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Spatial Distribution of Access to Service: Theory and Evidence from Ride-Sharing

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Abstract. We study access to ride-sharing across geographical regions using both theoretical and empirical analyses. We specifically model and examine the effects of economies of density in ride-sharing. Our model predicts that (i) economies of density skew access to ride-sharing away from less dense regions; (ii) the skew will be more pronounced for smaller platforms (i.e., "thinner markets"); and (iii) ride-sharing platforms do not find this skew efficient and thus, use price and wage levers to mitigate (but not eliminate) it. We show that these insights are robust to whether the source of economies of density is the supply side or the demand side. We then calibrate our model using ride-level Uber data from New York City. We use the model to simulate counterfactual scenarios, offering a quantitative evaluation of our theoretical results and informing platform strategy and policy.

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Keywords: ride-sharing • spatial markets • transportation • economies of density • market thickness

1. Introduction

Ride-sharing markets form a critical part of transportation networks in major metropolitan areas (Fortune Business Insights 2021). In these markets, ride-sharing firms act as two-sided platforms, intermediating between consumer (passenger) demand and driver supply. Ride-sharing markets are *spatial*, where the characteristics of demand and supply depend on location. Access to ride-sharing service is an important issue that has drawn attention from regulators and lawmakers as well as consumer and community advocates (Jin et al. 2019, Diao et al. 2021). We focus on access, operationalized as the proportion of potential demand that is realized within a region. We examine how market factors drive inequality in access to rides across different geographic areas within a large metropolitan city.

We use a combination of theoretical and empirical analyses to characterize access across regions. We first develop a theoretical model of a multiregion ride-sharing market with a monopolist platform. We then take the model to data using trip-level data from New York City (NYC) focusing on the leading platform, Uber. Finally, we use the calibrated model parameters to evaluate counterfactual scenarios, which provide insights into the findings as well as the underlying mechanisms.

In the theoretical model, each region has an arrival rate of potential demand for rides that could end in the same region or a different one. Actual demand is a fraction of potential demand depending on price (and pickup time) in the region. We incorporate drivers' and passengers' decision making among a set of regions. We model driver free entry, with each driver choosing whether and in which region to enter the market. Each driver makes this choice to maximize her revenue given other drivers' choices. Driver revenue in each region is positively related to the wage per ride in that region and negatively related to the "total wait time" that each driver has to wait in the region to give a ride to a passenger. Total wait time consists of (i) "idle time," which is the time that it takes for the driver to be assigned to a passenger requesting a ride, and (ii) "pickup time," which is the time that it takes to arrive at the pickup location after being assigned to a passenger. Demand results from consumers choosing between ride-sharing and an outside option, with price and pickup time factoring into their decision. The platform sets prices for consumers and wages for drivers in each region.

The elements of wait time play an important role in the resulting accesses in each region and the differences across them. Both idle and pickup times are directly dependent on the number of drivers operating in a region. For a given demand, having more drivers operating in a region implies a higher expected idle time because drivers are competing for the same pool of customers. The impact on pickup time is the inverse of the above. Having more drivers in a region implies a lower expected pickup time because on average, drivers are closer to passengers. Observe that although the idle time causes drivers to spread out across regions, the pickup time incentivizes drivers to agglomerate into fewer regions. We examine how the spatial distribution of access to rides is shaped in response to the incentives of the platform, drivers, and passengers. We consider two different sources of economies of density (EOD) or agglomeration: drivers directly preferring shorter pickup times (supply-side EOD) or demand responding positively to shorter pickup times (demand-side EOD).

The theoretical model's equilibrium analysis leads to some notable results. First, we find that access is skewed in equilibrium in favor of regions with higher density of demand. The underlying mechanism is that sparser regions have higher pickup times, so fewer drivers enter in equilibrium to balance this with idle times. Second, we find that platform size plays a significant role, with smaller platforms having more unequal access. Larger platforms have more demand and correspondingly, more driver entry, leading to lower pickup times in all regions. This reduces the importance of pickup times relative to idle times, resulting in more equal access across regions. Third, we find that a profit-maximizing ride-sharing platform would optimally use price and wage levers to mitigate but not fully eliminate the access skew. The platform implements this by offering higher wages to drivers in sparser regions but only partially passing the extra wage on to passengers, effectively subsidizing sparser regions. The reason is that driver entry into sparser regions has a greater positive externality on other drivers than entry into denser regions, which is internalized by the platform but not the drivers. Finally, we note that these results hold for both sources of economies of density (i.e., supply side and demand side).

We next take the theoretical model to data using data from Uber, the largest ride-sharing platform in NYC, from March to June 2019. We leverage ride-level data on rides (including pickup and drop-off locations), driver wages, and prices across the regions (boroughs) of NYC. The data set is publicly available from NYC's Taxi and Limousine Commission (TLC), and it is rich in frequency of observations, with the complete rides within and across the regions of the city available and collected in a standardized way. We use these data to calibrate and quantify the parameters of our model (e.g., unobservable potential demand and price sensitivity). We consistently find that the density of the potential demand is highest in Manhattan and lowest in Queens. Our estimates for measures, such as the number of drivers and price elasticity, are consistent with regulatory data and existing literature. We test a spectrum of models with different combinations of the supply-side and demand-side EODs and find these results to be robust.

We use our calibrated model to simulate several counterfactual scenarios of interest to complement our theoretical analysis. First, we simulate the platform's optimal heterogeneous price and wage policy and find that in equilibrium, access in the most dense region (Manhattan) is higher by 25% than the least dense region (Queens). Next, we restrict the platform to using the same price and wage across regions. We find that under such a counterfactual, geographical skew in access to rides gets exacerbated; access in the most dense region is higher by 55% than that in the least dense region. These results indicate that the platform would use spatially differentiated pricing to mitigate the access inequality. The implication is that imposing equality in actions taken by the platform across regions could well exacerbate inequality in access that policymakers might care about. Finally, we assess the impact of platform size (i.e., market thickness) on outcomes by scaling up potential demand across all regions. Consistent with our theoretical predictions, we find that as platform size increases, driver entry rises, access levels improve in all regions, and access inequality diminishes. For instance, in one specification, when Uber's potential demand grows from 80% to 120% of the estimated size, the access disparity between the most dense and least dense regions decreases, with the densest region being 28% denser at 80% demand and 22% denser at 120% demand, a 21% decrease in access disparity.

These results are of relevance to platforms, demonstrating the value of different strategies used, specifically decoupled price and wage levers across regions. The findings are also relevant to policymakers who are considering a few ways to regulate platforms, which will impact access disparity. First, regulations imposing a standard wage rate or price across different regions (Parrott and Reich 2018) can hurt access equity by not allowing the platform flexibility to incentivize drivers to serve sparser regions. Second, we consider a policymaker who wants to go to the extreme case of trying to equalize access across regions. Our model suggests that contrary to the optimal pricing policy of the platform (where prices are higher in sparser regions), prices for equalized access would need to be lower in sparser regions. Wages would also need to be substantially higher in sparser regions, leading to more pronounced wage differences across regions. Third, we examine a regulation capping the number of drivers on a platform that has been tried is to reduce platform size (CBS News 2018). Our simulations show that imposing such a cap, although seeming to promote equality of outcomes across firms or higher pay for drivers, can actually make access disparity across regions worse.

In summary, our paper contributes to the study of access differences and economies of density across regions in ride-sharing markets along several aspects. First, our model endows each region with a nontrivial size, which allows us to capture the notion of pickup time in each area and how it varies with driver density. This, in turn, allows us to model economies of density both on the supply side and on the demand side, unlike prior research. Second, our empirical strategy to recover access differences across regions based on relative flows of crossregion rides is powerful and generalizable to other passenger-transportation markets for inferring unfulfilled demand. This approach helps infer unobservable access levels using only ride-level data, which are what is commonly available in most markets, without requiring data based on individual drivers or consumers. Third, our model accommodates and characterizes economies of density based on region characteristics and driver behavior as well as strategic choices made by the platform that contribute to access differences. Finally, we extensively show (both theoretically and empirically) that the major implications of economies of density for ride-sharing markets—as summarized in our main results—are robust to what proportion of economies of density arises from the supply side and what proportion of economies of density arises from the demand side.

There are a few aspects of our model that generalize beyond ride-sharing to spatial markets more broadly. First, our results point to the fact that imposing constraints on firm actions (e.g., prices and wages) to make them more equal across regions may backfire by making other outcomes (e.g., access) more unequal across regions. Second, the concept of relative outflows across regions is generalizable to other passenger-transportation markets for inferring unfulfilled demand. Third, the idea that economies of density create inequity in spatial distribution is likely to exist across many other markets.

2. Literature Review

Our paper relates to multiple strands of literature: (i) the recent and growing literature on the empirical analysis of the geographical distribution of supply and its possible distortion from that of demand in spatial markets, (ii) the literature on transportation markets (in particular, ride-sharing), and (iii) the literature on the effects of market thickness in two-sided markets.

The empirical literature on spatial supply-demand matching is relatively new and limited. To our knowledge, only Buchholz (2022) and Brancaccio et al. (2023) directly examine this issue. These studies extend the empirical methods in the matching literature techniques (see Petrongolo and Pissarides 2001 for a survey) to infer the size of unobserved demand (e.g., passengers searching for rides) in different locations of a decentralized matching market when only the size of supply (e.g., available drivers) and the number of demand-supply matches (e.g., realized rides) are observed. Our calibration based on relative outflows complements this approach. On the one hand, our method requires the additional assumption that potential demand for rides from region i to region i' is the same as that for rides in the opposite direction, which is plausible for passengers with a home base over a daily period. On the other hand, unlike prior methods, our method (i) requires only ride data rather than vacant supply; (ii) applies broadly to centralized (e.g. ride-sharing) and decentralized (e.g., taxis) passenger-transportation markets; and (iii) detects supply skew from a given region even when passengers stop searching because of low supply, which might otherwise appear as low demand.

The second strand of literature relevant to our paper focuses on the market performance and design of transportation, particularly ride-sharing, markets. Although some studies focus on nonspatial questions (e.g., Cohen et al. 2016, Nikzad 2018), others explore spatial aspects (such as Fréchette et al. 2019 and Castillo et al. 2025) without examining the spatial distribution of supply and potential mismatches with demand. Research on geographical supply-demand (im-)balances (e.g., Banerjee et al. 2018, Besbes et al. 2021, Afèche et al. 2023) focuses on short-run, intraday aspects. In contrast, some other papers (such as Shapiro 2018, Bimpikis et al. 2019, and Buchholz 2022) take a long-term view. Our paper complements this literature by providing a detailed theoretical and empirical analysis of economies of density (arising from both supply and demand sides) and market thickness, abstracting away from some of the phenomena considered in these papers. It is worth noting that a significant portion of this literature explores how ride-sharing platforms improve upon traditional taxi systems, particularly through flexible pricing and advanced matching algorithms (Cohen et al. 2016, Cramer and Krueger 2016, Lam and Liu 2017, Shapiro 2018, Besbes et al. 2021, Castillo et al. 2025). We contribute to this body of work by showing that even within centrally matched ride-sharing systems, platform size impacts driver incentives and access disparity across regions.

