Spatial Heterogeneous Consumers: The Welfare Effect of UberPool

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Many economic research studies have been focusing on the demand and welfare estimation of the ride-hailing market, specifically for platforms like Uber and Lyft. In this paper, I estimate the welfare effect of UberPool as a new product in the ride-hailing market accounting for heterogeneous preferences within and across locations by using a discrete-type random coefficient nested logit model. I find that, relative to the counterfactual worlds without UberPool, UberPool can increase consumer surplus by $31.58\% \sim 33.51\%$*. Even a partially accessible UberPool by location is* 2.57% *higher on consumer surplus, compared to if only UberX were provided but with lower prices, which shows the magnitude of the variety effect in the ride-hailing market.* *Keywords: Ride Hailing, Spatial Differentiation, Product Variety, Welfare Estimation*

I. Introduction

Ride-sharing platforms like Uber and Lyft debuted within the last decade. Several research studies have examined the value of the ride-sharing economy on social welfare based on its special features - real-time matching on the apps, dynamic pricing on both supply and demand, flexible schedules for drivers, and various choices for consumers based on their preferences for faster or cheaper services. Buchholz et al. (2020) focused on the real-time matching feature and the price auction, Castillo, Knoepfle and Weyl (2017) and Castillo (2020) exploited the dynamic pricing feature, Chen et al. (2019) focused on the driver utilization of work flexibility, and Cohen et al. (2016) and Lam and Liu (2017) combined multiple features to estimate the consumer surplus and economic values of the ride-sharing platforms as a whole.

In this paper, I will focus on the feature that has not been fully explored or concentrated on in the past literature on the ride-sharing economy, which is the different services provided by the platforms to capture consumers' various preferences for faster or cheaper services, and its impact to the economy. To be more precise, how UberPool, a pooled ride-sharing service, as a new product can contribute to the product characteristic space in the ride-hailing market, consumer surplus, and social welfare in general.

The main idea of this paper is to follow the steps of Waldfogel (2008), Thomas (2011) and Quan and Williams (2018), and examine the benefit of the new product on a spatial heterogeneous demand. Even though Uber is widely accessible and certainly ubiquitous in big cities, the benefits of the product variety are different by each location level. For example, the access to UberPool will be of little value to consumers in a popular Uber pickup point surrounded by office buildings in downtown Chicago, especially during the rush hours of weekdays. These consumers, if using Uber to commute, will likely be compensated by the company for commuting, and are in need of quicker ways of transportation. UberPool, as a cheaper but slower way of transporting, is of little value in these areas. Therefore, in order to accurately quantify the benefit of product varieties from UberPool, it is important to estimate heterogeneous preferences varied both within and across locations.

The major difference between this paper and previous research studies on the demand and consumer surplus of Uber is that I specifically focus solely on the benefit of the product variety in the context of the ride-sharing market with heterogeneous preferences, which, either within or across locations, have not been fully explored in this market. Previous research either used homogeneous consumer preferences or due to the detailed pricing and surge multiplier revealed to the consumers from the platform, focused on the dynamic surge pricing feature. Cohen et al. (2016) used only UberX data and estimated gains in consumer surplus on a homogeneous type of consumer from surge pricing. They concluded that consumer demand for Uber is inelastic, which resulted in a large consumer surplus(with a daily CS of $18 million). Cachon, Daniels and Lobel (2017) and Castillo (2020) additionally focused on the impact of surge pricing on the two-sided market with spatial equilibrium, and Castillo (2020) estimated a 5.25% increase in consumer surplus from surge pricing.

Lam and Liu (2017)'s and Castillo (2020)'s research have already touched upon Uber product differentiation and spatial heterogeneity on consumer welfare, respectively. Their research showed the economic values of these two factors in this market, but neither of them has this neat categorization of consumer *types* of their tastes of time and price (business vs. leisure), which is endogenized in this paper to quantify the underlying mechanisms of spatially differentiated substitution patterns. Castillo (2020) limits the data only to "frequent riders" and differentiates consumers by an income proxy. However, what differentiates consumers' behaviors is more than their incomes, but their *types* and their locations.[1] Lam and Liu (2017) included a comprehensive analysis of Uber's product assortment and showed the differentiated consumer surplus for different Uber products in different locations. However, by focusing only on UberPool and type distributions of consumers, I am able to directly compare two products differentiated mainly by prices and travel time, figuring out *why* and *how* different consumer types and their distributions affect substitution patterns. Building upon these two papers mostly on their explorations on Uber products differentiation and heterogeneous demand, respectively,[2] this paper contributes to the past literature by quantifying the mechanisms of spatially differentiated substitution patterns through heterogeneous consumer preferences of time and price, as well as providing an estimation of the welfare effect of only adding the UberPool.

Besides the strand of literature about the ride-hailing market, this article can also be

[1] Also in his paper, since the consumer income level is unobservable, He used the average income level of the zip code of the frequent late-night end point of frequent riders(as the assumption of their home) as the proxy, which greatly limits the consumer set.

[2] Buchholz et al. (2020) also incorporated individual differences in values of time in demand estimation, and they also discussed their distributions geographically. Since their focus was not on the variety effect of Uber products, they did not discuss how within and across locations heterogeneities interact or incorporated this into the estimation strategy.

viewed as an extension of the strand of literature analyzing the economic value of a new product. This paper mostly follows the line of Brynjolfsson, Hu and Smith (2003), Waldfogel (2008), Thomas (2011) and Quan and Williams (2018). They have proven heterogeneous consumer preferences, both within and across locations, are critical to estimating the demand and benefits of variety more accurately. In addition, Brynjolfsson, Hu and Smith (2003) and Quan and Williams (2018) conclude a more significant impact of product variety on welfare. However, past literature usually focuses on the retail industry where there are abundant choices and varieties of products.[3] This paper contributes to this strand of literature by introducing their methods to the ride-hailing market where there are much fewer choices and varieties for the consumers, to find some quantitative estimates of the welfare effect of UberPool and qualitative evidence of the magnitude of its variety effect.

In this article, I find a strong case of spatial heterogeneity where the distributions of two types of consumers are different in two types of locations. In the counterfactual analysis, I found UberPool brings on average $31.58\% \sim 33.51\%$ more consumer surplus. Given the result of spatial heterogeneity, I conduct a counterfactual where Uber exploits the heterogeneity of consumer tastes in different locations by only letting UberPool be operated in locations with more price-sensitive consumers, and found it generates a higher(2.57% more) consumer surplus compared to if only UberX is allowed to operate but in a uniformly lower price. This has major policy implications that potentially in the ride-hailing market with fewer choices for consumers, the variety effect still has a bigger impact on welfare with one additional product. The antitrust enforcers and policymakers for the ride-hailing market should focus more on the impact of potential changes in the variety. Another policy implication is that the spatial heterogeneity can show the extent of potential price discrimination Uber can perform based on their prior knowledge of consumer distribution, which can have a further impact on consumer surplus. Bonatti and Cisternas (2020) argued that Uber personalized prices based on individual characteristics, like the usage of a personal versus business credit card, and also the locations where the ride is requested. This "micro-price-discrimination" of consumers based on their price and time sensitivities should also be considered by antitrust enforcers and policymakers when calculating welfare in the ride-hailing market.

Roadmap: I will first present the data and the summary statistics in II, providing a descriptive analysis of spatial heterogeneity. Then, I will present the demand estimation model in III to estimate the preference for time and price for different types of consumers across different locations. After that, I will present my empirical results in IV, and discuss the comparison with the existing results and potential limitations. Finally, I will present a counterfactual analysis of the consumer surplus without UberPool in V to calculate the welfare change brought by UberPool and follow with the conclusion in VI.

[3] Definitely more than two options. In this paper, I will only be considering two options, UberX and UberPool.

II. Data and Summary Statistics

The data I will be using is a public dataset from the City of Chicago. Since 2016, the City of Chicago requires all taxi companies to report each trip with its pickup timestamp and location, dropoff timestamp and location, trip duration, distance, and price. Since 2018, the same requirements are applied to ride-share services like Uber and Lyft, which means every ride-sharing trip either started or ended inside the City of Chicago is recorded in the dataset. For the ride-hailing market, the dataset also included the information if the trip is authorized by the consumer to be "pooled" with other consumers, which will be used as an indicator of UberPool in this paper.

