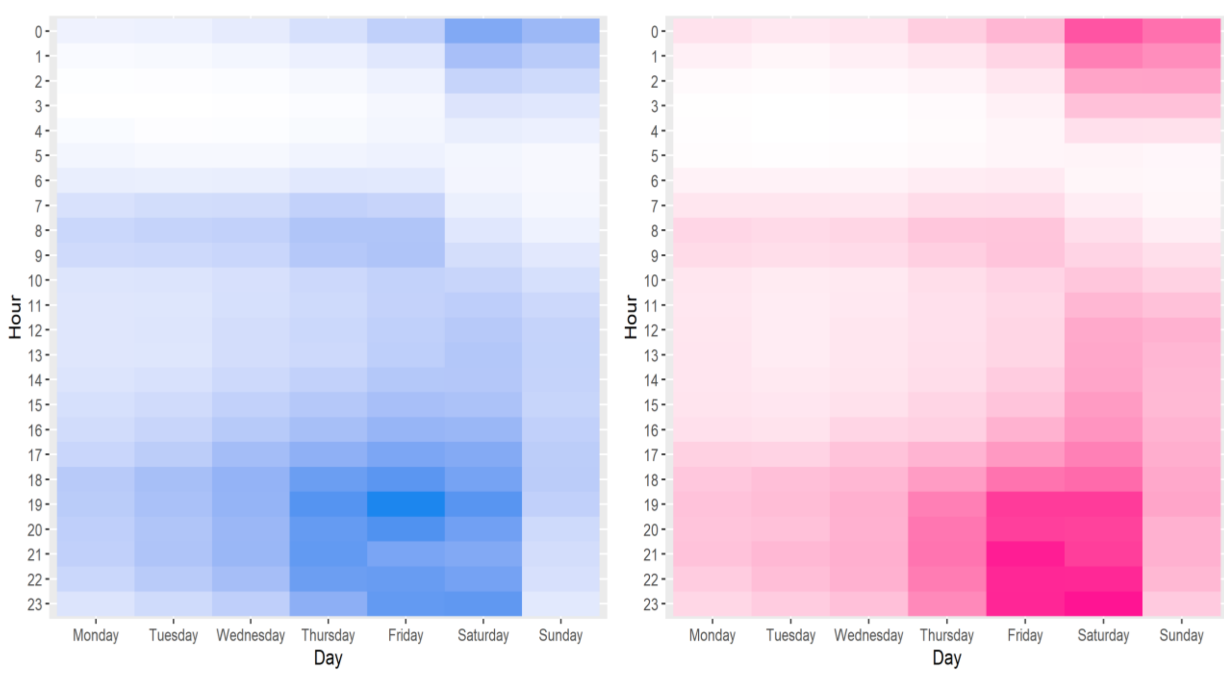
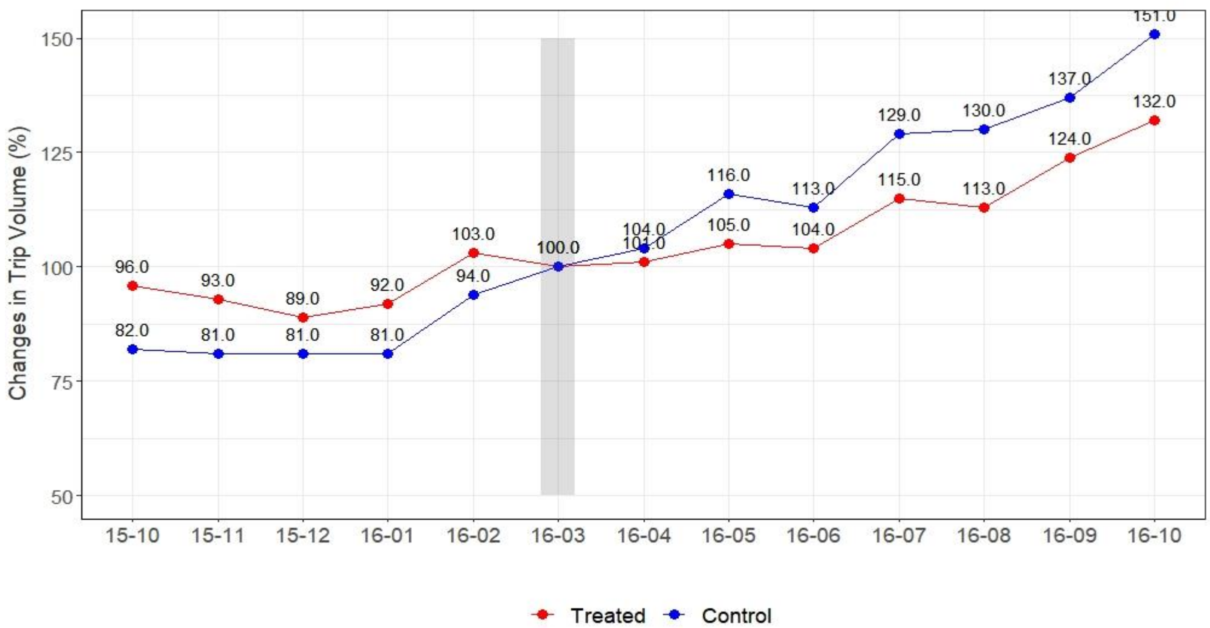