Also relevant to our work is Rosaia (2023), which examines the NYC ride-sharing market using comprehensive data from Uber and Lyft and employs exogenous price shocks to model drivers' dynamic decision making under platform competition. Compared with Rosaia (2023), our focus is on studying access inequity, and our approach uses a model that expands on the geographic aspects, focusing on the economies of density and market thickness but abstracting from competition. We derive theoretical and empirical insights into these spatial implications, analyzing a broader geographical market that characterizes dense and sparse regions, empirically measuring access differences using relative flows, and conducting counterfactual analyses to inform firm strategy and policy.[1]

The third set of papers to which we relate is a large, mostly theoretical literature on the impact of market thickness on the functioning of two-sided platforms in general (such as Ashlagi et al. 2019 and Akbarpour et al. 2020) and transportation markets in particular (such as Nikzad 2018 and Fréchette et al. 2019). This literature, to our knowledge, has not examined how the spatial distribution of supply—and its (mis-)alignment with that of potential demand—responds to a change in market thickness. Our paper focuses on this both empirically and theoretically.

3. Theoretical Model

We develop a model to study the spatial distribution of access to ride-sharing services in the presence of economies of density. We aim to use the model to understand (i) whether access will be skewed in favor of some regions over others in equilibrium; (ii) whether the skew will be exacerbated or moderated as the platform grows in size; (iii) whether the platform would like to use prices and wages as levers to influence the skew of access and if so, the direction of this influence; and (iv) whether the answers to the previous questions are sensitive to whether economies of density arise from supply or demand side of the market. We abstract away from aspects of the ride-sharing market that are not directly relevant to answering the above questions.

We develop a three-stage model where a monopolistic ride-sharing platform optimally sets prices and wages, drivers decide whether to operate and in which region to operate, and passengers decide whether to take the ride-sharing service. We start with a setting without interregion rides across regions (Section 3.1) and then introduce two variants of the model. First, we model the drivers' equilibrium spatial distribution, where the economies of density come only from the supply-side (referred to as the "model with supply-side EOD" or "supply-side model" for brevity) in Section 3.2. That is, drivers benefit from a larger number of drivers on the platform as it reduces the pickup time and thus, increases revenue. Second, in Section 3.3, we model the equilibrium spatial distribution of drivers with only demand-side economies of density, where we assume that ride demand decreases with pickup time and increases with the number of drivers (referred to as the "model with demand-side EOD" or the "demand-side model" for brevity).[2]

We prove that the following set of results holds for both models. (i) Under the platform's optimal strategy, the equilibrium spatial distribution of rides is skewed toward regions with higher demand densities. (ii) The skew is more intensified for smaller ride-sharing platforms. (iii) The platform's optimal strategy would involve charging lower margins for rides in regions with lower demand densities. Then, we extend the results to the setting with interregion rides across regions in the supply-side model and the demand-side model in Section 3.4.

3.1. Model Setup

We model a market with regions $i \in \{1, \ldots, I\}$ and a monopolist ride-sharing platform serving them. The regions (e.g., neighborhoods and boroughs) are modeled as circumferences of circles à la Salop. The time that it takes a driver to travel a full circumference of circle i is denoted t'_i. Let t' denote the vector $(t'_1, \ldots, t'_I)$. For ease of exposition, we assume that t'_i is measured in hours. Intuitively, t'_i captures the geographical size of the region. For any given numbers of drivers and riders, the drivers and the riders distribute more sparsely in a region as t'_i becomes larger.

In each region, the platform decides price per ride p_i and wage per ride c_i.[3] Let p denote the vector of $(p_1, \ldots, p_I)$ and c denote the vector of $(c_1, \ldots, c_I)$. A distribution of drivers is denoted by vector $n = (n_1, \ldots, n_I)$, where n_i denotes the number of drivers in region i. To ease the analysis, we assume that n_i are real numbers as opposed to integers. Let ω_i denote the pickup time of each ride in region i. Passengers arrive at a rate λ_i per unit of time (i.e., λ_i passengers arrive per hour). Demand arrival rate is a function of price per ride p_i and can also be a function of ω_i depending on our assumption of the source of economies of density. We discuss this in further detail in the subsequent sections. For now, we assume that the demand arrival rate takes the following form:

$$\lambda_i(p_i, \omega_i) = \bar{\lambda}_i f(p_i, \omega_i).$$

$\bar{\lambda}_i$ is the "potential demand" in region i, which captures the total demand of transportation in region i per hour and thus, is the maximum number of realized rides achievable in region i for the ride-sharing platform. Equivalently, this is the volume of demand when both p_i and ω_i are zero. Function $f(\cdot)$—which is assumed to be uniform across regions—captures the fraction of $\bar{\lambda}_i$ that would be willing to pay p_i for a ride given that they observe pickup time ω_i, which is the time that it takes a driver (after being assigned to a ride request) to drive and arrive at the passenger's pickup location. Notation $f(\cdot)$ takes values between zero and one. Notation $\bar{\lambda}$ represents the vector $(\bar{\lambda}_1, \ldots, \bar{\lambda}_I)$.

Given t'_i, λ_i, and n_i, there is a wait time for drivers before they can provide a ride to a passenger. This total wait time is denoted by $W_i(n_i)$ and is a function of n_i, the number of drivers present in the region (this notation suppresses the implicit dependence of W_i on prices as we detail later). Total wait time in each region has two components: idle time and pickup time. Idle time is the time that it takes a driver to get assigned to a ride requested by a passenger. Idle time in region i is increasing in n_i. That is, the more drivers in region i, the longer it takes for each of them to get assigned to a passenger. Pickup time ω_i in region i is decreasing in n_i. This is because the more drivers who are in region i, the more densely the region is populated with them. Therefore, each driver becomes less likely to be asked to pick up a passenger who is far away in the region.[4] We assume that each arriving passenger's location is uniformly distributed on the circumference of the circle. Then, the pickup time ω_i as a function of n_i can be written as

$$\omega_i(n_i; t'_i) = \frac{t'_i}{4n_i}.$$

The total wait time for each region i is given by

$$\underbrace{W_i(n_i)}_{\text{Total Wait Time}} = \underbrace{\frac{n_i}{\lambda_i}}_{\text{Idle Time}} + \underbrace{\frac{t'_i}{4n_i}}_{\text{Pickup Time}} = \left(\frac{n_i}{\lambda_i} + \frac{t_i}{n_i}\right), \tag{1}$$

where $t_i = \frac{t'_i}{4}$. In Online Appendix C, we provide a microfoundation for this functional form. From this point on, we refer to t_i (instead of t'_i) as the size of region i. Let t denote the vector $(t_1, \ldots, t_I)$. Given t_i and $\bar{\lambda}_i$, we define the density of potential demand for region i as $\frac{\bar{\lambda}_i}{t_i}$. Without loss of generality, we assume that the density of potential demand decreases in region index: $\forall i < j : \frac{\bar{\lambda}_i}{t_i} \geq \frac{\bar{\lambda}_j}{t_j}$.

We model a game of three stages. In the first stage, the platform optimally decides prices per ride p_i and wages per ride c_i for each region i to maximize the total profit across all regions. In the second stage, drivers from an infinitely large pool simultaneously decide whether to enter the market and if so, which region to operate in. In the third stage, consumers observe both price p_i and pickup time ω_i and decide whether to choose the ride-sharing service. Then, actual demand λ_i is realized.

We solve the equilibrium using backward induction starting from the third stage. In the third stage, given $\bar{\lambda}_i$, p_i, and ω_i, the actual demand per hour is $\lambda_i = \bar{\lambda}_i f(p_i, \omega_i)$. In the second stage, each driver seeks to maximize her expected hourly revenue. The hourly revenue for a driver in each region i equals the wage per ride in that region multiplied by the frequency of rides assigned to each driver in the region. That is, the revenue is $\frac{c_i}{W_i(n_i)}$.[5] Let $\bar{c}$ denote the exogenously given reservation value (i.e., the hourly revenue that each driver can make by leaving the market and taking the outside option).

Now, we formally define the partial equilibrium distribution of drivers (given p_i and c_i) as follows.

Definition 1. Under "market primitives" $(\bar{\lambda}, t, \bar{c})$ and given the platform's strategy (p, c), a distribution of drivers $n^* = (n^*_1, \ldots, n^*_I)$ among the I regions is called an equilibrium if no small mass of drivers currently operating in region i can strictly profit from changing their strategy and operating instead in region j, where $i, j \in I$.[6] That is, $\exists \delta > 0$ s.t. $\forall i, j \in I$, $\forall \delta' \in [0, \delta]$; we have[7]

$$\frac{c_i}{W_i(n^*_i; p_i)} \geq \frac{c_j}{W_j(n^*_j + \delta'; p_j)}.$$

We call n^* an "all-regions" equilibrium allocation if it is an equilibrium and if $n^*_i > 0$ for all i.

Directly following the definition above, we have the following statement that gives the necessary condition for the partial equilibrium of driver distribution.

Lemma 1. *Suppose function $W_i(\cdot;\cdot)$ is continuous. For any given (p, c), if $n = (n^*_1, \ldots, n^*_I)$ with $n^*_i > 0$ $\forall i$ is the equilibrium distribution of drivers, then*

$$\frac{c_i}{W_i(n^*_i; p_i)} = \bar{c}, \ \ \forall i. \tag{2}$$

Given the drivers' response, in the first stage of the game, the platform optimally chooses (p, c) based on market primitives $(\bar{\lambda}, t, \bar{c})$ to maximize the platform profit, which is the sum of the regional profits. The total number of rides per hour in region i, denoted $r_i(n_i)$, is given by the total number of drivers in that region divided by the time that each driver has to wait before giving a ride: $r_i(n_i) \equiv \frac{n_i}{W_i(n_i)}$. If the distribution of drivers satisfies Equation (2), then $r_i(n^*_i) = \frac{n^*_i(p_i, c_i)}{c_i/\bar{c}}$ in equilibrium. The platform's profit per hour, which is the object that the platform seeks to maximize by choosing regional prices and wages, is given by

$$\pi(p, c) = \Sigma_{i=1}^{I} (p_i - c_i) r_i(n_i(p_i, c_i)).$$

Then, the equilibrium of the game is given by $(p^*, c^*, n^*, \lambda^*)$, where p^* and c^* are the prices and wages, respectively, that maximize platform profit; n^* is the equilibrium driver distribution given (p^*, c^*); and λ^* is the actual demand corresponding to prices p^* and pickup times $\omega_i(n^*)$ of each region.