A. Data Utilization Compared to Previous Research

There are three challenges in utilizing this dataset compared to the previous research on the ride-hailing market. The first challenge is that it does not include detailed information between riders requesting the trip and starting the trip. All the data in this dataset was recorded *after* riders got in the car. Previous literature tended to focus on the decision of requesting the ride or not after the consumer opens the app(Cohen et al. (2016),Lam and Liu (2017), and Castillo (2020)), namely by observing the ETA of the driver, price and travel time, the consumer makes the decision between requesting the ride or choosing the outside option(s). Nevertheless, in this paper, I am focusing on the consumer's decision between different types of ride-hailing services(UberX and UberPool) given the travel time and price for both products. Within the context of this decision, the missing information on the ETA of the driver seems trivial and the differences between these two products are price and the travel time. In addition, from the summary statistics of Lam and Liu (2017)[4], where they have the recordings of all the trips of UberX, UberPool, Lyft, and LyftLine[5] in New York City from June-August 2016. The ETA of the driver for UberX and UberPool, as well as Lyft and LyftLine, share similar mean and standard deviation[6], meaning that even if the consumers might weigh in the information of the ETA while making the decision, the effect on the demand would be trivial.

The second challenge is the lack of information on surge pricing. Surge pricing, namely a dynamic way of changing the price to balance the supply and demand side of the rider and driver market has been ubiquitous in the ride-hailing market. Unfortunately in this dataset, I don't observe the information on surge multiplier or surge frequency, instead, only the final price paid by the rider is recorded. Almost all the research about the consumer surplus of the ride-hailing market has tackled the issue of surge pricing one way or another, like in Cohen et al. (2016), Castillo, Knoepfle and Weyl (2017), Lam and Liu (2017), and Castillo (2020). Since 2016, a new pricing policy called "upfront pricing" is implemented by both Uber and Lyft. This means only the final price (which is not

[4]Table 5

[5]LyftLine is the UberPool equivalent service

[6]In the data of NYC, UberX has the mean ETA of 6.949 mins with a standard deviation of 8.912 mins, and UberPool has the mean ETA of 7.496 mins with a standard deviation of 9.870 mins. Lyft has a mean ETA of 7.034 mins with a standard deviation of 9,882 mins, and UberPool has a mean ETA of 6,884 mins with a standard deviation of 9.869 mins. All the summary statistics are from Lam and Liu (2017)

the base price. This final price is essentially what is recorded in this dataset) is quoted to the rider. This means, the rider does not have a clear indication of surge pricing timing, location, and the multiplier itself, but can only make assumptions on these based on her expected price of this route.[7]. Therefore, within the context of this paper to estimate the welfare effect of UberPool, it is necessary to tackle the consumer's choice between different products given the quotes of *final* prices and travel times, and the quoted final fare without the surge multiplier is sufficient.

In addition, the final fare in the dataset should suffice as the proxy of the quoted final price for that time of the day and that route since the point of "upfront pricing" is to reduce fee surprises to the consumers.[8] For example, the estimated quoted price from the Art Institute of Chicago to Willis Tower at 4 pm can be estimated by the average final price for all the rides for this route at 4 pm. In fact, Uber actually used a similar strategy when estimating the price in real-time, therefore this proxy will not be too far off.[9] One potential problem with this proxy is that it assumes the demand patterns will be similar at that specific time of the day throughout the week. However, if I limit all the data to weekdays, this will be a relatively accurate statement. In addition, according to Cohen et al. (2016), the surge multiplier heat map shows similar patterns from Monday to Friday, especially between 7 am and 11 pm[10]. In addition, the summary statistics from Lam and Liu (2017) show that surge pricing behaves similarly for UberX and UberPool, which means even if the surge multiplier has a role in affecting consumer choices, the effect would be minimal.

The third challenge is the lack of quoted travel time for each trip, instead only the final travel time of the actual trip is observed, which is especially problematic for UberPool. The quoted and the actual travel time for UberPool are not always the same since Uber when quoting the travel time cannot be certain whether the trip can be pooled. The quoted traveling time could be overestimated because a larger portion of the UberPool rides actually did not get matched with other UberPool riders and thus the final traveling time is much smaller than the quoted one. For instance, if a rider requests UberPool and gets quoted 10 minutes for a route that only needs 7 minutes if traveling in UberX, there is a chance she will be traveling for only 7 minutes if she doesn't get matched with other pooled riders. In addition, a rider may not expect the same traveling time as the quoted travel time given the huge variance of its accuracy. Risk-averse riders may be more likely to choose UberX, not for the price-time tradeoff, but simply for the fact that UberX offers more accurate and less unstable estimates on the traveling time. The discussion of risk aversion for the riders is certainly important but unfortunately beyond the scope of this paper. As of the current state of the paper, I will be using a nonparametric method to

[7]Uber and Lyft had presented the detailed base price and the surge multiplier when the ride-sharing businesses were first established, but they dropped this pricing strategy and switch to "upfront pricing" since 2016, meaning the rider will be quoted with the final price(including taxes, additional charges like tolls) and the travel time once opening the app based on current supply and demand in that particular location

[8]According to this news piece on verge.com, https://www.theverge.com/2016/6/23/12017002/uber-surge-pricing-upfront-fare-app-update-announcement

[9]On their website: https://www.uber.com/us/en/marketplace/pricing/upfront-pricing/. They said the upfront pricing will be determined by many factors, one of which is "the demand patterns for that route at that time".

[10]which is the focused time period in this paper

estimate this quoted travel time with the given variables in the dataset, i.e. the on-average travel time for this specific route at this time of the day. To tackle the consumer behavior pattern with risk aversion, I would need more detailed data from the riders.

B. *Overall Summary Statistics*

To simplify the problem, I limit the geographical area to the Loop of Chicago, which contains abundant riders in both business and leisure categories.[11] In order to disregard the seasonal effect and assume Uber offers a consistent price throughout different days, I limit the dataset from June 2019 to September 2019.[12] Lastly, I limit the data to only weekdays from 7 am to 11 pm to capture the changes in the distributions of different riders without the noise from late-night riders and irregular behaviors from the riders on weekends, which left me 152636 taxi trips and 234504 Uber trips, of which around 6% of all Uber trips are UberPool. Noted that the dataset does not differentiate the platform of the ride-hailing market, namely I do not know if the specific trip is requested through Uber or Lyft, or other platforms. Nevertheless, since the supply side is not the focus of this paper, I will use UberX to represent all the "regular" ride-sharing trips, and UberPool to represent all the pooled ride-sharing trips, regardless of the platforms.

I aggregated all the data into panel data for each time of the day and for each route[13]. All trips have already been discretized into 15 minutes window in the original dataset, starting from 7 am, 7:15 am, etc. I discretized the pickup and dropoff longitude and latitude using a k-means clustering method into discrete locations and each route is a pair of locations. The categorization of the discrete locations into different baskets is relatively simple within the Chicago Loop(which will be discussed in II.C in detail). The summary statistics are reported in A.A1. Within the scope of this paper, I will treat the taxi as the outside option. I have also attached the graph of the price and travel time patterns across different times of the day in A1.

C. *Spatial Difference*

One important difference compared to previous demand estimation literature in the ride-hailing market is the local difference in the distributions of the business and leisure riders. Ideally, business locations should have higher proportions of business riders and vice versa. Within this paper, the categorization of the location will be exogenous from the information on different pickup and dropoff locations. I first clustered Uber and taxi pickup and dropoff locations in the Loop using k-means on both the longitude and latitude data and resulted in 5 locations, which is shown in A2. The route of each trip

[11] An important side note here is that even though I follow the notation in the traditional literature of airlines, denoting consumers who are sensitive in price and less sensitive in time as "leisure", and consumers who are vice versa as "business". The categorization, even though can be applied in the ride-hailing industry, does not limit the riders who are sensitive in price and less sensitive in time to only be tourists, as well as the other riders to only be business workers. Tourists, in fact, can also be sensitive about the time when they tried to catch an opera show for example. The notations of "leisure" and "business" riders here are more for the categorization of two types of consumers.