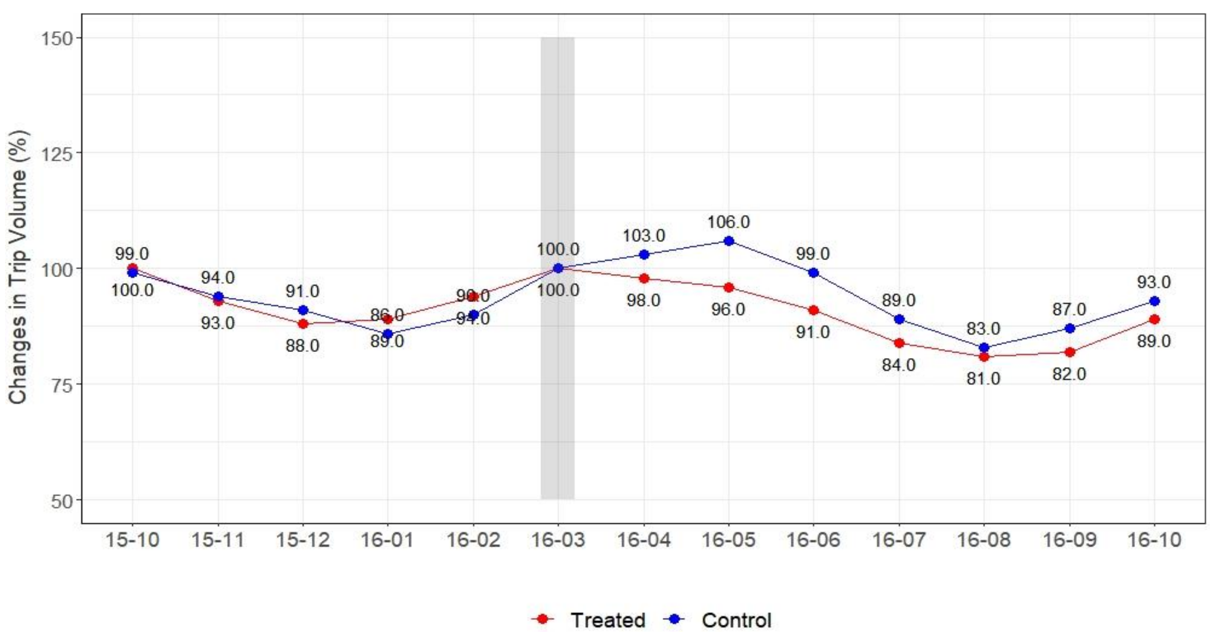