Next, we introduce the notion of "access" to rides in region i by $A_i(n_i)$ and define it as the fraction of the potential demand $\bar{\lambda}_i$ that leads to rides. That is,

$$A_i(n_i) \equiv \frac{r_i(n_i)}{\bar{\lambda}_i}. \tag{3}$$

3.2. Supply-Side Economies of Density

In this section, we assume that the market involves supply-side economies of density (but does not involve demand-side economies of density). That is, a driver in a given region i can benefit from the presence of other drivers in that region because with higher driver density, she is less likely to be asked to pick up a passenger far away in the region. On the other hand, to abstract from the effect from the demand-side EOD, we assume that passengers' arrival rate does not depend on the number of drivers (and hence, on pickup time). Specifically, given $\bar{\lambda}_i$, the demand arrival rate of region i is only a function of p_i, and we assume that $f(p_i, \omega_i) = 1 - \alpha p_i$ so that[8]

$$\lambda_i = \bar{\lambda}_i(1 - \alpha p_i).$$

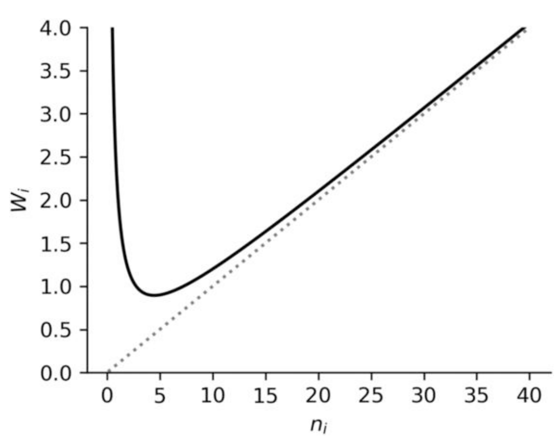
Accordingly, the wait time is given by

$$W_i(n_i) = \frac{n_i}{\bar{\lambda}_i(1 - \alpha p_i)} + \frac{t_i}{n_i}, \tag{4}$$

where the first component is the idle time and the second component is the pickup time. The wait time curve given by Equation (4) is illustrated in Figure 1. As can be seen, $W_i(\cdot)$ is initially decreasing in n_i because the effect of pickup time is dominant. When n_i is large enough, pickup time becomes less important and $W_i(\cdot)$ becomes increasing in n_i because of the effect of idle time.

In the propositions below, we characterize the equilibrium spatial distribution of supply and how this distribution changes in response to a changed market thickness.

Figure 1. Wait Time as a Function of the Number of Drivers



Notes. The function is given by Equation (4). The figure is illustrated with $\lambda_i(p_i) = 10$ and $t_i = 2$. The dashed line is $\frac{n_i}{\lambda_i}$, depicting how long the wait time would be if pickup time was zero.

Lemma 2. *Suppose prices and wages are both positive and flexible and that market primitives are $(\bar{\lambda}, t, \alpha, \bar{c})$. Then, an equilibrium (p^*, c^*, n^*) exists, and n^* is unique. Also, p_i^* and c_i^* for any i with $n_i^* > 0$ are unique.*

Proposition 1. *Suppose prices and wages are both flexible and that market primitives are $(\bar{\lambda}, t, \alpha, \bar{c})$. Also, suppose (p^*, c^*, n^*) is an equilibrium. Then, for any two regions i, j with $n_i^* \neq 0 \neq n_j^*$, we have*

$$\frac{\bar{\lambda}_i}{t_i} \geq \frac{\bar{\lambda}_j}{t_j} \Rightarrow A_i(n_i^*) \geq A_j(n_j^*),$$

where the latter comparison holds with equality only if the first one does. Moreover, regions that are not supplied are those with lowest demand densities:

$$\exists \mu > 0: \text{ s.t. } \forall i: \frac{\bar{\lambda}_i}{t_i} < \mu \Leftrightarrow n_i^* = 0.$$

The proof is provided in Online Appendix E.1, but here, we develop an informal intuition for the above proposition in two steps. First, we argue that if all prices and wages were spatially homogeneous, equilibrium driver allocation (fixing those prices and wages) would give higher access to rides in denser regions relative to sparser ones. Next, we argue that the platform does not have the incentive to use prices and wages to fully eliminate such an access skew.

For intuition of the first argument in the previous paragraph, consider regions i and j with $\frac{\bar{\lambda}_i}{t_i} > \frac{\bar{\lambda}_j}{t_j}$ and observe that with spatially homogeneous prices and wages, the total wait time for drivers should be the same between the two regions. This directly implies that the distribution of drivers should be skewed toward i: that is, $\frac{n_i}{n_j} > \frac{\bar{\lambda}_i}{\bar{\lambda}_j}$. To see why, note that if we instead had $\frac{n_i}{n_j} = \frac{\bar{\lambda}_i}{\bar{\lambda}_j}$, then idle times would be equal between the two regions, but pickup time in region i would be shorter than that in j, incentivizing drivers to relocate from j to i. But, given that total driver wait times are equal between the regions, $\frac{n_i}{n_j} > \frac{\bar{\lambda}_i}{\bar{\lambda}_j}$ is equivalent to $\frac{r_i}{r_j} > \frac{\bar{\lambda}_i}{\bar{\lambda}_j}$, which by definition, means $A_i > A_j$.

It is helpful to understand the intuition for why the platform does not benefit from fully eliminating the access gap. The simple argument here is that long times en route for pickups spent by drivers hurts not only drivers themselves but also, the profitability of the platform. As a result, it should not be surprising that the platform's optimal decision accounts for driver incentives (and pays drivers more to compensate for longer pickup times).

Consider the case of equal access across all regions. Drivers in less dense regions would have a greater pickup time, whereas the idle time would be the same across all regions if the price and the wage are the same. In such a case, drivers would have a higher wait time in sparser regions and would have to be compensated more.

Next, we turn to examining the impact of platform size (i.e., market thickness) on the access skew across regions. Before that, we provide a formal definition of market thickening.

Definition 2. Consider a market with the primitive of potential demand as $\bar{\lambda}$. We call a market with potential demand $\gamma\bar{\lambda}$ with $\gamma > 1$ and all other primitives remaining the same a "thickening" of the market with potential demand $\bar{\lambda}$.

Intuitively, market thickening increases the potential demand in each region proportionally so that the ratio of potential demand is *preserved* between any two regions. Nevertheless, as our next result shows, making a market thicker will mitigate the skew of supply distribution.

Proposition 2. *Suppose prices and wages are both flexible and that market primitives are $(\bar{\lambda}, t, \alpha, \bar{c})$, for which (p^*, c^*, n^*) is an equilibrium. Consider a thickening of the market from $(\bar{\lambda}, t, \alpha, \bar{c})$ to $(\gamma\bar{\lambda}, t, \alpha, \bar{c})$ where $\gamma > 1$. Then, the following are true.*

1. *There exists an equilibrium $(p^{*'}, c^{*'}, n^{*'})$ under the new primitives $(\gamma\bar{\lambda}, t, \alpha, \bar{c})$, where $n^{*'}$ is unique. Also, $p_i^{*'}$ and $c_i^{*'}$ for any i with $n_i^{*'} > 0$ are unique.*
2. *For any i, $n_i^* > 0 \Rightarrow n_i^{*'} > 0$.*
3. *For any i, j,*

$$\frac{\bar{\lambda}_i}{t_i} \geq \frac{\bar{\lambda}_j}{t_j} \Rightarrow \frac{A_j(n_j^*)}{A_i(n_i^*)} \leq \frac{A_j(n_j^{*'})}{A_i(n_i^{*'})} \leq 1.$$

4. *There will be equitable access to rides as the market gets sufficiently thick*:

$$\forall i, j: \lim_{\gamma \to \infty} \frac{A_j(n_j^{*'})}{A_i(n_i^{*'})} = 1.$$

Recall that we assume that passengers are matched with the closest drivers.[9] The intuition for the result is that as the market thickens (i.e., the platform grows), all regions become denser with both drivers and passengers. As such, the importance of pickup times relative to idle times decreases in drivers' decision making, leading to a supply distribution that is more balanced with demand.

We now delve deeper into the incentives of the platform and how they align with those of the drivers. In interpreting Proposition 1, we argued that the platform, similarly to drivers, does suffer from long pickup times and hence, is not willing to use prices and wages to fully eliminate access skew among regions of different densities. The next natural question is as follows. Does the platform have the incentive to at least mitigate the skew? The following proposition sheds light on this.

Proposition 3. *Suppose prices and wages are both flexible and that market primitives are $(\bar{\lambda}, t, \alpha, \bar{c})$. Also, suppose (p^*, c^*, n^*) is an equilibrium. For any regions i, j with $n_i^* \neq 0 \neq n_j^*$, we have*

$$\frac{\bar{\lambda}_i}{t_i} \geq \frac{\bar{\lambda}_j}{t_j} \Rightarrow \begin{cases} p_i^* \leq p_j^* \\ c_i^* \leq c_j^* \\ p_i^* - c_i^* \geq p_j^* - c_j^*, \end{cases}$$

where the latter three comparisons hold with equality only if the first one does.

As this proposition shows, the platform obtains lower margins $(p_i - c_i)$ for its services in less dense regions. That is, the platform optimally gives higher wages to drivers in sparser regions but does not pass the entire wage increase on to passengers in the form of higher prices. Thus, the platform effectively "subsidizes" sparser regions relative to denser ones. This is consistent with an incentive to mitigate the access skew across regions. The intuition for why the platform would like to mitigate the access skew has to do with *externalities*. Consider a driver's decision to operate in a denser region i as opposed to a sparser region j. This choice leaves region j even sparser, thereby increasing the pickup time in j and negatively affecting incentives of other drivers to choose j. Although the driver's decision to operate in region i makes the region even denser, the positive marginal impact of region i being denser does not compensate for the loss from region j being sparser. This externality on other drivers is internalized by the platform through profits but not directly internalized by the driver. This creates a wedge between platform and driver incentives and leads the platform to use price and wage levers to mitigate such externalities by drivers.

There are a few interesting observations. First, the platform's optimal strategy is more complex than what it might seem based on the intuition in the above paragraph. The complexity arises from the fact that the platform simultaneously determines optimal prices and optimal wages; offering higher wages in sparser regions puts some upward pressure on prices. Likewise, lower prices in sparser regions put some downward pressure on wages. One question, which Proposition 3 above helps answer, is which lever, prices or wages, the platform uses to mitigate the access skew. Proposition 3 suggests that in sparser regions, the platform optimally builds economies of density by providing higher wages. Despite the platform charging higher prices, which reduces the economies of density, the overall effect of lower wage dominates. Thus, the platform trades off getting a lower margin in sparser regions in order to build economies of density.

In the empirical section (Section 6.1), we connect the margin results in Proposition 3 to access. Specifically, in our counterfactual simulations, we show that access among regions becomes more skewed if the platform is restricted to spatially uniform prices and wages (and thus, spatially uniform margins). With our analysis of supply-side model completed, we now turn to a version of the model where economies of density arise only from the demand side, and we study if the above insights are robust to such a change in the model.

3.3. Demand-Side Economies of Density

The pickup time for a driver is equivalent to the total wait time experienced by a passenger riding with that driver, and it decreases as the number of drivers increases. Therefore, it is natural to model the riders' sensitivity to pickup time as demand-side EOD and examine the consequences of it. This would be a model for demand-side economies of density; longer pickup times in sparser regions diminish demand in those regions, making the market sparser and further increasing local pickup times.