[12] During the summertime of Chicago, we will have a large number of both the leisure and business riders

[13] the route is a pair of locations, like the unique origin-destination pair in the airline literature Berry, Carnall and Spiller (1996), Berry and Jia (2010), and Williams (2022)

will be exemplified as from one of the 5 locations to the other. The results of k-means will be discussed in detail in A2. I categorize these 5 locations into two categories with 1, 2, 3, and 5 as business locations, and 4 as a leisure location. This information is treated as exogenous information from the zoning plan on the website of the City of Chicago.[14] The summary statistics in terms of spatial heterogeneity are reported in A3, and I also include the market share of UberPool for different pickup and dropoff locations in A3, showing that there is potentially something different about Location 4 within the context of this paper.

To further investigate this location-specific effect on the UberPool market share, I performed an OLS and found additional evidence that there is something unique about Location 4 in A.A1. This further shows the necessity to endogenize this spatial differentiation of the distribution of consumer types.

III. Demand Estimation Model

I consider a model of the ride-hailing market with a monopoly platform and a fully efficient supply side to estimate the demand. The demand estimation follows the spirit of Berry (1994), Berry, Levinsohn and Pakes (1995), and Berry, Carnall and Spiller (1996), and is particularly close to Berry, Carnall and Spiller (1996) given the assumption of the discrete type of consumers. The utility function follows the line of previous ride-hailing market literature like Cohen et al. (2016), Castillo (2020) and Buchholz et al. (2020). The point of the paper is to apply the random-coefficient discrete-choice model within each location to the ride-hailing market for a more accurate, and locally differentiated demand estimation.

During this model, I assume a monopoly ride-sharing platform[15] offering only two products, UberX and UberPool in each of a large cross-section of "origin-destination-time" markets. Uber products are differentiated by their travel distances, travel time, and prices, which UberPool, given the possibility of getting pooled with other riders, will be larger in distances and duration. In addition, travel party size, consumer's distaste for sharing the ride with strangers, and consumer's expectation of travel time/distance vs. her actual travel time/distance(i.e. her level of risk aversion) are all important elements of product differentiation that are not observed in the data. Therefore, it is important to maintain the typical assumption that product-unobservable characteristics are correlated with price.

In addition, there is this issue that I do not observe the consumers who open the app but cannot request the ride or do not want to request the ride with longer travel time and high prices due to driver shortage. For instance, the two trips observed in the dataset might be an underestimation of the actual demand and there are four trip requests, and two of them failed to access the rides and therefore, failed to be recorded in the dataset. To solve this issue, I use the same logic as Williams (2022) to assume a fully efficient supply side. There is precisely a "correct amount" of the drivers which make the market

[14] https://gisapps.chicago.gov/ZoningMapWeb/?liab=1&config=zoning.
[15] I will use Uber for simplicity throughout the paper

efficient with the exogenous prices. For example, for a given price for this specific route at a given time, riders choose between UberX, UberPool, and outside options. If an Uber service is requested, there is always a driver nearby who is willing to offer a ride at this price. This is certainly unrealistic. However, within the scope of this paper, which is to measure the extra consumer surplus captured by UberPool, this assumption will not alter the demand estimation by a lot since I am more focused on the "actual" consumer surplus captured by UberPool. The ignored consumers who failed to request the rides for whatever reasons can be considered the "potential consumer surplus", which is not the focus of this paper.

Another assumption that is not typically made in the demand estimation of the ride-hailing market is that I treat the price for each market as exogenous. However, based on what I have discussed in II.A, with the "upfront pricing" deployed by Uber, consumers are likely to treat the price as exogenous even though technically they can alter the price. This, however, would be a problematic assumption if the supply side of the market were considered.

A. Demand

By building upon previous demand estimation models for the ride-hailing market and differentiated products for discrete types of consumers, I constructed a random-coefficient discrete-choice nested logit model. The utility function follows Cohen et al. (2016), Castillo (2020) and Buchholz et al. (2020), and the demand estimation method follows the spirit of McFadden (1981), Berry, Levinsohn and Pakes (1995) Berry, Carnall and Spiller (1996), and Berry and Jia (2010). Like Berry, Carnall and Spiller (1996) and Berry and Jia (2010), I use the random coefficient model with the "discrete-type" structure. Suppose there are R types of consumers. For product j at market tl (at time t for route l)[16], the utility of consumer i, who is of type r, is given by

$$u^r_{ijtl} = \beta^r_l D_{jtl} + \beta^r_h h_{jtl} - \alpha^r p_{jtl} + \xi_{jtl} + \nu_{itl}(\lambda) + \lambda \varepsilon_{ijtl} \tag{1}$$

where D_{jtl} is the travel distance of the ride, which depends on route l, time t, and product j. This measures the utility of being transported from point A to point B. β^r_l measures the value of this term for consumer-type r. β^r_h is the marginal disutility of travel time for consumers of type r, and h_{jtl} denotes the travel time for product j for market tl. Only two terms are in the product characteristic space, which are D_j and h_j. ξ_{jtl} is the unobserved characteristics of product j for market tl to the researchers. ν_{itl} is a nested logit random taste that is constant for all Uber products and differentiates Uber from the outside option. λ is the nested logit parameter that varies between 0 and 1. ε_{ijtl} is drawn i.i.d. from Type-1 extreme value distribution, namely the "logit error". The utility of taking the taxi(the outside option) is given by

$$u^0_{itl} = \varepsilon^0_{itl} \tag{2}$$

[16]I use a single subscript l to represent a unique pickup and dropoff location combination (a route), to save a subscript in the large cross-section of "origin-destination-time" markets

and ε^0_{itl} is the logit error.

The error structure generates the standard nested logit purchase probability for consumers of type r, where the two nests consist of: both UberX and UberPool, and the outside option of taking a taxi. If $\lambda = 1$. then $\nu_{itl}(\lambda) = 0$, then the demand structure follows the simple multinomial logit form. If $\lambda = 0$, then the iid ε will have no effect. Conditioning on deciding to use Uber, all type r consumers choose either UberX or UberPool with the highest $\beta_l D_{tl} - \beta^r_p p_{jtl} - \beta^r_h h_{jtl} + \xi_{jtl}$. When $\lambda \in (0,1)$, the product shares have the traditional nested logit form.

If conditional on not using a taxi, the percentage of type r consumers who purchase product j in market tl is:

$$\begin{aligned} \pi^r_{jtl} &= \frac{\exp[(\beta_l D_{tl} - \beta^r_p p_{jtl} - \beta^r_h h_{jtl} + \xi_{jtl})/\lambda]}{R_{rtl}} \\ R_{rtl} &= \sum_{k=1}^{J} \exp[(\beta_l D_{tl} - \beta^r_p p_{ktl} - \beta^r_h h_{ktl} + \xi_{ktl})/\lambda] \end{aligned} \tag{3}$$

The proportion of type r consumers who choose to ride Uber regardless of UberX or UberPool is

$$s^r_{tl}(D_{jtl}, p_{jtl}, h_{jtl}, \xi_{jtl}, \theta) = \frac{R^\lambda_{rtl}}{1 + R^\lambda_{rtl}} \tag{4}$$

I will use γ^L_r to represent the percentage of type r consumers for location L. The overall market share of product j in market tl is

$$s^L_{jtl}(D_{jtl}, p_{jtl}, h_{jtl}, \xi_{jtl}, \theta) = \sum_r \gamma^L_r \pi^r_{jtl} s^r_{tl}(D_{jtl}, p_{jtl}, h_{jtl}, \xi_{jtl}, \theta) \tag{5}$$

Just like Berry, Carnall and Spiller (1996) and Berry and Jia (2010), this model is a special case of the random coefficient model (BLP). As opposed to assuming each consumer i draws her tastes β_l, β_h from parameterized distributions, I adopt the bi-model feature, meaning there are only two types of consumers, and the only difference between locations L is the distribution of the two types of consumers. As I have shown in 3 and 4, this feature can provide a simple closed-form expression for market shares without the need for numeric integration.[17] This is a parsimonious way to capture the correlation of tastes for product attributes within and across different locations.

In total, the parameters need to estimate, θ, including the parameters in the utility function β^r_l, β^r_p and β^r_h for each r, the nested logit parameter λ, and the consumer-type probability γ^L for each L. So for $r = 2$, and $L = 2$, there are 9 parameters in total.