FIGURE 3 Monthly Uber trip volumes for the treated group (red) and control group (blue)



The grey line indicates the date for Uber Eats' launch in Manhattan (March 22nd, 2016).

FIGURE 4 Monthly taxi trip volumes for the treated group (red) and control group (blue)



The grey line indicates the date for Uber Eats' launch in Manhattan (March 22nd, 2016).

TABLE 1 Summary statistics

	Variable	Definition	Mean	SD	Min	Max	(1)	(2)	(3)	(4)	(5)	(6)
(1)	Uber trip #	Uber trip number	74.45	82.73	0	2,044	1.00					
(2)	Lyft trip #	Lyft trip number	8.00	8.86	0	239	0.82	1.00				
(3)	Rush Hour	A binary variable that equals 1 for evening rush hours (7-10 am/5-8 pm) and 0 otherwise.	0.25	0.43	0	1	0.16	0.12	1.00			
(4)	Uber Eats Restaurants (%)	The proportion of restaurants that joined Uber Eats by October 2016	0.04	0.03	0	0.12	0.23	0.24	-0.01	1.00		
(5)	Total restaurant #	Total number of restaurants	169.96	127.15	0	677	0.50	0.43	-0.01	0.27	1.00	
(6)	Median age	Median population age in 2015	38.13	3.94	30.39	52.14	0.05	-0.08	0.00	-0.29	-0.03	1.00

TABLE 2 The effect of Uber Eats on Uber trip numbers

(log) Uber Trip #	(1)	(2)	(3)	(4)	(5)
Post × UE restaurants (%)	-2.119 (0.633) [0.001]	-2.566 (0.684) [0.000]	-2.434 (0.689) [0.001]	-2.192 (0.618) [0.001]	-2.567 (0.684) [0.000]
Post × UE restaurants (%) × RH (7-10 am, 5-8 pm)	-	1.867 (0.490) [0.000]	-	-	-
Post × RH (7-10 am, 5-8 pm)	-	0.207 (0.028) [0.000]	-	-	-
UE restaurants (%) × RH (7-10 am, 5-8 pm)	-	-0.459 (0.971) [0.638]	-	-	-
Post × UE restaurants (%) × MRH (7-10 am)	-	-	2.577 (0.772) [0.001]	-	2.711 (0.783) [0.001]
Post ×MRH (7-10 am)	-	-	0.331 (0.041) [0.000]	-	0.342 (0.042) [0.000]
UE restaurants (%) × MRH (7-10 am)	-	-	-1.871 (1.574) [0.239]	-	-1.743 (1.543) [0.263]
Post × UE restaurants (%) × ERH (5-8 pm)	-	-	-	0.607 (0.387) [0.122]	0.981 (0.403) [0.018]
Post × ERH (5-8 pm)	-	-	-	0.025 (0.024) [0.292]	0.075 (0.025) [0.004]
UE restaurants (%) × ERH (5-8 pm)	-	-	-	1.093 (1.386) [0.433]	0.846 (1.347) [0.532]
(log) Total restaurant #	-0.058 (0.014) [0.000]	-0.061 (0.014) [0.000]	-0.059 (0.015) [0.000]	-0.059 (0.015) [0.000]	-0.060 (0.015) [0.000]
Zone FEs	Yes	Yes	Yes	Yes	Yes
Week FEs	Yes	Yes	Yes	Yes	Yes
Day-of-the-week FEs	Yes	Yes	Yes	Yes	Yes
Hour FEs	Yes	Yes	Yes	Yes	Yes
Observations	61702	61702	61702	61702	61702
Adjusted R^2	0.831	0.833	0.834	0.831	0.834

Robust standard errors clustered at the zone level are included in parentheses. *p*-values are included in square brackets.