We model demand-side EOD *only*, where pickup times do not directly impact driver behavior or revenue but impact passengers. To incorporate the latter assumption, we need to make demand λ_i a function of not only prices but also, pickup times:

$$\lambda_i(p_i, n_i) = \bar{\lambda}_i(1 - \alpha p_i)\left(1 - \beta \frac{t_i}{n_i}\right),$$

where $\alpha > 0$ measures the price sensitivity and $\beta > 0$ measures the sensitivity to pickup time, thereby capturing the magnitude of demand-side economies of density.

To capture the idea that pickup times do not directly impact drivers, we need to make two assumptions. First, region sizes t_i (and hence, pickup times) are so small that driver wait time is approximated by idle time only. Second, in spite of all t_i values being vanishingly small, the sensitivity to pickup times β is sufficiently large so that $\beta \times t_i$ values are nonnegligible, and hence, passengers still care about pickup times. In this setting, driver wait times are given by

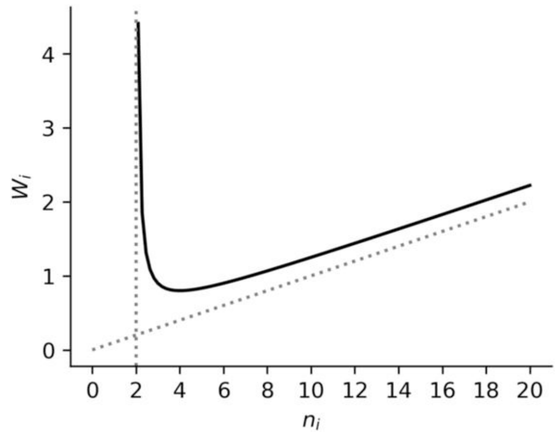
$$W_i(n_i) = \frac{n_i}{\lambda_i(p_i, n_i)} = \frac{n_i}{\bar{\lambda}_i(1 - \alpha p_i)(1 - \beta \frac{t_i}{n_i})}. \qquad (5)$$

The wait time curve is illustrated in Figure 2. Similar to the model with supply-side EOD, $W_i(\cdot)$ initially decreases in n_i as the effect of pickup time dominates. As n_i is large enough, $W_i(\cdot)$ becomes increasing in n_i because of the effect of idle time. The number of rides per hour, r_i, and access, A_i, are as previously defined.

The following proposition characterizes the equilibrium spatial distribution of supply and its response to market thickness under demand-side economies of density.

Proposition 4. *Suppose the market primitives are* $(\bar{\lambda}, t, \alpha, \beta, \bar{c})$. *Both prices and wages are flexible. Under the model with demand-side economies of density, all propositions with the model with supply-side economies of density (Lemma 2 and Propositions 1–3) continue to hold.*[10]

Figure 2. Wait Time as a Function of the Number of Drivers



Notes. The function is given by Equation (5). The figure is illustrated with $\bar{\lambda}_i(1 - \alpha p_i) = 10$ and $\beta t_i = 2$.

The key lesson from this proposition is that our main insights are robust to the source of economies of density. This is because both supply-side and demand-side models share a similar mechanism. We detail the underlying intuition connecting the models.[11] In equilibrium, drivers distribute across regions to balance the idle time and pickup time in different regions. Recall that idle time increases with the number of drivers in a region, whereas pickup time asymptotically goes to zero as the number of drivers grows. The difference between the supply-side and demand-side models lies in how the pickup time affects drivers' payoffs. In the supply-side model, pickup time directly affects drivers' payoffs because they internalize this as a cost, similar to idle time. In the demand-side model, drivers are not directly sensitive to pickup time. However, they are indirectly impacted by it because consumer demand is responsive to pickup time (in addition to price). Specifically, demand decreases as pickup time increases. Thus, in both models, pickup time has either a direct or indirect impact on the drivers in the same direction. Because both direct and indirect effects above are directionally (and qualitatively) similar in terms of the impact on drivers, we should expect the main results to hold regardless of the source of economies of density (supply side or demand side). Proposition 4 verifies that this is indeed the case.

In addition to being interesting in its own right, the robustness of our main insights to the source of economies of density will play a key role in our empirical analysis; there, we will argue that demand- and supply-side economies of density are not separately identifiable from each other (at least with ride-level data). Hence, robustness of our main insights to the source of economies of density becomes crucial when it comes to practical recommendations to firms and policymakers. Next, we include interregion rides to make the model realistic for empirical analysis.

3.4. Interregion Rides

An abstraction in our model so far is the assumption that rides take place only within regions. In this section, we first define the equilibrium notion with interregion rides. Then, we show that Propositions 1–4 continue to hold with interregion rides.

Let $\bar{\lambda}_{ij}$ denote the potential demand for rides from region i to region j. By construction, we have $\bar{\lambda}_i = \Sigma_j \bar{\lambda}_{ij}$. Define realized demand $\lambda_{ij}(p_i, \omega_i)$ in a similar way: $\lambda_{ij}(p_i, \omega_i) = \bar{\lambda}_{ij} f(p_i, \omega_i)$. Define r_{ij} as the realized number of rides from i to j. In this framework, one can think of n_i, the number of drivers in region i, as a stock variable with flows in and out. Realized r_{ij} values lead to "crossregional flows" of drivers. These flows of drivers are already in the market. In addition, we also allow for a (negative or positive) net flow of drivers ρ_i from each region i to the outside option. In this setting, we need a new notion of equilibrium, which is given by Definition 3.

Definition 3. Suppose the "market primitives" $(\bar{\lambda}, t, \bar{c})$ and platform strategy (p, c) are given. Let ρ_i denote the (positive or negative) net flow of drivers out of each region i. $n^* = (n_1^*, \ldots, n_I^*)$ denotes the distribution of drivers among the I regions. The pair of vectors (n^*, ρ^*) is an equilibrium if it satisfies the following two conditions.

1. Steady state. Net flow out of each region i is zero: $\forall i: \rho_i^* + \sum_j r_{ij}^* - \sum_j r_{ji}^* = 0$.
2. Optimality. No small perturbation in rates ρ^* is able to strictly improve driver revenue in any region. Formally, fixing some elapsed time $\bar{T} > 0$ and perturbation $\Delta\rho \neq 0$, the following will hold $\forall i \in I$, $\forall T \in (0, \bar{T})$:

$$\frac{c_i}{W_i(n_i^*)} \geq \frac{c_i}{W(n_i^* + T \times \Delta\rho)}.$$

Also, we call n^* an "all-regions" equilibrium allocation if (n^*, ρ^*) it is an equilibrium and if $n_i^* > 0$ for all i.

We now show that the results provided in the previous sections (i.e., without interregion rides) all hold with interregion rides as well. Proposition 5 formalizes this.

Proposition 5. *Suppose market primitives* $(\bar{\lambda}, t, \bar{c})$ *and platform strategy* (c, p) *are given. Then, for any* (n^*, ρ^*) *with* $n^* \gg 0$, *the pair* (n^*, ρ^*) *is a driver equilibrium according to* Definition 3 *if and only if* n^* *is a driver equilibrium in the no interregion ride version of the problem.*

The proof of this proposition is straightforward, and it is provided in Online Appendix E.3. This result shows that as long as we focus on all-region equilibria, all of our results from Section 3.2 and Section 3.3 should hold. The intuition is simple. If there are too many incoming rides into a region i with overall low payoff, that will lead to many drivers opting to exit the market and pursue an outside option upon dropping a passenger in i. Similarly, attractive payoff in a region i with low inflow of rides will garner higher entry of local drivers.

Note that the purpose of Proposition 5 is *not* to provide conceptually new insights on economies of density (the proposition only claims that the old results hold). The purpose is, rather, to connect our theory to the forthcoming empirical analysis, where we will use relative magnitudes of interregion rides to identify the strength of economies of density and measure access skew. Next, we detail the data used in the empirical analysis.

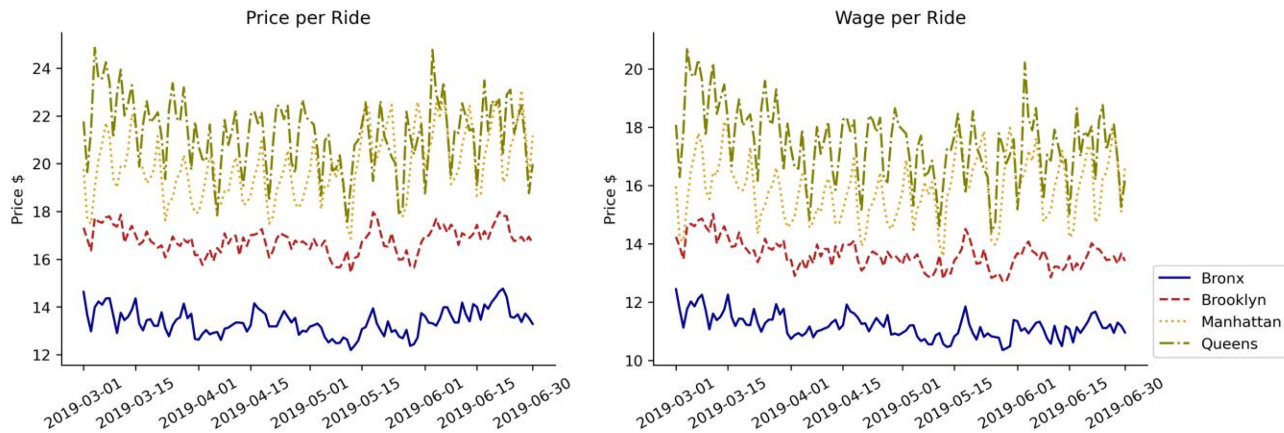
4. Data and Summary Statistics

The primary source of data is the ride-level data on Uber in New York City from March to June in 2019. The data set is publicly available from NYC's Taxi and Limousine Commission. Uber is the largest ridesharing platform, whose total number of rides given in NYC per month was about 14.4 million in June 2019. The regions are defined as the four boroughs of NYC: Bronx, Brooklyn, Manhattan, and Queens.[12] We use the terms *region* and *borough* interchangeably in the following sections of this paper. For each ride, we observe the exact date, time, and location for both the pickup and the drop-off. Besides, we observe the wage paid to the driver and the price paid by the passenger.[13]

There are a number of reasons why we chose the NYC TLC data from March to June 2019 as the setting for our empirical analysis. First, TLC provides data on both pickup and drop-off locations. Second, starting in February 2019, additional ride-level price and wage data became available. Both of these features play key roles in our analysis. Third, NYC is one of the densest cities in the world. Therefore, if frictions from low density impact the spatial distribution of supply and access in NYC, it is reasonable to conclude that they must also be relevant in other ride-sharing markets.