Following the GMM estimation methods from Berry, Levinsohn and Pakes (1995), where ξ interacted with exogenous instruments. I will first guess an initial value for ξ

[17] Actually as shown by Berry, Carnall and Spiller (1996), any discrete number of types of consumers larger than 2 can achieve that.

and follow the modified contraction mapping method as in Berry, Carnall and Spiller (2006) till ξ converges. According to them, for the multiple-type nested logit model, i.e., the "step" between each iteration of ξ_{tl} should be multiplied by λ, the nested logit parameter, and the same will be used in this paper.[18]

$$\xi_{jtl}^{M} = \xi_{jtl}^{M-1} + \lambda[\log s_{jtl} - \log s_{jtl}(D_{jtl}, p_{jtl}, h_{jtl}, \xi_{jtl}, \theta)] \tag{6}$$

where M is the iteration number, s_{jtl} is the observed share, and $s_{jtl}(D_{tl}, p_{tl}, h_{tl}, \xi_{tl}, \theta)$ is the product share calculated in 5. The moment conditions used would be

$$E(h(z_{jtl})\xi(D_{jtl}, p_{jtl}, h_{jtl}, \xi_{jtl}, \theta)) = 0 \tag{7}$$

for a specific vector of functions $h(\cdot)$ and a specific set of instruments z_{tl}. The choice of the instruments will be discussed in detail in the later section. The GMM method will choose a set of parameters θ to make the condition in 7 as close to zero as possible.

B. *The Product-level Unobservable*

As I have stated before, ξ_{jtl} will likely account for some characteristics of the product that are unobserved by the researcher, which might affect the model accuracy due to their potential correlation with price.

The first is the distaste for sharing a ride with strangers. When a rider requested an UberPool ride, there is a possibility that she will be sharing the ride with a stranger, sometimes even multiple strangers, which is apart from the observed tradeoffs like longer travel time vs. cheaper price. This disutility brought by UberPool's "mechanism" may lower its market share not recorded in the data. This feature enters ξ_{jtl}, which is a standard procedure when estimating demand in a discrete choice model. For example, Small, Winston and Yan (2002) and Bento, Roth and Waxman (2020) observe consumers' choices among different types of road[19] to estimate the tradeoffs and demand. Unobserved characteristics like the "thrill" of driving at a higher speed on the higher speed limit road and smoother pavement in express lanes etc. cannot be observed and enter ξ_{jtl}. In this paper, I will also put the distaste of sharing a ride with a stranger into ξ_{jtl}, and use the instruments to account for its correlation with prices.

Another omitted variable is the travel party size. In the dataset, I don't observe how many people are traveling together in a single trip. This may be an issue due to the fact that Uber made sure travelers with more than 2 people can only request UberX. This omitted variable poses a threat to the identification, and it may not necessarily be a product-level unobservable, but more a consumer-level unobservable. However, when regarding the traveling pattern within Chicago Loop from 7 am to 11 pm on weekdays, this bias will not be huge for business travelers since the majority of the rides are for commuting. Among the commuters who use cars, at least 90% of them travel alone.[20]

[18]As in the current state of the paper, I have not implemented the method from Dubé, Fox and Su (2012), so that I can set the convergence tolerance to be very low. This could potentially be implemented in the future.

[19]Like paid toll road vs. free interstate

[20]Source: U.S. Census Bureau, 2013 American Community Survey, Table S0801.

However, for leisure travelers, this indeed may cause a bias, and β_h is expected to be relatively larger, and this bias will be partially captured by ξ_{jtl}. Therefore, within the scope of this paper, I will not try to estimate the difference in the value of time between different types of consumers due to this caveat brought by the omitted variables, and β_h can be considered as the upper bound. A more precise estimation would require a more detailed dataset.

IV. Empirical Estimation and Result

The empirical estimation mainly follows the GMM method discussed in III and uses the data discussed in II. As discussed before, I will focus on two types of products, UberX and UberPool, while Taxi serves as the outside option. I implement a similar strategy as in Berry, Carnall and Spiller (1996), where they put all the "inside" goods options in one "nest" and the outside goods in the other. I put both UberX and UberPool under one "nest" under the nested logit with two types of consumers, type A and type B. I will discuss the identification strategy in the following subsection IV.A.

On the other hand, based on the examination of the data, and the k-means clustering, I impose these assumptions for the discrete geographical level data: 1. I assume for the 5 locations, there are two types of locations. Only the probability of the arrival of a certain type of consumer γ_L is different for these two types of locations. 2. By exogenous information from the Chicago Zoning map, I treat location 4 as different from other locations. (See A2), namely, any route that has a pickup or dropoff location at location 4 will have a different γ_L from the other routes. 3. The only difference between different types of locations is γ_L, namely the distribution of each type of consumer at each location. Since there are only two types of consumers and two types of locations, I need γ_1^A(the probability of a consumer being type A in type 1 location) and γ_2^A(the probability of a consumer being type A in type 2 location) to fully capture the spatial differences.

Therefore, summarizing the parameters that need to be estimated in the model, I have $\beta_l^A, \beta_h^A, \alpha^A$, $\beta_l^B, \beta_h^B, \alpha^B, \lambda, \gamma_1^A, \gamma_2^A$ 9 parameters to estimate.

A. Identification Strategy

There are three major potential concerns regarding the identification. The first concern is how data can identify two unobserved types of consumers. The second one is how data can identify the spatial difference among the distribution of consumers. The third one is how data can justify the different "nests" in the nested logit. In this subsection, I will discuss these three concerns in detail.

Consumer Heterogeneity: When treating the method of Berry, Carnall and Spiller (1996) as a special case of BLP in Berry, Levinsohn and Pakes (1995), I regard this question as a special case of the identification of the random coefficients in BLP. Namely, the difference between $\beta_l^A, \beta_h^A, \alpha^A$, and $\beta_l^B, \beta_h^B, \alpha^B$ is a measurement of if and how consumers substitute between "similar" products. So the idea here is to pick up the data pattern where two products are very close in the product characteristic space, but consumers demonstrate different patterns of behaviors. I pick the outbound and inbound routes (like routes 12 & 21) of the exact time period, which in theory should be the closest in the product characteristic space, and observe the percentage change in the share of UberPool among the Uber products (the within-group share) in A4.

In the plots, the first observation is that for the inbound and outbound pair of routes, the percentage difference between the price of UberX/UberPool, and the duration of UberX/UberPool are very close to 0 for all pairs of routes for all time periods, meaning indeed these pairs are similar in the product characteristic space. However, the percentage differences of the within-group share of UberPool move a lot, both in terms of the frequencies and the levels. If consumers were homogeneous, this would certainly mean an abnormal substitution pattern between the two products, which means this pattern in the dataset could potentially identify the parameters of consumer heterogeneity, namely $\beta_l^A, \beta_h^A, \alpha^A$, $\beta_l^B, \beta_h^B, \alpha^B$.

A valid concern, given that the consumer types are unobservable, would be the existence of more than two discrete types of consumers. The estimation method from Berry, Carnall and Spiller (1996) can certainly be applied to more than two types of consumers. However, from IV.B, the two pairs of demand parameters for duration and price are fairly different and robust, meaning given the extent of the data, the consumers can be categorized into two baskets based on their elasticities on travel time and price. This fits the procedures implemented by Berry and Jia (2010) and Williams (2022) to describe two types of consumers, based on their tastes of price and time, to be tourists and business travelers. However, given the large standard error on β_l^A, β_l^B, it could be the case that there are more than two consumers regarding their utilities of point-to-point traveling(β_l^r). I plan to conduct empirical estimations with more than two types of consumers in the future to further investigate the possibility of more than two discrete types of consumers.

Spatial Heterogeneity: I follow the identification strategy of the literature with spacial heterogeneity in their demand estimations, specifically, Quan and Williams (2018). They used the fraction of markets where no sales of the product occur to identify the across-market demand heterogeneity. In this paper, both γ_1^A and γ_2^A control the spatial heterogeneity. The more different the two parameters are, the more different the tourist and business locations are. The probability of not observing a sale of UberPool increases as the demand is more concentrated in UberX, which is a location-specific event, given that the differences between locations are their consumer compositions.[21] Therefore, the fraction of markets with no UberPool sales can identify spatial heterogeneity.[22] Combining 3 and 4, the probability a product j is observed to have zero sales at location l at time t for consumer type r is

$$P0_{jtl}(D_{jtl}, p_{jtl}, h_{jtl}, \xi_{jtl}) = (1 - \pi_{jtl}^r s_{tl}(D_{jtl}, p_{jtl}, h_{jtl}, \xi_{jtl}))^{N_{tl}}$$

which is the probability that all N_{tl} consumers at location l choose not to purchase good

[21] In addition, what makes consumers different are their preferences on duration and price, which differentiate their demands of UberX and UberPool.