TABLE 3 The effect of Uber Eats on Lyft trip numbers

(log) Lyft Trip #	(1)	(2)	(3)	(4)	(5)
Post × UE restaurants (%)	-6.429 (1.984) [0.002]	-6.918 (1.940) [0.001]	-6.844 (1.969) [0.001]	-6.440 (1.961) [0.002]	-6.918 (1.940) [0.001]
Post × UE restaurants (%) × RH (7-10 am, 5-8 pm)	-	2.080 (0.880) [0.021]	-	-	-
Post × RH (7-10 am, 5-8 pm)	-	0.332 (0.053) [0.000]	-	-	-
UE restaurants (%) × RH (7-10 am, 5-8 pm)	-	-0.407 (1.505) [0.788]	-	-	-
Post × UE restaurants (%) × MRH (7-10 am)	-	-	3.426 (1.345) [0.013]	-	3.502 (1.367) [0.013]
Post × MRH (7-10 am)	-	-	0.539 (0.077) [0.000]	-	0.556 (0.079) [0.000]
UE restaurants (%) × MRH (7-10 am)	-	-	-3.876 (2.370) [0.107]	-	-3.479 (2.356) [0.145]
Post × UE restaurants (%) × ERH (5-8 pm)	-	-	-	0.124 (0.739) [0.867]	0.601 (0.769) [0.437]
Post × ERH (5-8 pm)	-	-	-	0.031 (0.046) [0.511]	0.112 (0.049) [0.025]
UE restaurants (%) × ERH (5-8 pm)	-	-	-	3.174 (1.887) [0.097]	2.679 (1.860) [0.155]
(log) Total restaurant #	-0.163 (0.089) [0.072]	-0.168 (0.089) [0.064]	-0.165 (0.089) [0.069]	-0.164 (0.089) [0.070]	-0.167 (0.089) [0.066]
Zone FEs	Yes	Yes	Yes	Yes	Yes
Week FEs	Yes	Yes	Yes	Yes	Yes
Day-of-the-week FEs	Yes	Yes	Yes	Yes	Yes
Hour FEs	Yes	Yes	Yes	Yes	Yes
Observations	61702	61702	61702	61702	61702
Adjusted R^2	0.636	0.639	0.641	0.637	0.642

Robust standard errors clustered at the zone level are included in parentheses. *p*-values are included in square brackets.

TABLE 4 The effect of Uber Eats on taxi trip numbers

(log) Taxi Trip #	(1)	(2)	(3)	(4)	(5)
Post × UE restaurants (%)	-0.248 (0.647) [0.703]	-0.576 (0.674) [0.396]	-0.445 (0.660) [0.502]	-0.336 (0.658) [0.611]	-0.577 (0.674) [0.396]
Post × UE restaurants (%) × RH (7-10 am, 5-8 pm)	-	1.406 (0.446) [0.002]	-	-	-
Post × RH (7-10 am, 5-8 pm)	-	0.234 (0.027) [0.000]	-	-	-
UE restaurants (%) × RH (7-10 am, 5-8 pm)	-	-0.968 (1.350) [0.476]	-	-	-
Post × UE restaurants (%) × MRH (7-10 am)	-	-	1.644 (0.735) [0.029]	-	1.776 (0.741) [0.019]
Post × MRH (7-10 am)	-	-	0.301 (0.046) [0.000]	-	0.322 (0.047) [0.000]
UE restaurants (%) × MRH (7-10 am)	-	-	-2.352 (1.723) [0.177]	-	-2.291 (1.815) [0.211]
Post × UE restaurants (%) × ERH (5-8 pm)	-	-	-	0.778 (0.407) [0.061]	1.017 (0.407) [0.015]
Post × ERH (5-8 pm)	-	-	-	0.101 (0.023) [0.000]	0.148 (0.023) [0.000]
UE restaurants (%) × ERH (5-8 pm)	-	-	-	0.683 (1.144) [0.553]	0.356 (1.261) [0.779]
(log) Total restaurant #	0.030 (0.019) [0.110]	0.026 (0.019) [0.162]	0.029 (0.019) [0.126]	0.028 (0.018) [0.129]	0.027 (0.018) [0.156]
Zone FEs	Yes	Yes	Yes	Yes	Yes
Week FEs	Yes	Yes	Yes	Yes	Yes
Day-of-the-week FEs	Yes	Yes	Yes	Yes	Yes
Hour FEs	Yes	Yes	Yes	Yes	Yes
Observations	61702	61702	61702	61702	61702
Adjusted R^2	0.906	0.907	0.907	0.906	0.907

Robust standard errors clustered at the zone level are included in parentheses. *p*-values are included in square brackets.