We aggregate the ride-level data at the borough-day level. For each borough i and day d, we calculate the average price per ride, p_{id}, and the average wage per ride, c_{id}, for all rides originating from borough i on day d. Figure 3 illustrates the daily average prices and wages by borough throughout the data set. Additionally, we compute the average number of rides picked up from each borough per hour, denoted as r_{id}. Table 1 reports the summary statistics of these variables for each borough across days, revealing

Figure 3. (Color online) Price and Wage Across Days and Boroughs



substantial variation in all three variables across regions and days. For the reservation level of wage, $\bar{c}$, set to \$24, we rely on figures from Hall and Krueger (2017), who report this as the mean hourly gross earnings before expenses for NYC UberX drivers for October 2015.[14] We set $\bar{c}$ to be uniform across boroughs and across days. Finally, we use data on the borough areas (in square miles)[15] and calculate the square root of each area, denoted as s_i.[16]

Before introducing the empirical model, we present some data patterns that shed light on connections between our theoretical results and the empirical analysis. Figure 4 provides evidence suggesting that access is skewed toward denser regions. The first panel of Figure 4 shows population density (people per square miles) by borough, whereas the second panel of Figure 4 displays the average number of drop-offs per hour normalized by region size s_i as previously defined. Both measures serve as loose proxies for ride demand. The third panel of Figure 4 presents the average number of pickups per hour normalized by s_i. Perhaps unsurprisingly, as shown in Figure 4, the rank ordering among the four boroughs is consistent across the first three panels of Figure 4: Manhattan, Brooklyn, Bronx, and Queens. The fourth panel of Figure 4 displays the pickup/drop-off ratio for each borough. If every passenger who used Uber to leave a borough also used Uber to return, all these ratios would equal one. Interestingly, however, the ratios differ from one and follow the same rank ordering as the other measures: Manhattan, Brooklyn, Bronx, and Queens. This suggests that access to rides is easier in denser regions, consistent with the predictions of our theory.

Based on the intuition provided by Figure 4, we now construct a measure that will prove directly useful in our empirical analysis. Using the interregion rides r_{ijd}, defined as the average number of rides per hour starting in borough i and ending in borough j on a given day d, we construct the "relative outflow" between i and j as follows:

$$RO_{ijd} = \frac{r_{ijd}}{r_{jid}}. \tag{6}$$

Table 2 displays all such pair-wise relative outflows from our data averaged across days. Interestingly, for any two boroughs i, j, where i is denser than j in any of the first three panels of Figure 4, we have $RO_{ij} > 1$. Again, this suggests that rides are more accessible in those denser regions, consistent with our theory. The next section further formalizes this idea, clearly sets out the assumptions underneath it, and develops it into an identification/estimation strategy.

5. Empirical Model

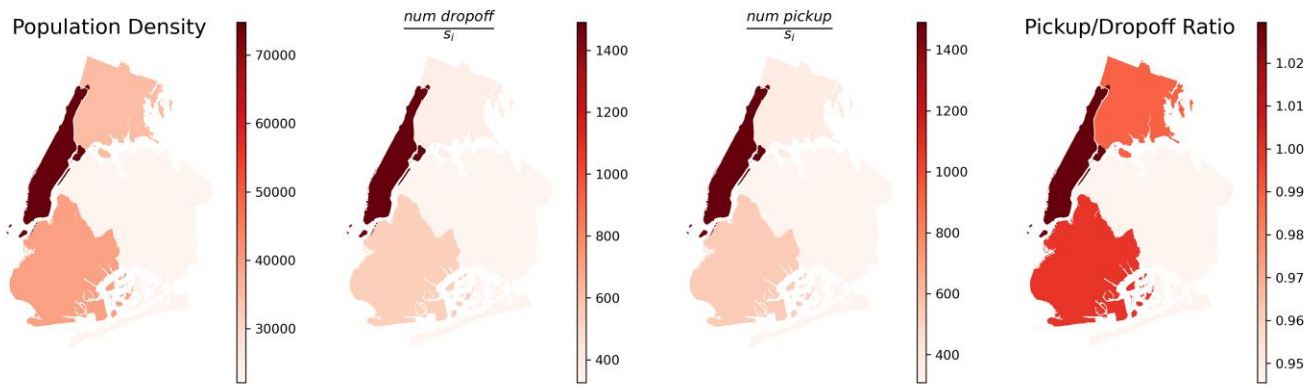
Our theory model characterizes platform, driver, and passenger behavior under a profit-maximizing assumption for platforms and drivers. We now take the model

Table 1. Summary Statistics of the Number of Rides, Price, and Wage at the Borough-Day Level

	Number of rides (r_{id})			Price (p_{id})			Wage (c_{id})		
Borough	q25	Median	q75	q25	Median	q75	q25	Median	q75
Bronx	2,181	2,334	2,654	13.0	13.3	13.7	10.9	11.1	11.4
Brooklyn	3,853	4,334	5,012	16.5	16.8	17.1	13.3	13.6	13.9
Manhattan	6,559	7,265	7,944	18.9	19.8	21.0	15.1	15.9	16.6
Queens	2,934	3,146	3,504	20.3	21.4	22.3	16.6	17.6	18.2

Note. q25 and q75 denote the 25th and 75th percentiles (first and third quartiles), respectively.

Figure 4. (Color online) Population Density, Drop-offs, Pickups, and Pickup/Drop-off Ratios by Borough



to data to obtain parameter estimates of model primitives and to run counterfactual analyses to provide policy recommendations. Section 5.1 sets up the empirical calibration problem, specifying observable data and parameters to be calibrated. Section 5.2 presents the empirical model with supply-side EOD. Section 5.3 presents the empirical model with demand-side EOD. Section 5.4 introduces a comprehensive model that incorporates both supply-side and demand-side EOD. Before describing the model, we summarize the notation used for both the theoretical and empirical models in Online Appendix A.

5.1. Connecting the Model to Data and the Role of Interregion Rides

This section sets up the empirical calibration problem. We detail a proposition that will prove useful in finding the solution to the problem.

Start by noting that each driver makes $\frac{1}{W_{id}}$ trips per unit of time, which in our context, corresponds to trips per hour. Thus, the number of rides is given by $r_{id} = \frac{n_{id}}{W_{id}}$. Free entry of drivers ensures that drivers' revenue is equivalent to the outside option in equilibrium, implying $W_{id} = \frac{c_{id}}{\bar{c}}$. These relationships imply that the number of drivers can be directly estimated on the data from the number of trips, driver wage, and the outside option:

$$n_{id} = r_{id} \times \frac{c_{id}}{\bar{c}}. \tag{7}$$

Let $\mathcal{D}$ denote the set of observable data and the variables that can be derived from the data as described above: $\mathcal{D} = \{p_{id}, c_{id}, r_{id}, n_{id}\}_{i\in I, d\in D} \cup \{r_{ijd}\}_{i,j\in I, d\in D} \cup \{\bar{c}\}$, where I denotes the set of regions and D denotes the set of days covered in our data set. The objective of our empirical exercise will be to recover using $\mathcal{D}$ the following set of parameters: $\{\bar{\lambda}_{id}\}_{i\in I, d\in D}, \{t_i\}_{i\in I}, \alpha, \beta$.

In recovering the above parameters, we leverage additional parameterization as well as additional results based on our model. Starting by region sizes t_i, we assume $\forall i : t_i = a \times s_i$, where s_i is the square root of borough i's area (hence, observable) and a is a parameter to be estimated. This parameter could be interpreted as the expected pickup time in a region if the region had one driver per unit of size. We assume that a is homogeneous across regions.[17] This approach reduces the estimation burden for sizes t_i to only one scalar.

For unobservable potential demand $\bar{\lambda}_{id}$, we leverage an assumption that crossregional demand is balanced: $\forall i, j \in I$, $\bar{\lambda}_{ij} = \bar{\lambda}_{ji}$. The motivation for this assumption is that given that our time periods are daily, for every trip, there is a "return trip" shortly after. We now show that this assumption combined with the rest of the structure of our model creates a tight connection between the unobservable potential demand and the observable ride counts.

Proposition 6. *Let I denote the set of regions served by the platform. (n, ρ) is a steady-state (not necessarily equilibrium) driver allocation according to* Definition 3 *under $(c, p, \bar{\lambda}, t)$. Suppose that potential demand for rides is "balanced": $\forall i, j \in I$, $\bar{\lambda}_{ij} = \bar{\lambda}_{ji}$. Also, suppose that the proportion of unfulfilled demand does not depend on destination: $\forall i, j \in I$, $\frac{r_{ij}}{\bar{\lambda}_{ij}} = \frac{r_i}{\bar{\lambda}_i} = A_i$.*[18] *Then, we have*

$$\forall i, j \in I, \frac{\frac{r_i}{\bar{\lambda}_i}}{\frac{r_j}{\bar{\lambda}_j}} \equiv \frac{A_i}{A_j} = \frac{r_{ij}}{r_{ji}} \equiv RO_{ij}.$$

The proof can be found in Online Appendix F.1. This result shows that the access ratio between two regions is equal to the relative outflow. To interpret the result, if region i has a lower access than region j (that is, the supply is more skewed to region j rather

Table 2. Average Relative Outflows RO_{ij} Across Days

	Region j			
Region i	Bronx	Brooklyn	Manhattan	Queens
Bronx	—	0.93	0.93	1.05
Brooklyn	1.07	—	0.91	1.14
Manhattan	1.07	1.1	—	1.25
Queens	0.96	0.87	0.8	—

than region i), then there are more interregion rides from j to i than those from i to j following our assumptions. This illustrates how observable relative flows RO_{ij} help infer the skew among unobservable access levels A_i and A_j, which in turn, helps calibrate the magnitude of economies of density. We carry out this calibration exercise for both supply-side and demand-side models.

Although the assumptions in Proposition 6 are nontrivial, the approach provides meaningful advantages. First, the data requirement is mild: only the numbers of rides rather than vacant cars, search behavior, etc. Second, it can help identify spatial supply-demand mismatch (i.e., skew in access) in passenger transportation markets regardless of whether the matching technology is centralized or decentralized. The measure of potential demand that it helps infer (as we do later in the calibration procedure) includes not just the set of passengers who searched for rides by showing up on their app but failed to obtain a ride but also, those who skipped searching for rides in the first place because of anticipating that one would be difficult to find or that the rides are too expensive.[19]

With this result at hand, we next turn to empirically calibrating our model.

5.2. Supply-Side Economies of Density

We adapt the theory model with supply-side economies of density to the empirical setting here. Next, we describe the procedure to estimate the model parameters with the data. Finally, we show the identification of the model parameters.

In contrast to the theory section, here we do not (need to) assume that the platform optimally sets prices and wages in the empirical model. Instead, we focus on estimating the model parameters from the driver and passenger behavior, and our approach is agnostic to the price- and wage-setting process. Our focus in on using the estimated model parameters to make recommendations to the platform in our counterfactual analysis.