[22] The reason for not using the fraction of markets with no UberX is that from the dataset, no market doesn't have an UberX sale.

j. The empirical analogue of this would be

$$\widehat{P0_{jtl}} = \mathbb{1}\{\widehat{\pi_{jtl} s_{tl}} = 0\}$$

where $\widehat{\tilde{\pi_{jtl}}}$ is the observed location-time level market share for product j. Then the micromoment identify spatial heterogeneity is

$$mm_{jtl}(D_{jtl}, p_{jtl}, h_{jtl}, \xi_{jtl}) = P0_{jtl}(D_{jtl}, p_{jtl}, h_{jtl}, \xi_{jtl}) - \widehat{P0_{jtl}}$$

In the dataset, I observe the difference in the fraction of markets with zero UberPool sales between types of locations in A5, proving that there exist variations in data to identify spatial heterogeneity through this micromoment. In this meantime, I also include the result without the micromoment when doing GMM estimation which will be discussed in IV.B.

Nested Logit Parameter: To identify λ, Berry (1994) implemented an instrument, that is correlated with the within-category share but uncorrelated with the unobserved product quality. In other words, I need an instrument to identify how "close" Uber products are vs. the outside goods. The instrument I choose is the average market price of the taxi. This price is uncorrelated to the product level unobservables, which based on our discussion, are all specific features of Uber products that are unobserved in the data. It is also correlated with the within category share since taxis remain competitive and influential with their low travel time and comparable prices. Therefore, this instrument can identify how "close" Uber products vs. taxis. In the meantime, I also include the result of the simple logit without the λ parameter (namely set $\lambda = 1$). The results and comparisons will be discussed in IV.B.

Instruments: Besides the nested logit parameter, I will be using Hausman instruments(Hausman (1996)) to solve this endogeneity issue brought by prices, namely the prices at the same time of the day for the same product but different routes outside of the Chicago Loop. I used the prices and the travel time within the Near North area, the community area north of Chicago Loop. This instrument picked up common cost shocks, meaning that if there's an encouragement towards the driver[23] to pick up riders for a specific Uber product, which will distort the prices and travel time, the instrument will pick up the same shock. In addition, this instrument does not pick up common demand shocks, meaning a sudden surge in the number of riders for a particular route in the loop will not affect the price in the routes in the Near North. This can generally be considered valid since the surge pricing and the demand shock in Uber is very localized(Castillo (2020)). Therefore the Hausman instrument is valid in this setting. Just like in BLP, the product characteristics are valid instruments for themselves. Combining both all the instruments into matrix Z, the set of moments is $m = E[Z'\xi]$

In addition to the moments discussed above, I add two additional moments to reduce the standard error, which are $m_v = \pi_{jtl}^2 - E[\hat{\pi}^2|\theta]$ for both UberPool and UberX. In IV.B, I will include the result without m_v as well. Stacking the moments, moments for standard

[23]like reward bonus given by Uber

error and micromoments, I have

$$G(\theta; D_{jtl}, p_{jtl}, h_{jtl}) = \begin{bmatrix} m \\ mm \\ m_v \end{bmatrix}$$

and the GMM minimize criterion is $G(\theta;\cdot)'WG(\theta;\cdot)$, with weighting matrix W. In the first stage, $W_0 = (G(\theta_0;\cdot)G(\theta_0;\cdot)')^{-1}$ for the initial value θ_0. Then in the second stage. $\hat{W} = (G(\hat{\theta}_1;\cdot)G(\hat{\theta}_1;\cdot)')^{-1}$ to get the final estimates $\hat{\theta}_2$.

B. Results

The empirical results, as discussed in IV.A contain four results, which are reported in A.A3. Column I is the simple logit model with two types of consumers in two types of locations, including both the micromoments and the moments to reduce the standard errors. Column II is the nested logit model but without the micromoments. Column III is the nested logit model without the moments to reduce the standard errors. Column IV, which is the baseline model, is the nested logit model with both types of moments. I will use Column IV as the benchmark model, to infer the necessity of using nested logit to yield more credible estimates of consumer surplus, as well as the inclusion of specific types of moments, and then compare the results with other literature in the ride-hailing market, and finally, point out some caveats of the result.

When comparing Columns I and IV, we can see that the inclusion of the nested logit parameter λ not only captures the correlation of the demands for both Uber products, compared to the outside option but helps reduce the standard errors as well. However, even the simple logit model results in two distinct types of consumers with $\alpha^A < \alpha^B, \&, \beta_H^A > \beta_H^B$, and small standard errors, meaning there exists a differentiation between business(type A) and leisure(type B) types of consumers, but the results are not comparable with other literature. The estimations of the rest of the parameters have large standard errors, making it difficult for inference. On the other hand, the fact that the inclusion of λ reduces the standard error, as well as the estimation results for λ is very far from 1(for Columns II and III as well), show indeed a strong correlation between UberPool and UberX demands, and the importance of using the nested logit model.

When comparing Columns II and IV, I am testing the importance of including the micromoments. The most important difference is that for Column II, γ_B^A and γ_T^A are very close and with large standard errors, but for Column IV, γ_B^A and γ_T^A are fairly different with smaller SE.[24] This shows that the inclusion of the micromoments helps identify the spatial differences, as well as increase the robustness of other parameters. When comparing Columns III and IV, I am testing if these specific moments help reduce the standard error. For most parameters, results in Column IV have smaller standard errors, showing the necessity to include these moments in the model. Interestingly, the result in Column III makes the estimation between γ_B^A and γ_T^A closer, which means these moments

[24]The standard error for γ_B^A in Column IV is still fairly big, but the inclusion of the micromoments definitely helps with the robustness.

can to some degree help with identifying spatial heterogeneity as well.

Therefore, by showing the results of simple logit, and nested logit without some specific moments, I establish the reason for the empirical estimation strategy. I will now discuss and then compare the benchmark result (Column IV) to other literature. The model produces robust results in estimating $\alpha^A, \alpha^B, \beta_H^A, \beta_H^B$. With $\alpha^A < \alpha^B \&, \beta_H^A > \beta_H^B$ (which also exists in Columns II and III as well), it shows that consumers in the ride-hailing market demonstrated differentiation in their tastes of trip duration and price, showing a similar dichotomy - business and leisure - as the one used in estimating demand in the airline market.[25] The difference between γ_B^A and γ_T^A is fairly large with a caveat that the standard error for γ_B^A is fairly big. Nevertheless, there certainly exists some spatial heterogeneity and micromoments have been identified through variations in the data. The potential reason behind a slightly bigger than expected standard error for γ_B^A could be the not well-defined "business" location in the Chicago Loop area. The way I defined "tourist" location is the location surrounded by the Chicago landmark area in the Chicago Zoning map, and the rest are "business" locations. So this is more of defined as "non-tourist" locations instead of "business" locations. It is possible that we might need more than two types of locations to fully capture the spatial heterogeneity.

The empirical estimation offers comparable results to the past literature on the ride-hailing market. Lam and Liu (2017) estimated consumer tastes in various locations in NYC for various time periods. My estimated result for type A consumers(0.0322) of price effect is close to their results in Midtown Manhattan for weekdays daytime, and morning and evening rush(0.058 to 0.094). Given that I choose the dataset to be in Chicago Loop and from 7 am to 10 pm on weekdays, my results are certainly comparable to theirs. However, their estimates of the trip duration effect seem to be bigger than mine. Buchholz et al. (2020) estimated the coefficient of waiting time to be ranging from 0.018 to 0.089. The result of type B consumer(0.0596), which is the tourist consumer falls in this range, but the result of business consumer(0.1857) is larger than their estimation. Castillo (2020) estimates the price parameter to be 0.0476 and the travel time parameter to be 0.1164, which is close to the parameters of type A in my model. Given that type A is the dominant type in both business locations and leisure locations in my estimation, the result is consistent with the demand estimation in Castillo (2020). To sum up, the estimation results offer robust, comparable, and consistent results compared to similar demand estimation results for price effect and travel time effect in the ride-hailing market. The results are most consistent with the Midtown Manhattan during the weekday in Lam and Liu (2017) and Castillo (2020), where he used downtown Houston Uber data. These locations are indeed the closest resemblance of the demand, consumer types, and geographical characteristics of this paper, which is the Chicago Loop area.