TABLE 5 The effect of Uber Eats on Uber and Lyft trip numbers across zones with different population median ages

	(log) Uber Trip #		(log) Lyft Trip #	
	(1)	(2)	(3)	(4)
Post × UE restaurants (%)	-2.119 (0.633) [0.001]	0.276 (8.751) [0.975]	-6.429 (1.984) [0.002]	8.607 (17.663) [0.628]
Post × UE restaurants (%) × Age	-	-0.072 (0.236) [0.762]	-	-0.431 (0.452) [0.343]
Post × Age	-	-0.005 (0.006) [0.408]	-	-0.016 (0.018) [0.384]
(log) Total restaurant #	-0.058 (0.014) [0.000]	-0.045 (0.021) [0.034]	-0.163 (0.089) [0.072]	-0.126 (0.096) [0.195]
Zone FEs	Yes	Yes	Yes	Yes
Week FEs	Yes	Yes	Yes	Yes
Day-of-the-week FEs	Yes	Yes	Yes	Yes
Hour FEs	Yes	Yes	Yes	Yes
Observations	61702	61702	61702	61702
Adjusted R^2	0.831	0.831	0.636	0.637

Robust standard errors clustered at the zone level are included in parentheses. *p*-values are included in square brackets.

TABLE 6 The effect of Uber Eats on Uber and Lyft trip numbers (DID estimation with treatments being the proportion of restaurants that joined Uber Eats by October 2016 but *not* on competing food delivery platforms)

	(log) Uber Trip #		(log) Lyft Trip #	
	(1)	(2)	(3)	(4)
Post × UE restaurants (%)	-2.680 (1.210) [0.030]	-3.219 (1.359) [0.021]	-11.170 (3.382) [0.002]	-11.797 (3.369) [0.001]
Post × UE restaurants (%) × RH (7-10 am, 5-8 pm)	-	2.298 (1.033) [0.030]	-	2.725 (1.603) [0.094]
Post × RH (7-10 am, 5-8 pm)	-	0.241 (0.026) [0.000]	-	0.368 (0.045) [0.000]
UE restaurants (%) × RH (7-10 am, 5-8 pm)	-	2.056 (2.151) [0.343]	-	3.077 (3.272) [0.351]
(log) Total restaurant #	-0.060 (0.021) [0.006]	-0.064 (0.021) [0.003]	-0.163 (0.100) [0.109]	-0.169 (0.100) [0.097]
Zone FEs	Yes	Yes	Yes	Yes
Week FEs	Yes	Yes	Yes	Yes
Day-of-the-week FEs	Yes	Yes	Yes	Yes
Hour FEs	Yes	Yes	Yes	Yes
Observations	61702	61702	61702	61702
Adjusted R^2	0.831	0.833	0.636	0.639

Robust standard errors clustered at the zone level are included in parentheses. *p*-values are included in square brackets.