Recall from the theory in Section 3.2 that for each region i and each day d, given the market primitives $(\bar{\lambda}_{id}, t_i, \bar{c}, \alpha)$ and (p_{id}, c_{id}) chosen by the platform, the equilibrium number of drivers is given by

$$\frac{c_{id}}{W_{id}(n_{id})} = \bar{c}.$$

Following the theoretical model, the wait time is given by $W_{id} = \frac{n_{id}}{\bar{\lambda}_{id}(1-\alpha p_{id})} + \frac{t_i}{n_{id}}$.[20]

We had operationalized the region size parameter t as $t_i = as_i$, where s_i is the square root of the region (borough) size and therefore, is observable. Thus, having n_{id} estimated from Equation (7) and observable platform choices p_{id} and c_{id}, the driver free entry equilibrium ensures that the wait time obtained equates the drivers' ride-sharing wage to the outside option. This leads to the following estimating equation:

$$\frac{n_{id}}{\bar{\lambda}_{id}(1-\alpha p_{id})} + \frac{as_i}{n_{id}} = \frac{c_{id}}{\bar{c}}. \tag{8}$$

The parameters to be estimated in the supply-side model are, therefore, $(\alpha, a, \{\bar{\lambda}_{id}\}_{i\in I, d\in D})$.

5.2.1. Calibration. The model calibration follows two steps. First, for any candidate pair (α, a), we use the model structure and observable data to recover the potential demand $\bar{\lambda}_{id}$ for each region i and day d. Next, we use these recovered potential demand values to simulate relative outflows between pairs of regions, which are inherently a function of the initial (α, a). We then match these simulated relative outflows to the observed data by minimizing the sum of squared differences, yielding estimates $(\hat{\alpha}, \hat{a})$ (McFadden 1989). Formally, our steps are as follows.

Step 1. We obtain the number of drivers from the data following Equation (7). Using the number of drivers, Equation (8) allows us to express $\bar{\lambda}_{id}$ in terms of data (p_{id}, c_{id}, s_i, and now, n_{id}) and parameters (a, α) as follows:

$$\bar{\lambda}_{id}(a, \alpha; \mathcal{D}) = \frac{n_{id}}{(1-\alpha p_{id})(\frac{c_{id}}{\bar{c}} - \frac{as_i}{n_{id}})}. \tag{9}$$

Step 2. Given the observables and following Step 1, we express the relative outflow given by the empirical model between each pair of regions i, j on each day d as a function of the parameters (a, α):

$$RO^{model}_{ijd} = \frac{A_{id}}{A_{jd}} = \frac{r_i/\bar{\lambda}_{id}(a, \alpha; \mathcal{D})}{r_j/\bar{\lambda}_{jd}(a, \alpha; \mathcal{D})},$$

where the first equality is given by Proposition 6 and the second equality is given by the definition of access as in Equation (3). We estimate (a, α) by matching the moments of RO_{ij} for every pair of regions i, j, where we take the average difference in RO_{ij} across $d \in D$ between the model simulation and the data. Specifically, for each pair of regions i, j, denote $d_{ij}(a, \alpha; \mathcal{D}) = |\frac{1}{|D|}\sum_d RO^{model}_{ijd}(a, \alpha; \mathcal{D}) - \frac{1}{|D|}\sum_d RO^{data}_{ijd}(a, \alpha; \mathcal{D})|$, and let $d(\alpha, a; \mathcal{D})$ be the vector consisting of d_{ij}. To obtain the estimates $(\hat{\alpha}, \hat{a})$, we minimize

$$\min_{\alpha, a} d(\alpha, a; \mathcal{D})' d(\alpha, a; \mathcal{D}). \tag{10}$$

The estimates of $\bar{\lambda}_{id}$ are then obtained from $\bar{\lambda}_{id}(a, \alpha; \mathcal{D})$ following Equation (9).

5.2.2. Identification. We informally discuss the identification of model parameters here and relegate the formal statement and proof of the identification to Online Appendix F.2. Below, we outline the intuition behind this process.

Using the number of drivers obtained from Equation (7), Equation (8) allows us to express $\bar{\lambda}_{id}$ in terms of data and parameters (a, α). Next, observe that each $\bar{\lambda}_{id}$ can be written as an explicit function of a, α, and data as in Equation (9). Therefore, the identification problem involves only the parameters α and a using variation in the RO moments. We consider the relative outflow across regions for a single day d. For notational brevity, we drop the day subscript d. The model relative outflow can be written as

$$RO_{ij}^{model} = \frac{A_i}{A_j} = \frac{r_i/\bar{\lambda}_i}{r_j/\bar{\lambda}_j} = \frac{\frac{n_i}{c_i}/\bar{\lambda}_i}{\frac{n_j}{c_j}/\bar{\lambda}_j} = \frac{(1-\alpha p_i)\left(1 - a\frac{s_i\bar{c}}{n_i c_i}\right)}{(1-\alpha p_j)\left(1 - a\frac{s_j\bar{c}}{n_j c_j}\right)}. \quad (11)$$

The third equality holds given the assumption of driver equilibrium distribution. The fourth equality is obtained if we substitute $\bar{\lambda}_i$ and $\bar{\lambda}_j$ with a, α, and observable data $\mathcal{D}$ following Equation (9). Note that in this equation, everything is data except for a and α.

The formal proof of how matching the moments in Equation (10) identifies both a and α is relegated to Online Appendix F.2. To see the intuition, first let us assume $\alpha = 0$. In this case, roughly, a is identified by the variation in relative outflows; the larger the magnitude of a is, the larger the imbalance of flows is between denser and less dense regions.[21] In addition, variation in wage levels over time and regions also contributes to the identification.

Price sensitivity α would be identified in a similar fashion if we assumed $a = 0$; the larger the magnitude of α is, the larger the imbalance of flows is between more and less expensive regions.[22] Now, note that if there is sufficient independence between regional price variation and regional density variation, both a and α are identified.[23]

5.3. Demand-Side Economies of Density

In this section, we adapt the theory model with demand-side economies of density to the empirical setting. The overall strategy is analogous to the case of supply-side EOD, so we skip details when they are similar. We describe the estimation procedure and identification for this model in Online Appendix D.

Again, we do not assume that the platform optimally sets prices and wages, and we focus on estimating the model parameters from the driver and passenger behavior. Following the theoretical model with demand-side economies of density, the wait time is given by $W_{id} = \frac{n_{id}}{\bar{\lambda}_{id}(1-\alpha p_{id})\left(1-\beta'\frac{t_i}{n_{id}}\right)}$. Recall from our discussion in the theory in Section 3.3 that to model demand-side-*only* EOD, we need to assume that $t_i \equiv a \times s_i$ is vanishingly small but that β' is so large as to make $\beta s_i \equiv \beta' \times a \times s_i$ of nontrivial magnitude. Thus, in equilibrium, we will have

$$\frac{c_{id}}{W_{id}(n_{id})} = \bar{c} \Longleftrightarrow \frac{n_{id}}{\bar{\lambda}_{id}(1-\alpha p_{id})\left(1 - \frac{\beta s_i}{n_{id}}\right)} = \frac{c_{id}}{\bar{c}}. \quad (12)$$

The parameter β can be interpreted as the reduced-form aggregation of (i) the model parameter of pickup time as a function of region size and the number of drivers and (ii) the sensitivity of ride demand to pickup time. Therefore, β captures the demand-side EOD. In this model, the parameters to be estimated are $(\alpha, \beta, \{\bar{\lambda}_{id}\}_{i\in I, d\in D})$.

5.4. The Comprehensive Model

In taking the model to data, we construct a comprehensive model here that includes both supply-side and demand-side economies of density that we have separately examined above. In the comprehensive model, the passenger pickup time affects both the demand arrival rate and drivers' supply decisions, where the total wait time per ride is given by

$$W_{id}(n_{id}; \bar{\lambda}_{id}, \alpha, \beta, a) = \frac{n_{id}}{\bar{\lambda}_{id}(1-\alpha p_{id})\left(1 - \frac{\beta s_i}{n_{id}}\right)} + \frac{a s_i}{n_{id}}. \quad (13)$$

The distribution of drivers on a given day d is still obtained as an equilibrium outcome, where the ratio of wage per ride to wait time equals the value of the outside option:

$$\forall i, \ \frac{c_i}{W_{id}(n_{id}; \bar{\lambda}_{id}, \alpha, \beta, a)} = \bar{c}. \quad (14)$$

As before, the number of rides is given by $r_{id} = \frac{n_{id}}{W_{id}}$.

The parameters to be estimated are $(a, \alpha, \beta, \{\bar{\lambda}_{id}\}_{i\in I, d\in D})$. This general model encompasses as special cases the two models that we have examined so far: the supply-side-only EOD ($\beta = 0$) and the demand-side-only EOD ($a = 0$). As discussed, separately identifying a and β is not feasible given our data. As demonstrated earlier, each parameter can be identified if we assume that the other is zero. Similarly, a and β would be identified if we assume that the ratio between them is known. This effectively translates to the idea that the relative contributions of the supply-side EOD and the demand-side EOD are known.

We can use this idea to test for robustness across a wide range of relative contributions of these effects. Specifically, we calibrate the model using the following ratios: $\frac{a}{\beta} \in \{10, 1, 0.1\}$. A larger ratio implies that supply-side effects are stronger, whereas a smaller ratio implies that demand-side effects have a greater contribution. Observe that a model estimated with each of these assumptions on $\frac{a}{\beta}$ is in nature "arbitrary" and uninformative on its own because we cannot test this assumption. However, the analysis across this wide range of $\frac{a}{\beta}$ is useful because it helps to show that our results are robust across a wide range of possible ratios of the relative importance between supply-side and demand-side EODs as opposed to just the two extreme cases.[24]

Table 3. Parameter Estimates from the Supply- and Demand-Side Models

	Supply-side model	Demand-side model
α	0.0201 (33.36)	0.0138 (21.17)
A	23.27 (29.82)	N/A
β	N/A	42.64 (26.88)
Average $\bar{\lambda}_{id}$ by regions		
Bronx	4,674	3,943
Brooklyn	7,824	6,791
Manhattan	12,650	10,535
Queens	6,565	5,629

Notes. We report the point estimates (with *t*-statistics in parentheses) for the parameters (α, a, β). Because our model estimates $\bar{\lambda}_{id}$ for each day and each region, we only present the average of the point estimates of $\bar{\lambda}_{id}$ across days for each region. N/A, not applicable.

5.5. Empirical Results

We present estimates from the models with supply-side EOD, demand-side EOD, and the comprehensive model with both sources of EOD. Table 3 presents the estimates of the parameters from the supply-side model and the demand-side model. The parameter estimates are qualitatively similar. Table 4 shows the price elasticities implied by the model estimates. As a benchmark, Rosaia (2020) finds a broadly consistent price elasticity ranging from 0.55 to 1.09.[25] Cohen et al. (2016) finds an overall price elasticity of 0.61 for NYC.

Table 5 displays the average potential demand densities and accesses across days in each region as estimated by each model. The results reveal significant variation in the demand density across regions, with Manhattan exhibiting more than four times the density of Queens according to both of the models. This spatial disparity highlights the importance of characterizing and estimating these regional differences.

Furthermore, the access levels follow an ordering that is consistent with the demand density. Specifically, Queens, the least dense region, is found to have the lowest access, and Manhattan, the most dense region, is found to have the highest access. These results remain robust across varying model specifications that allow for different relative levels of supply-side EOD and demand-side EOD as detailed in Online Appendix G, where we present the demand densities and accesses from the alternative models. With model calibration results at hand, we next turn to counterfactual analysis.