Besides the standard error issue for γ_B^A, the standard error for β_l^B is also quite big. Even though type B consumer (business type) is not the dominant type, this may still raise concerns about the robustness of the model. In this model, the structures of the utility function for both types of consumers are the same, especially for β_l^r, which measures the pure utility of traveling from point A to point B. However this effect is affected by

[25]Like in Berry and Jia (2010) and Williams (2022)

the actual travel distance of the trip, meaning the longer the distance, the higher the utility. This is not the case in real life, since consumers demonstrated a "bliss point" of travel distance and when drivers are doing detours, which is very evident in UberPool, it will decrease the actual utility. This travel distance "bliss point" will certainly make the estimation more accurate. In fact, across Columns I to IV, the standard errors for business type consumer β_l^B are all pretty big, meaning it is necessary to have a better demand structure for the business type consumer and it could be the addition of the "bliss point" or could be other reasons. The business type consumer could be very sensitive when the driver takes a detour when they travel.

In conclusion, the empirical estimation result shows that 1. Making a categorization of consumers based on their tastes of price and travel time is justified. 2. Quantitatively, the results are consistent with the demand estimation of the ride-hailing market in related literature. 3. The micromoments identify at least partial, if not fully spatial heterogeneity. It could be the case that we need more types of locations to differentiate the types of spaces further. Nevertheless, the existence of spatial heterogeneity, based on the difference in consumer-type distributions, is guaranteed. 4. The demand structure and the product characteristics space for Uber products may need to be changed in order to get a more robust result for coefficients other than prices and travel time.

V. Counterfactual Analysis

Given the empirical results of consumer and spatial heterogeneities, I will establish methods to calculate the consumer surplus gained from UberPool as a form of a new product. The usage of consumer surplus as a measurement of welfare is consistent with literature analyzing the impact of new products like Brynjolfsson, Hu and Smith (2003) and Aguiar and Waldfogel (2018). The consumer surplus with product choice set J is given by:

$$\begin{aligned} CS_{tl}^J = {} & \frac{1}{\alpha^a}\log(\sum_j^J \exp((\xi_j + \beta_l^a D_{tl} - \alpha^a p_{jtl} - \beta_h^a h_{jtl})/\lambda) + 1) * \gamma_l^A * q_{tl} + \\ & \frac{1}{\alpha^b}\log(\sum_j \exp((\xi_j + \beta_l^b D_{tl} - \alpha^b p_{jtl} - \beta_h^b h_{jtl})/\lambda) + 1) * (1-\gamma_l^A) * q_{tl} \end{aligned} \tag{8}$$

The q_{tl} here is the arriving consumers choosing between Uber products and the outside options at time t for a given route l, and the average consumer surplus for a certain time of the day t is $CS_t = \frac{1}{L}\sum_l^L CS_{tl}$. The revenue for Uber is:

$$Y_{tl} = p_{jtl} * s_{tl}^A(p_{jtl}) * \gamma_l^A * q_{tl} + p_{jtl} * s_{tl}^B(p_{jtl}) * (1-\gamma_l^A) * q_{tl} \tag{9}$$

where s_{tl}^r is the share of consumers of type r ride with Uber, regardless of which product of Uber, which is from 4. The share depends on mean utility $\delta_{jtl}(p_{jtl})$. Therefore, if given a new set of prices $\tilde{p_{jtl}}$, the share of consumers who choose Uber will change.

The measuring of welfare change is the ratio between the consumer surplus with the product set $\tilde{J}$ without UberPool and the ones with the product set J with UberPool. The same goes for revenue as well. The choice set is the only thing that changes through the comparison. The parameters and indirect utility functions will be kept the same as the real-world scenario, namely in the world of product set J with UberPool. This way of calculating welfare gain is like the "ex-post" measure discussed in Trajtenberg (1989). Basically, the object of interest is $\frac{CS_t^{\tilde{J}}}{CS_t^{J}}$. The "counterfactual" part would be the alternative prices for $CS_t^{\tilde{J}}$. I don't observe the price without UberPool so assumptions would be made in order to estimate the welfare gain from the new product. So fundamentally, this is to measure how much income could be taken away from the consumer so as to leave her indifferent between facing current choice sets (UberX, UberPool, and Taxi) and the choice sets before (UberX and Taxi), in the light of her current tastes.[26]

A. *Single Product Pricing*

The most straightforward way of counterfactual pricing is to offer the same product across locations with the same pricing formula. In this section, I will present the upper and lower bounds of the counterfactual price in the single product pricing scenario and calculate the upper and lower bounds of the welfare gains from UberPool accordingly. Due to the fact that I don't have information on the supply side, the real-world scenarios will be much more dynamic. For instance, the change in price will certainly change the driver's cut, which will change the supply side, which will in turn affect the demand side. Therefore, the counterfactuals in this paper will be the changes in consumer surplus and revenue given the market size unchanged on both sides, i.e. there will still be the same amount of riders deciding between Uber and outside options and drivers for a specific route at a specific time of the day.

For the current state, I will perform two most direct and uniform ways of defining $\tilde{p}$, the counterfactual price for Uber if we only have UberX provided, which are the real UberX price and the real UberPool price. With the price discrimination between two products, both prices can be regarded as the upper and lower bound for the counterfactual uniform prices[27] for the single product, given that UberPool price is on average lower than UberX price. Ideally, the most accurate counterfactual prices should be in between, given that Uber would need to maintain its market share and revenue.

The results are in A6. I also include the 95% CI with the Gaussian assumption with the standard error calculated in the GMM. For the upper bound of counterfactual price ($\tilde{p} = p_X$), and the lower bound of the CS ratio, the result is indicated in the red lines in A6. For the consumer surplus, the counterfactual predicts the mean ratio will be 0.760, with a standard deviation of 0.018. This means on average if the new Uber price is set to equal to the UberX price, getting rid of UberPool will reduce the consumer surplus 76.0% of the previous welfare level. This can be seen as the lower bound of the counterfactual CS ratio. For the upper bound of counterfactual price ($\tilde{p} = p_{pool}$), and the upper bound of

[26]According to Trajtenberg (1989), both "ex-ante" and "ex-post" measures of welfare gain from a new product are valid and produced qualitatively equal and quantitatively similar results.

[27]Uniform price here means it's the same pricing strategy between locations and time, which is not the same that price is exactly the same across locations and times.

the CS ratio, the result is indicated in the blue lines in A6. For the consumer surplus, the analysis predicts the mean ratio will be 0.769, with a standard deviation of 0.017. This means on average, getting rid of UberPool, given that the new UberX price is set to the previous UberPool price, consumer welfare will be reduced to 76.9% of the previous level. This can be seen as the upper bound of the counterfactual consumer surplus.

Thus given that the upper and lower bound for the counterfactual consumer surplus produce very close results, the ratio between the counterfactual consumer welfare of only UberX, and the actual consumer welfare is between $[0.760, 0.769]$, which showed a strong case that UberPool brings on average $31.58\% \sim 33.51\%$ more on the consumer surplus. The 95% CI can be a bit more robust given that some estimations are having big standard errors. However, I can still make a strong case regarding the welfare gains from UberPool, particularly qualitatively. To address the concern of Ackerberg and Rysman (2005),[28], I will argue that the addition of UberPool provides significant product differentiation in the characteristics space of products in the ride-hailing market. Therefore, this estimated qualitative gain in CS is significant, in terms of UberPool capturing the differentiated consumer types with its different characteristics in the product space.

In addition, I would like to briefly discuss the pattern across different times of the day. It seems that during both early in the morning and late at night (before 10 am and after 8 pm), the ratio is higher, meaning the welfare loss is lower in these periods and higher in the middle of the day. This pattern holds true for both the lower and the upper bounds of the CS ratio, as well as the 95% CI. In this paper, I did not make temporal differentiation, and a strong case can be made that the optimal pricing policy should be different across different times of the day.