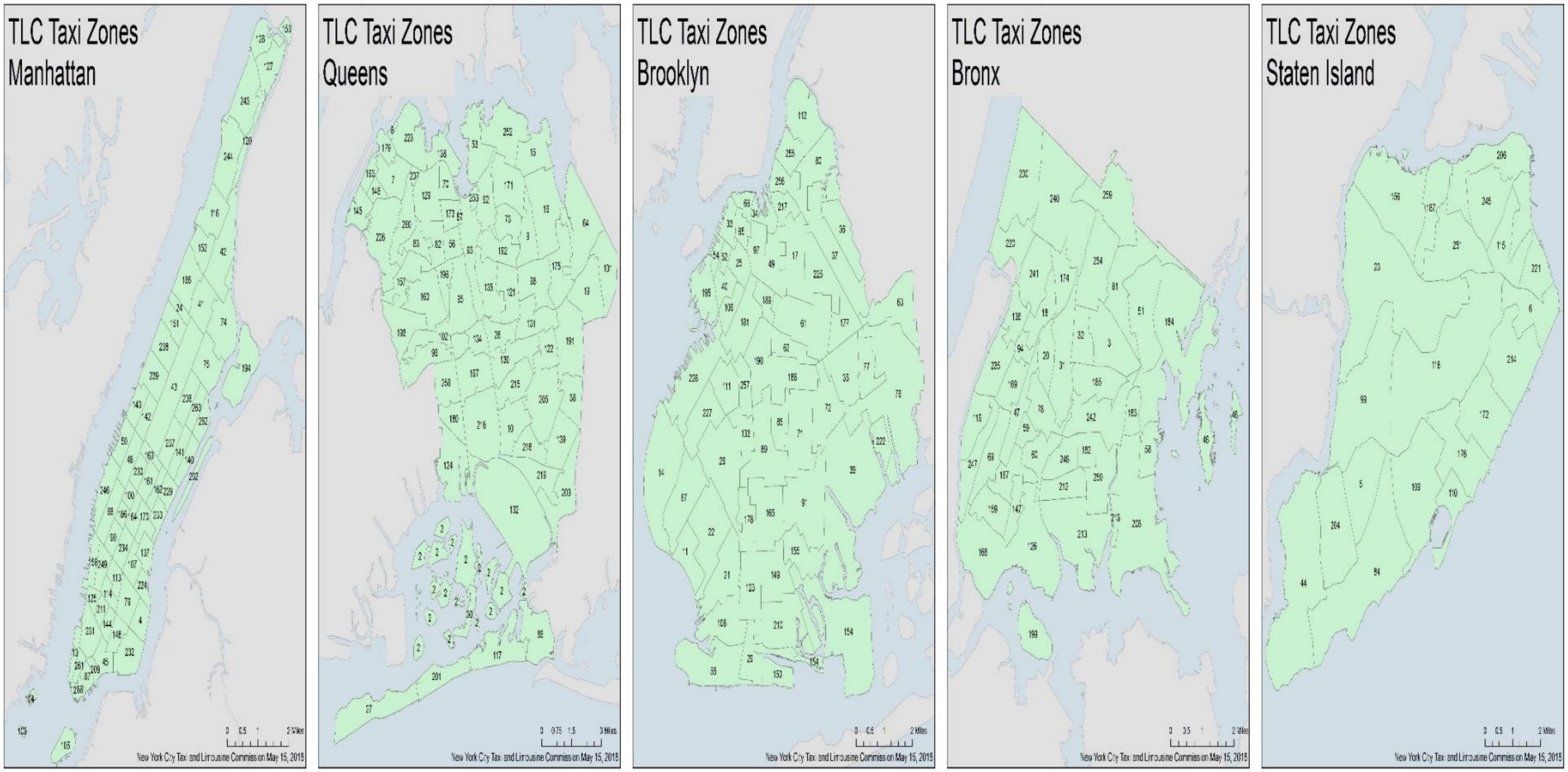
TABLE 7 The effect of DoorDash on Uber and Lyft trip numbers

	(log) Uber Trip #		(log) Lyft Trip #	
	(1)	(2)	(3)	(4)
Post × Brooklyn	-0.005 (0.021) [0.807]	-0.001 (0.021) [0.948]	0.146 (0.119) [0.223]	0.143 (0.122) [0.240]
Post × Brooklyn × RH (7-10 am, 5-8 pm)	-	-0.015 (0.016) [0.362]	-	0.009 (0.027) [0.732]
Brooklyn × RH (7-10 am, 5-8 pm)	-	-0.021 (0.029) [0.475]	-	-0.003 (0.005) [0.577]
Brooklyn × RH (7-10 am, 5-8 pm)	-	-0.035 (0.010) [0.001]	-	-0.009 (0.016) [0.577]
Zone FEs	Yes	Yes	Yes	Yes
Week FEs	Yes	Yes	Yes	Yes
Day-of-the-week FEs	Yes	Yes	Yes	Yes
Hour FEs	Yes	Yes	Yes	Yes
Observations	189419	189419	189419	189419
Adjusted R^2	0.760	0.760	0.359	0.359

Robust standard errors clustered at the zone level are included in parentheses. *p*-values are included in square brackets.