Table 4. Price Elasticities by Regions

Region	Supply-side model	Demand-side model
Bronx	0.37	0.34
Brooklyn	0.51	0.36
Manhattan	0.67	0.40
Queens	0.75	0.55
All regions	0.60	0.41

Notes. The table shows the average demand elasticities across days with respect to prices given by supply-side and demand-side models separately. The averages are weighted by the number of rides, r_{id}.

Table 5. Model Outcomes (Regions Ordered by Demand Density)

Model specifications	Supply-side model	Demand-side model
Demand density $\left(\frac{\bar{\lambda}_i}{s_i}\right)$		
Queens	630	540
Bronx	719	607
Brooklyn	939	815
Manhattan	2,655	2,211
Access $\left(\frac{r_i}{\bar{\lambda}_i}\right)$		
Queens	0.49	0.57
Bronx	0.51	0.61
Brooklyn	0.57	0.66
Manhattan	0.58	0.69

Note. The results presented correspond to averages across days over the data time periods.

6. Counterfactual Analysis

We next simulate several counterfactual scenarios using the estimated model parameters. Our primary objective is to empirically quantify the key theoretical insights presented in Section 3. First, we simulate the platform's optimal price and wage policy in Section 6.1 to assess the extent to which economies of density skew access away from less dense regions and to what degree the platform might counter such a skew. We demonstrate that the platform mitigates but does not eliminate the access skew by comparing the access skew under the optimal heterogeneous and homogeneous pricing strategies. Second, we simulate the platform's optimal policy with the demand levels in each region scaled by a uniform factor as described in Section 6.2 to quantify how much the access skew becomes more pronounced for smaller platforms. Finally, in Section 6.3, we go beyond quantifying the theoretical insights and explore the region-specific prices/wages necessary to achieve equalized access across regions.

Our counterfactual analysis reveals findings that are robust across different models regardless of whether and to what extent economies of density originate from the supply side, the demand side, or both. Note that we do not have theory results in the case of mixed supply-and-demand EOD, but we can obtain counterfactual findings for this case too. The counterfactual demonstrates that our insights are consistent across all models empirically. To avoid redundancy, we provide the counterfactual results only for the supply-side model here. Online Appendix G has the results for all models: the supply-side model, the demand-side model, and the model with both supply-side and demand-side EODs.

6.1. The Platform's Optimal Strategy

Recall that our estimation did no rely on any assumptions about the platform's pricing policy. In this section, we first simulate the platform's optimal prices and wages to quantify the idea that the platform might set higher prices and wages but accepts lower margins in less dense regions. Further, we examine the platform's responses when it is restricted—either by regulation or by company policy—to implement a uniform price and wage across all regions. Comparing these scenarios, we find that although the platform does not fully eliminate spatial access skew, its optimal strategy is to mitigate access skew using flexibility in setting prices and wages across regions.

Based on our model estimates, we first simulate the platform's optimal prices and wages across each of the regions for each day over the four-month span of data. Figure 5(a) illustrates the optimal prices and wages for each region (averaged across days), with regions arranged in descending order by demand density from left to right. The platform's optimal policy pays drivers approximately 77% more per ride in the least dense region (Queens) compared with the most dense region (Manhattan). However, the platform does not pass on more than 25% of this wage difference to passengers. Overall, our simulation recommends a higher price relative to what Uber charged during the data period. This recommendation aligns with Uber's more recent pricing adjustments that have been implemented after the period of our data.[26]

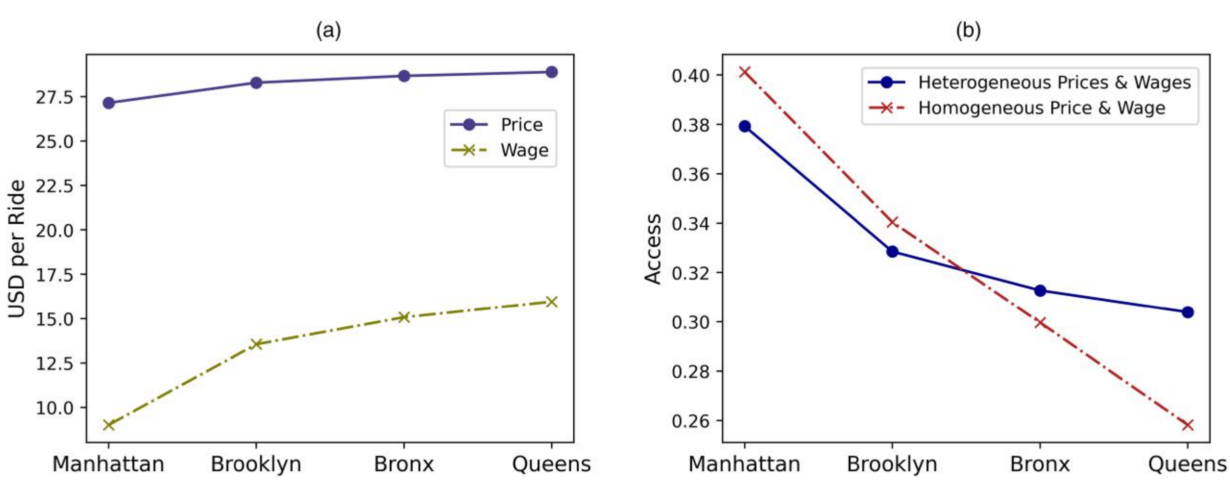
Next, we examine access levels. Figure 5(b) displays the access levels across regions (averaged across days) under the optimal heterogeneous and homogeneous price and wage policies.[27] Two key patterns emerge. First, lower-density regions exhibit lower access levels. Under optimal heterogeneous prices and wages, access in the most dense region (Manhattan) is higher by 25% compared with access in the least dense region (Queens).

Second, compared with the scenario where the platform is restricted to set uniform price and wage across regions, the platform mitigates but does not fully eliminate access inequality across regions with pricing flexibility. Specifically, as Figure 5(b) illustrates, access in the most dense region is higher by 55% than the least dense region under homogeneous pricing but only 25% higher under heterogeneous pricing. This aligns with our interpretation of Proposition 3 and Proposition 4, which suggest that the platform optimally charges smaller margins in sparser regions under full pricing flexibility (effectively "subsidizing" sparser regions) in order to build economies of density and mitigate spatial access skew.

6.2. Impact of Platform Size

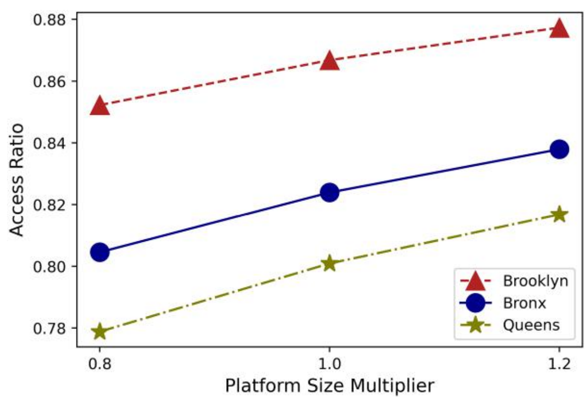
There have been regulations that cap the number of drivers on ride-sharing platforms, effectively reducing platform size (CBS News 2018). To illustrate how the degree of access skew changes as the market thickens, we scale the demand levels for each region by a uniform factor to simulate a larger or smaller platform. This allows us to observe how access skew is either mitigated or intensified. We use the average potential demand ($\bar{\lambda}_{id}$) across days as the base demand levels for each region. We then scale these demand levels by

Figure 5. (Color online) (a) The Platform's Optimal Heterogeneous Prices and Wages and (b) Accesses with and Without Flexibility in Prices and Wages



Notes. The regions (boroughs) are arranged in descending order by demand density from left to right. USD, U.S. dollars.

Figure 6. (Color online) Access Ratio (Relative to Manhattan) as Market Thickens with the Supply-Side EOD Model



a uniform platform size multiplier, with values set to 0.8 and 1.2. Following this adjustment, we calculate the optimal prices and wages as well as the associated access levels in equilibrium. Under the supply-side EOD model, if Uber's size was to shrink by 20%, then the access of the most dense region is 28% higher than that of the least dense region. On the other hand, if Uber's potential demand grows by 20% of the estimated size, the access in Manhattan is higher by 22% than the access in Queens. Consistently, as depicted in Figure 6, the access ratios of the three less dense regions (Brooklyn, Bronx, and Queens) relative to Manhattan approach one as the platform expands. This indicates that the access skew is mitigated as the platform grows larger.

6.3. Equalizing Accesses

Policymakers are sensitive to unequal access to important services, like transportation. We examine the extreme case where the policymaker might want to equalize access across all regions to provide insight into what such a policy would require. Specifically, we evaluate the extent to which Uber would need to adjust its regional prices/wages in order to achieve uniform access across regions set to the average access level across regions, which is closest to that of Brooklyn.

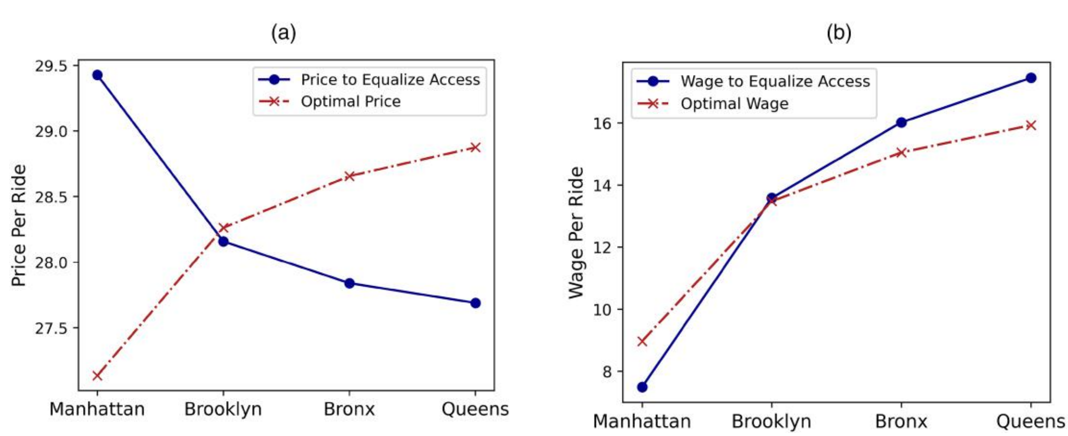
We set the potential demands of each borough at the estimated ones (averaged across days). We then fix either wages (c^*) or prices (p^*) at the optimal level as determined when the platform jointly optimizes (p^*, c^*). We then vary the other lever—prices or wages accordingly.

First, we fix the wage at c^* and then, calculate the regional price levels p_i needed to equalize access across all regions (at the average access level under the full equilibrium). We find that to equalize access as shown in Figure 7(a), the upward trend in prices (where prices are higher in sparser regions) is reversed, resulting in a downward trend. Specifically, the price in the most dense region increases by 8.4%, whereas the price in the least dense region decreases by 4.1%.