B. Spatial Differentiated Product Placement

This subsection is to find the magnitude of the variety effect in the ride-hailing market. Instead of the complete removal of UberPool from the market, one can argue from the firm's perspective, a better pricing/product placement strategy is to partially remove UberPool from some locations in order to tailor specific types of products to certain types of consumers. I define this counterfactual to be operated this way: only letting UberPool be operated when departing from leisure locations, and letting both products be operated when departing from business locations. Even though when doing demand estimation, I let both routes depart from and arrive at location 4 to be associated with leisure locations. However, in terms of feasibility, it is much more feasible for Uber to differentiate consumers when they request the ride, not only consumers have the possibility to change their destination mid-ride, but also it will make it easier to actually "share the ride" for consumers sharing the same route.[29]

[28]In their paper, they stated that in a saturated market, any new product will bring seemingly new characteristics, which will qualitatively add to the consumer surplus, but actually, many of the characteristics are not very much cared about by the majority of the consumers, like the color of packaging in the cereal market.

[29]This product placement is by no means feasible. Given that Uber is a city-wise business, it will be impossible to offer one product at one location, but not the others. If there are any differences in drivers' earnings between products, it will incentivize drivers to travel to the locations where the higher-paying products are offered.

The result is reported in A7. For revenue, this counterfactual result has a mean ratio of 1.08, with a standard deviation of 0.093. For consumer surplus, the split product placement generates the highest consumer surplus, even though still below 1. It has a mean ratio of 0.79 and a standard deviation of 0.016, which means consumer welfare will be reduced on average by 21% compared to the real world. These results have many implications in terms of policies. The red lines in A7 are the upper bounds for potential revenue and lower bounds for potential CS, and the blue lines are the lower bounds for revenue and the upper bounds for CS. The spatial differentiation product placement can match the upper bound of counterfactual revenue but can generate an even higher(2.57% more) consumer surplus than its upper bound. The upper bound of consumer surplus is calculated using UberPool price as the counterfactual price. The fact that partially have two products can have an even higher consumer surplus than the single product but with the lower bound of price can potentially be evidence of the variety effect is more significant than the price effect shown by Quan and Williams (2018), which should not be ignored by policymakers when calculating social welfare.

Another policy implication is the potential consumer surplus Uber can capture with more detailed price discrimination. A more targeted product placement strategy regarding the spatial differentiation of consumers will presumably capture more consumer surplus in terms of price discrimination. The counterfactual analysis still offers some insights into the possibility Uber could do in terms of micro-managing different types of consumers in different locations.[30] Even within the same type of product, like UberX, there could be some micro-product differentiation so that consumers may not even know they have been price discriminated against. In fact, some researchers have pointed out that Uber has already been doing this. According to Bonatti and Cisternas (2020), Uber personalized prices on the basis of individual characteristics.[31] The detailed investigation of Uber's optimum price discrimination and product placing strategy is certainly worth further exploring, and spatial differentiation lays the foundation.

VI. Conclusion

In this paper, I quantified the effect of the addition of the product UberPool on consumer surplus with spatial heterogeneity of consumer types, differentiated by their tastes of travel time and price. Applying the model to the public data of Chicago Loop from the City of Chicago containing the market share of UberX, UberPool, and taxis, I found that consumers demonstrated substantial heterogeneity in demand within and across locations.

With a nested logit demand estimation model, I conclude that the exogenously determined business locations have a large proportion (99.16%) of consumers with relatively lower sensitivity to prices and higher sensitivity to travel time, which is precisely the behavior of business type consumers, while leisure location has a smaller proportion

[30]For example, in leisure locations, Uber will have prior knowledge that consumers there are more sensitive to prices but less sensitive to time. It can operate a pricing strategy to make the ride cheaper but the overall travel time longer.

[31]For instance, the usage of a personal versus business credit card in the app, and also the locations where the ride is requested.

(68.87%). This means the demand estimation model successfully captures the required spatial differentiation, where business locations have more business-type consumers, and leisure location has (relatively) more leisure-type consumers. In addition, the estimates of price and time effects of business type consumer (which is also the dominant type in both types of locations) are comparable with existing results from Lam and Liu (2017), Castillo (2020), and Buchholz et al. (2020).

The presence of this spatial heterogeneity has important implications for consumer welfare, as well as potential policy decisions. On the consumer side, if I don't allow the heterogeneous preferences, the estimated additional consumer surplus brought by UberPool would be much smaller. Given my estimation, UberPool brings on average $31.58\% \sim 33.51\%$ more on the consumer surplus. This is pretty significant given that based on the calculation from Lam and Liu (2017), ride-sharing platforms themselves bring 56.52% more consumer surplus compared to the "only taxi" world.[32]. On the other side of the policy implication, I argue that ride-sharing platform firms can exploit spatial heterogeneity to perform price discrimination. This means they can charge different prices given their prior knowledge of consumer type composition for a given location. I performed the "simplest" exploitation of spatial heterogeneity to eliminate the service of UberPool at the locations where leisure consumers are not abundant, and it generates higher revenues for the firm with the cost of some consumer welfare. The reduction of consumer welfare is smaller than uniformly pricing at UberPool price(the on average lower price) can be viewed as a piece of evidence that the variety effect is more significant than the price effect in the ride-hailing market, which should be taken into effect for antitrust enforcers and policymakers in this market.

The conclusions come with some caveats. First, I assume the supply side to be fully efficient and consistent. Namely, the drivers are homogeneously and efficiently distributed across different locations. The addition of the supply side, and the choice on the drivers' side when accepting UberX or UberPool rides based on their profitability is a necessary next step given the access to more detailed data sources. Second, the product level unobservables have potentially omitted variable biases like the traveling party, or people's distaste for sharing a ride with strangers. This can potentially up-skew the estimates on time effect for both types of consumers. The traveling party omitted variable bias can be endogenized once I have this data and can certainly help to alleviate the problem. Third, I limit the location types to two to have an easy-to-interpret dichotomy of business and leisure locations. More types of locations are certainly worth exploring in further research. Lastly, like the existing literature, I do not observe the scenario where UberPool is not offered in the data. Thus, an analysis with the style of regression discontinuity cannot be performed. Instead, my results come from an "ex-post" measure where I first estimate the demand and then construct a hypothetical world with only UberX offered. Given that the counterfactual prices are hard to define, I used the existing UberPool and UberX as the lower and upper bounds for the counterfactual prices. Further research on the welfare effect from UberPool can be done with the construction of a more plausible counterfactual price to obtain a more accurate estimation of welfare gains.

[32]I used their estimations on the amount of consumer surplus per dollar spent in Table 10 of their literature

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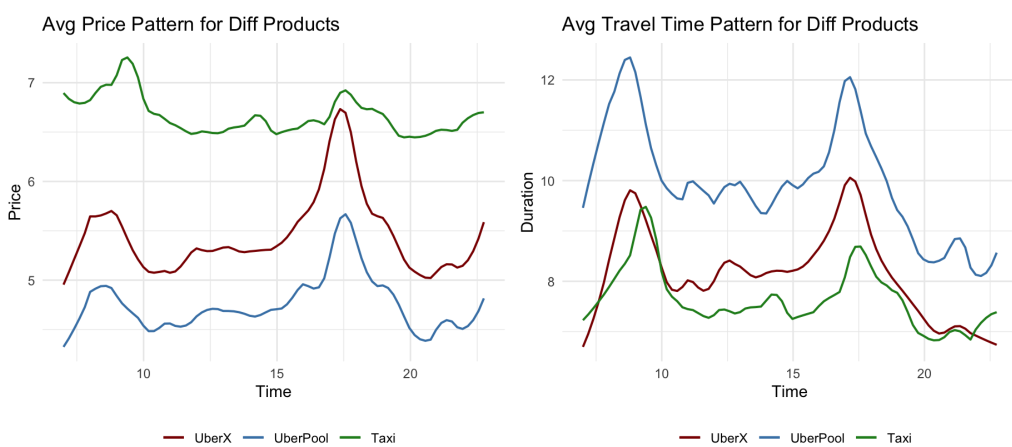
Appendix

A1. Summary Statistics

UberAll	Mean	SD	Taxi	Mean	SD
Duration (min)	9.1063	4.1403	Duration	7.4646	4.0202
Distance (mile)	1.1450	0.4967	Distance	0.9365	0.4192
Fare ($)	5.704	2.120	Fare	6.447	1.428
Market Share	0.7520	0.1767	Market Share	0.2479	0.1767
UberX	Mean	SD	UberPool	Mean	SD
Duration (min)	8.983	3.996	Duration	10.68	5.427
Distance (mile)	1.133	0.4829	Distance	1.297	0.6292
Fare ($)	5.712	2.119	Fare	4.750	0.7612
Market Share	0.695	0.161	Market Share	0.05695	0.04219

Notes: In the original dataset, all trips are recorded in the unit of second, I scale them to minutes. The UberAll here combines the trips of UberX and UberPool, and the market share of UberX and UberPool is not the within group share of Uber products, but the overall market percentage.