APPENDIX

FIGURE A1 New York taxi zone map



New York City is divided into five boroughs (Manhattan, Bronx, Staten Island, Brooklyn, and Queens), which are further segmented into 263 taxi zones.

Source: TLC Trip Record Data (https://www1.nyc.gov/site/tlc/about/tlc-trip-record-data.page)

TABLE A1 The effect of Uber Eats on Uber and Lyft trip numbers across zones with different population median ages

: Age = 1 if the median population age in a given zone was above 38.67 in 2015 and 0 otherwise

	(log) Uber Trip #		(log) Lyft Trip #	
	(1)	(2)	(3)	(4)
Post × UE restaurants (%)	-2.119 (0.633) [0.001]	-1.481 (1.404) [0.295]	-6.429 (1.984) [0.002]	-6.762 (1.671) [0.000]
Post × UE restaurants (%) × Age (1/0)	-	-0.986 (1.605) [0.541]	-	-0.806 (3.310) [0.808]
Post × Age (1/0)	-	0.056 (0.066) [0.396]	-	0.245 (0.198) [0.221]
(log) Total restaurant #	-0.058 (0.014) [0.000]	-0.050 (0.015) [0.001]	-0.163 (0.089) [0.072]	-0.127 (0.083) [0.128]
Zone FEs	Yes	Yes	Yes	Yes
Week FEs	Yes	Yes	Yes	Yes
Day-of-the-week FEs	Yes	Yes	Yes	Yes
Hour FEs	Yes	Yes	Yes	Yes
Observations	61702	61702	61702	61702
Adjusted R^2	0.831	0.831	0.636	0.637

Robust standard errors clustered at the zone level are included in parentheses. *p*-values are included in square brackets.

TABLE A2 The effect of Uber Eats on Uber and Lyft trip numbers (DID estimation with a binary treatment effect)

	(log) Uber Trip #		(log) Lyft Trip #	
	(1)	(2)	(3)	(4)
Post × UE restaurants (1/0)	-0.202 (0.057) [0.001]	-0.224 (0.060) [0.000]	-0.439 (0.212) [0.042]	-0.493 (0.203) [0.018]
Post × UE restaurants (1/0) × RH (7-10 am, 5-8 pm)	-	0.095 (0.057) [0.103]	-	0.225 (0.108) [0.041]
Post × RH (7-10 am, 5-8 pm)	-	0.200 (0.055) [0.001]	-	0.224 (0.106) [0.039]
UE restaurants (1/0) × RH (7-10 am, 5-8 pm)	-	0.071 (0.074) [0.346]	-	-0.046 (0.082) [0.573]
(log) Total restaurant #	-0.091 (0.024) [0.000]	-0.094 (0.024) [0.000]	-0.241 (0.134) [0.077]	-0.245 (0.135) [0.074]
Zone FEs	Yes	Yes	Yes	Yes
Week FEs	Yes	Yes	Yes	Yes
Day-of-the-week FEs	Yes	Yes	Yes	Yes
Hour FEs	Yes	Yes	Yes	Yes
Observations	61702	61702	61702	61702
Adjusted R^2	0.831	0.833	0.635	0.638

Robust standard errors clustered at the zone level are included in parentheses. *p*-values are included in square brackets.