Next, we fix prices at p^* and adjust regional wages to set all access levels to the global average. The upward trend in wages as demand density decreases becomes more pronounced as illustrated in Figure 7(b). To achieve equal access, the wage in the most dense region needs to be reduced by 16.5%, whereas the wage in the least dense region must increase by 9.6%. This adjustment further amplifies the wage disparity across regions.

These finding aligns with the idea that to build economies of density, the platform increases wages in less dense regions but does not pass these costs fully onto passengers. Furthermore, under optimal prices

Figure 7. (Color online) (a) Optimal Prices and the Prices That Equalize Accesses and (b) Optimal Wages and the Wages That Equalize Accesses



Notes. Consider the prices and wages denoted as (p^*, c^*) determined under the optimal heterogeneous pricing scheme described in Section 6.1. Panel (a) illustrates a comparison between p^* and the prices required to achieve equal access when the wages are fixed at c^*. Panel (b) compares c^* with the wages necessary to ensure equal access when prices are fixed at p^*. The regions (boroughs) are arranged in descending order by demand density from left to right.

and wages, the margin in the least dense region is 29% lower than in the most dense region, a percentage that increases to 43% and 42% when accesses are equalized using price and wage levers, respectively. This implies that the sparser regions are effectively subsidized to an even greater extent.

6.3.1. Robustness of Findings. We carry out a battery of additional robustness checks to evaluate the validity of the findings in the paper. First, we adjust for and incorporate trip time into the empirical model. Specifically, we construct a price measure adjusted for trip distance and time, and we incorporate an additional average trip time in the model. We re-estimate the extended model with this new price measure. See Online Appendix H for more details on how we implement this. Second, we allow for region-dependent parameters, such as price sensitivity, in both theory and empirical models. Third, we conduct empirical analysis using finer grid partitions of each NYC boroughs. Finally, we examine alternative functional forms for modeling pickup time and customer responses to price and pickup time. Our main insights continue to hold across all of these specifications.[28]

7. Conclusion

This paper examines the effects of economies of density and market thickness on spatial distribution of access to service. We focus on ride-sharing and analyze this market both theoretically and empirically. Theoretically, we show that in equilibrium, relative to lower-density regions, regions with higher densities of potential demand get more supply—even after normalizing by their higher demand. We show that this "spatial access skew" is more intense for smaller platforms. Finally, we show that a ride-sharing platform's optimal pricing strategy would involve mitigating but not fully eliminating the spatial mismatch between supply and demand. All of these results are robust to whether the source of economies of density is the supply side or the demand side.

Empirically, we calibrate our model using ride-level data on Uber from New York City. A key aspect of our calibration exercise is the identification of relative access to service across regions, which is achieved by leveraging the "relative outflows" of rides between pairs of regions. The core idea behind our strategy for identifying the extent of economies of density is broadly applicable beyond our specific context to all passenger-transportation markets, whether the matching technology is centralized (e.g., ride-sharing) or decentralized (e.g., taxicabs). Using our calibrated model, we address several important questions, including the platform's optimal prices and wages across regions, the impact of constraining the platform to set spatially homogeneous prices and wages, the role of platform size (i.e., market thickness), and the extent of price/wage adjustment needed to homogenize access across regions.

The analysis in this paper can be extended in multiple directions, especially if additional driver-level and passenger-level data are available. First, extending the model to markets with decentralized matching, such as the taxicab market, would provide useful insights on the relative effectiveness of policies in that market compared with ride-sharing. Second, incorporating a trip-level structural model could help explore how trip-level dynamics contribute to access differences, allowing for heterogeneity in trip characteristics. Such an extension would also facilitate the empirical disentanglement of supply- and demand-side economies of density. This would also allow us to better examine competitive dynamics between platforms (Rosaia 2023). Third, research could examine the differing incentives of social planners and platforms in terms of access differences across regions and the conditions under which they converge and diverge. Fourth, a useful next step would be to examine the trade-off between platform size, which we find to have a positive effect here, and the effect of competition in considering whether platforms should be allowed to coordinate or even merge. Finally, understanding the value of other policy instruments, like regulating the total number of drivers in a region or congestion pricing, would be of broad interest in other spatial markets beyond ride-sharing.

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Endnotes

[1] For a comparison of the geographical scope of the data used in our paper and Rosaia (2023), see Online Appendix J.

[2] Nevertheless, in both the supply-side model and the demand-side model, the agglomeration of drivers in a region increases the idle time and "turns away" drivers if the region becomes too dense. Therefore, under the assumption of a pool of infinite drivers and free entry of drivers, the equilibrium spatial distribution of drivers is reached when the two forces, the pickup time and the idle time, are balanced.

[3] We assume that the rides are homogeneous.

[4] We assume that the centralized platform assigns each passenger to the closest driver. See Online Appendix C for details.

[5] Note that this formulation abstracts from the time that it takes to drive passengers to drop-off locations, simplifying some of our analysis. We do not expect the results to be qualitatively sensitive to it.

[6] The reason why we focus on "small-mass" deviations is that our continuous-mass model of drivers is an approximation for a large population. In this environment, allowing for "large-mass" deviations from any given strategy should be interpreted as drivers *coordinating* a deviation, which we do not allow.

[7] Note that the wait time W_i is a valid definition only if $n_i^* > 0$. If the drivers are currently taking the outside option in region i (i.e., $n_i^* = 0$), then the left-hand side of the inequality is replaced by $\bar{c}$. If the drivers are considering switching to outside option, then the right-hand side of the inequality is replaced by $\bar{c}$.

[8] The linear demand model has been used in literature. See, for example, Bimpikis et al. (2019). We also provide a microfoundation here. The demand function can be derived under the following assumptions. (1) There is one unit of potential customers, and (2) the valuation for each ride in region i, denoted v_i, follows a uniform distribution $unif(0, \frac{1}{\alpha})$. That is, at a given price p_i, only customers with $v_i > p_i$ will demand the ride from the platform, resulting in $1 - \alpha p_i$ of the population choosing to ride.

[9] See Online Appendix C for details.

[10] One small exception is that in the demand-side model, the first comparison in Proposition 3 (i.e., $p_i^* \leq p_j^*$) always holds with equality.

[11] We thank an anonymous reviewer for this point.

[12] We exclude rides either picked up or dropped off in Staten Island because the rides between Staten Island and other boroughs are scarce on some of the days within our data period. This leads to extreme outliers in the measures of relative outflows and biases the estimates.

[13] We exclude shared rides because the data do not provide separate wages and prices for each corider. We retain rides with positive trip time and distance, and we exclude rides where the passenger fare is lower than the driver pay.

[14] We use gross earnings before expenses rather than net earnings after expenses because our model assumes that the number of drivers is determined by c_i, the payment from the platform before expenses. Intuitively, for a driver comparing driving on Uber with a minimum-wage job (e.g., at a restaurant), Uber must offer higher gross earnings to account for vehicle maintenance and fuel costs. Parrott and Reich (2018) reports a similar gross earnings of \$22–\$23 for NYC in October 2017 and proposes a minimum gross earnings standard of \$25.76 for NYC drivers.

[15] See https://www.census.gov/quickfacts/fact/table/newyorkcountynewyork,richmondcountynewyork,kingscountynewyork,queenscountynewyork,bronxcountynewyork,newyorkcitynewyork/LND110220.

[16] We consider the square root of the borough area as its size based on the following simple hypothetical. If a borough's size doubles in each dimension (quadrupling its area), the average distance between two randomly picked points doubles rather than quadruples. The notion of measuring the region size in length as opposed to area is also implemented in the microfoundation for our theory model as detailed in Online Appendix C.

[17] In reality, a could be heterogeneous because of different regional extents of traffic congestion, etc. We abstract from those in this paper. Note that this abstraction likely understates economies of density given that denser regions tend to have higher traffic.

[18] A similar proportionality assumption can be found in Bimpikis et al. (2019, equation 2 on p. 748 and the subsequent explanation). One might think that an alternative assumption could be that the proportion of fulfilled demand over the actual demand does not depend on the destination (i.e., $\frac{r_{ij}}{\bar{\lambda}_{ij}} = \frac{r_i}{\bar{\lambda}_i}$). We note that both in our paper and in Bimpikis et al. (2019), these two assumptions are equivalent because of one key underlying assumption; we assume that passengers in any region i react the same way to prices (and to pickup time in our demand-side model) regardless of their destination. In this way, we have $\frac{\lambda_{ij}}{\bar{\lambda}_{ij}} = \frac{\lambda_i}{\bar{\lambda}_i} = f(p_i, \omega_i)$ for any region i, j. If one relaxed this assumption and allowed, for instance, those who travel from Manhattan to Bronx to be more/less price sensitive than those who travel from Manhattan to Brooklyn, then $r_{ij}/\lambda_{ij} = r_i/\lambda_i$ would no longer be equivalent to $r_{ij}/\bar{\lambda}_{ij} = r_i/\bar{\lambda}_i$.

[19] To illustrate, suppose passengers consistently use ride-sharing to go to region i but never open their apps to find a ride back out of region i because they have learned that supply is scarce in that region. Even hard-to-obtain data on app sessions cannot detect this phenomenon and would, hence, understate the low access to rides in region i, but a method based on relative ride flows can.

[20] We assume that the trip time is zero as in our theory model.

[21] More specifically, RO_{ij} being close to one is consistent with low values of a. As a increases, RO_{ij} would need to diverge from one. For example, if $\frac{s_i\bar{c}}{n_i c_i} > \frac{s_j\bar{c}}{n_j c_j}$, then RO_{ij} is less than one, and it decreases as a increases.

[22] In principle, the price variation across a region is prone to endogeneity, which might bias the results. One possible solution to this problem would be to calibrate the parameter α in a way that would lead to a similar price elasticity of demand to what is found in other research that leverages exogenous variation for the same market (such as Rosaia 2020) instead of directly recovering it from our data. We did not do so, however, given that the α that we found indeed implies that price elasticity levels that are close to Rosaia (2020). (See Table 4 for the results.)

[23] Broadly speaking, sufficient independence requires that the comparison of p between two regions cannot inform how $\frac{s\bar{c}}{nc}$ compares between the two regions and vice versa. Specifically, there exists a pair of regions where both p and $\frac{s\bar{c}}{nc}$ are high for one of the regions, and there also exists another pair of regions where one region has higher p and another region has higher $\frac{s\bar{c}}{nc}$. See the proof in Online Appendix F.2 for more details.

[24] In addition to $\frac{a}{\beta} \in \{10, 1, 0.1\}$, we also ran the analysis with $\frac{a}{\beta} \in \{0.01, 100\}$. The results were similarly robust.

[25] Rosaia (2020) is an older version of Rosaia (2023). It reports the price elasticities implied by the model estimates.

[26] See Online Appendix I for more details.

[27] Note that compared with accesses level calibrated from the model shown in Table 5, the accesses here are at a relatively lower level. This is because our model predicts prices that are higher than the observed levels.

[28] The complete set of results for these robustness checks is available from the authors.

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