TABLE A3 The effect of Uber Eats on Uber and Lyft trip numbers (DID estimation using Manhattan as the treated group and outer boroughs as the control group)

	(log) Uber Trip #		(log) Lyft Trip #	
	(1)	(2)	(3)	(4)
Post × Manhattan	-0.474 (0.030) [0.000]	-0.485 (0.032) [0.000]	-0.825 (0.070) [0.000]	-0.816 (0.069) [0.000]
Post × Manhattan × RH (7-10 am, 5-8 pm)	-	0.052 (0.019) [0.007]	-	-0.023 (0.033) [0.485]
Post × RH (7-10 am, 5-8 pm)	-	0.226 (0.011) [0.000]	-	0.437 (0.022) [0.000]
Manhattan × RH (7-10 am, 5-8 pm)	-	0.057 (0.036) [0.114]	-	0.033 (0.043) [0.439]
(log) Total restaurant #	-0.066 (0.036) [0.068]	-0.071 (0.036) [0.049]	-0.188 (0.161) [0.244]	-0.195 (0.161) [0.227]
Zone FEs	Yes	Yes	Yes	Yes
Week FEs	Yes	Yes	Yes	Yes
Day-of-the-week FEs	Yes	Yes	Yes	Yes
Hour FEs	Yes	Yes	Yes	Yes
Observations	220123	220123	220123	220123
Adjusted R^2	0.816	0.817	0.634	0.636

Robust standard errors clustered at the zone level are included in parentheses. *p*-values are included in square brackets.

TABLE A4 The effect of Uber Eats on Uber and Lyft trip numbers (4 weeks before and after the launch of Uber Eats)

: Manhattan core is a binary variable that equals one for zones in Manhattan core areas (below 100th street and 0 otherwise.

	(log) Uber Trip #		(log) Lyft Trip #	
	(1)	(2)	(3)	(4)
Post × Manhattan core	-0.050 (0.016) [0.003]	-0.049 (0.014) [0.001]	-0.038 (0.017) [0.031]	-0.024 (0.022) [0.285]
Post × Manhattan core × RH (7-10 am, 5-8 pm)	-	-0.006 (0.018) [0.752]	-	-0.055 (0.046) [0.235]
Post × RH (7-10 am, 5-8 pm)	-	-0.059 (0.017) [0.001]	-	0.003 (0.043) [0.945]
Manhattan core × RH (7-10 am, 5-8 pm)	-	0.072 (0.056) [0.199]	-	0.175 (0.066) [0.010]
Zone FEs	Yes	Yes	Yes	Yes
Week FEs	Yes	Yes	Yes	Yes
Day-of-the-week FEs	Yes	Yes	Yes	Yes
Hour FEs	Yes	Yes	Yes	Yes
Observations	61588	61588	61588	61588
Adjusted R^2	0.868	0.868	0.658	0.658

Robust standard errors clustered at the zone level are included in parentheses. *p*-values are included in square brackets.

TABLE A5 The effect of Uber Eats on Uber and Lyft trip numbers during weekends

	(log) Uber Trip #		(log) Lyft Trip #	
	(1)	(2)	(3)	(4)
Post × UE restaurants (%)	-2.633 (1.390) [0.063]	-3.189 (1.374) [0.023]	-4.438 (2.223) [0.050]	-4.597 (2.250) [0.045]
Post × UE restaurants (%) × Late Night (Sat 9 pm-Sun 3 am)	-	4.255 (1.516) [0.007]	-	1.089 (1.804) [0.548]
Post × Late Night (Sat 9 pm-Sun 3 am)	-	0.727 (0.090) [0.000]	-	0.581 (0.094) [0.000]
UE restaurants (%) × Late Night (Sat 9 pm-Sun 3 am)	-	0.991 (1.447) [0.496]	-	2.455 (2.105) [0.248]
Late Night (Sat 9 pm-Sun 3 am)	-	-0.306 (0.071) [0.000]	-	-0.350 (0.082) [0.000]
(log) Total restaurant #	-0.191 (0.032) [0.000]	-0.191 (0.032) [0.000]	-0.377 (0.103) [0.001]	-0.376 (0.103) [0.001]
Zone FEs	Yes	Yes	Yes	Yes
Week FEs	Yes	Yes	Yes	Yes
Day-of-the-week FEs	Yes	Yes	Yes	Yes
Hour FEs	Yes	Yes	Yes	Yes
Observations	24655	24655	24655	24655
Adjusted R^2	0.801	0.813	0.652	0.656

Robust standard errors clustered at the zone level are included in parentheses. *p*-values are included in square brackets.