Table A1—Summary Statistics of the Ride-hailing market



Notes: The price and travel time patterns for UberPool and UberX follow the hypothesis that UberX is the faster but more expensive option, and UberPool is the cheaper but slower one. The outside option Taxi, if only examined in the characteristic space of price and travel time, can be viewed as an even faster(on average) but more expensive option.

Figure A1. Summary Statistics For Different Time of the Day

From both A.A1 and A1, we can observe that as expected, UberPool trips on average take longer than UberX, traveled slightly further in the distance, and are cheaper. On the other hand, on average, taxis remain competitive in the market, with lower travel time and competitive prices. Uber in general is cheaper but has a longer travel time. At any time of the day, taxi on average always has higher prices. Based on these statistics, the correlation between demands is the main reason why both Uber products are in the "nest" when estimating demand. Within the Uber products, UberPool is always cheaper and takes a longer travel time, which pinpoints their different positions in the characteristic spaces. These summary statistics serve as the basis of the research question, which is the welfare gains from the addition of the new product as UberPool.

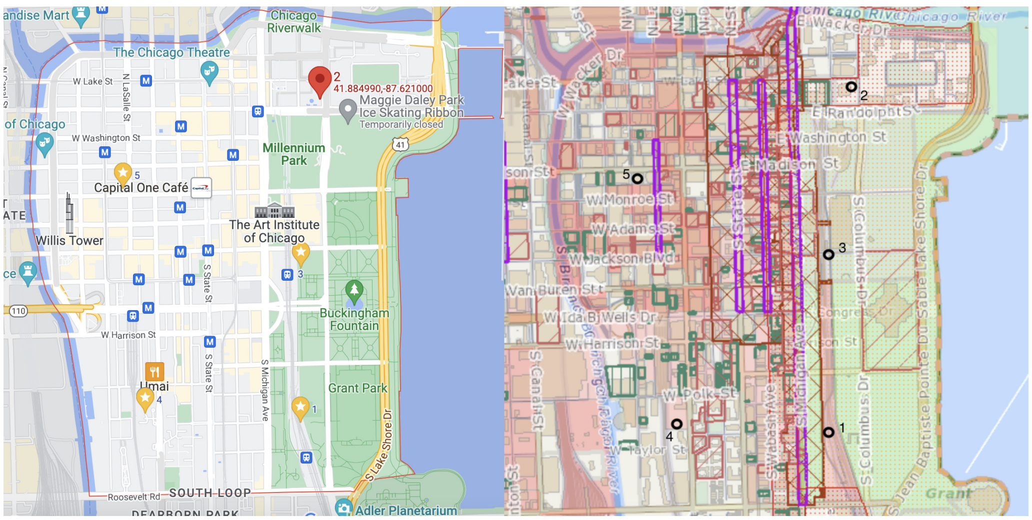


FIGURE A2. CHICAGO LOOP UBER & TAXI PICKUP AND DROPOFF K-MEANS CLUSTERING(L) AND ZONING(R)

No.	Latitude	Longitude	Within SS	Size
1	41.87102	-87.63141	$3.590100e^{-18}$	32265
2	41.88099	-87.63274	$7.078607e^{-16}$	75541
3	41.87061	-87.62217	$1.256882e^{-16}$	35586
4	41.87741	-87.62197	$1.232399e^{-17}$	26982
5	41.88499	-87.62100	$1.432680e^{-16}$	64130

Total Within SS: $9.92731e^{-16}$, between SS / total SS = 100.0 %

TABLE A2—RESULT SUMMARY OF K-MEANS CLUSTERING

The results of k-means serve as the basis for spatial heterogeneity. One of the major differences between this paper compared to other literature on the ride-hailing market is allowing consumers to arrive in different compositions for different locations. K-means provides a discrete categorization of all the Uber and taxi trips, and the Chicago Zoning map provides exogenous information on why certain location is different from other. As stated on the website, the light pink regions with angular stripes are denoted as "Chicago landmarks (Districts)", which are abundantly surrounding Location 4. For the other locations, it's either an even mix between business(light pink solid color) and Chicago landmarks, or private residential regions(light pick with dots). Since Location 4 is the only location that is surrounded by only the Chicago landmark area. I manually categorize it into "tourist" locations and the rest into "business" locations.

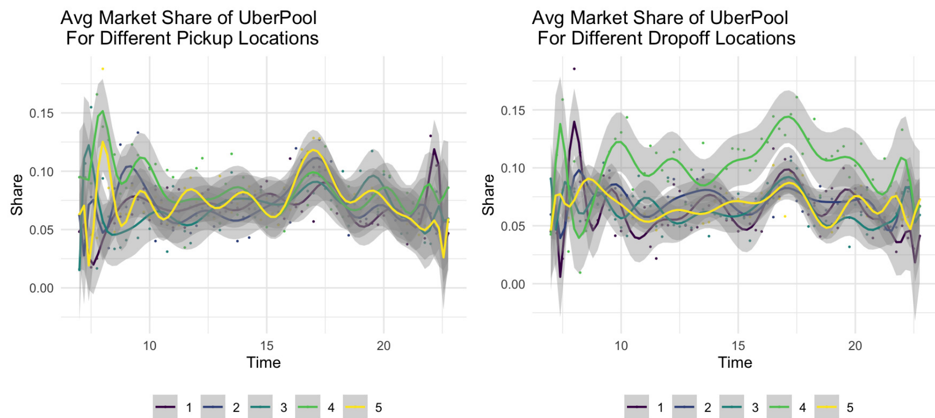


FIGURE A3. MARKET SHARE OF UBERPOOL AMONG DIFFERENT LOCATIONS (AGGREGATE ALL TRIPS INTO STARTING FROM A SPECIFIC LOCATION(L), AND ENDING AT A SPECIFIC LOCATION(R))

From 1	Mean	SD	To 1	Mean	SD
Duration (min)	9.800	4.425	Duration	8.156	3.940
Distance (mile)	1.216	0.477	Distance	1.221	0.540
Fare ($)	5.841	2.020	Fare	5.6130	2.241
From 2	Mean	SD	To 2	Mean	SD
Duration (min)	9.421	4.190	Duration	9.457	4.117
Distance (mile)	1.177	0.494	Distance	1.221	0.540
Fare ($)	5.879	2.232	Fare	5.835	2.119
From 3	Mean	SD	To 3	Mean	SD
Duration (min)	7.832	3.820	Duration	7.670	3.643
Distance (mile)	0.944	0.424	Distance	0.929	0.429
Fare ($)	5.302	2.063	Fare	5.263	2.041
From 4	Mean	SD	To 4	Mean	SD
Duration (min)	9.780	4.493	Duration	8.825	4.131
Distance (mile)	1.271	0.575	Distance	1.229	0.553
Fare ($)	5.720	1.988	Fare	5.686	2.229
From 5	Mean	SD	To 5	Mean	SD
Duration (min)	8.680	3.835	Duration	9.606	4.204
Distance (mile)	1.102	0.469	Distance	1.131	0.458
Fare ($)	5.629	2.122	Fare	5.768	2.066

TABLE A3—SUMMARY STATISTICS FOR DIFFERENT LOCATIONS

	Only Pickup	Only Dropoff	Mixed
Intercept	6.8144***	6.3598***	5.2911***
	(0.2755)	(0.2643)	(0.3937)
from2	0.3097		0.5340
	(0.3897)		(0.3764)
from3	0.1300		0.1726
	(0.3897)		(0.3764)
from4	1.6620***		2.7633***
	(0.3897)		(0.3764)
from5	0.6497		0.8048*
	(0.3897)		(0.3764)
to2		0.7635*	0.8970*
		(0.3738)	(0.3764)
to3		0.1273	0.1705
		(0.3738)	(0.3764)
to4		3.7146***	4.4055***
		(0.3738)	(0.3764)
to5		0.4192	0.6204
		(0.3738)	(0.3764)
Observations	1280	1280	1280
R^2	0.01809	0.09661	0.1436
F Statistic	5.872***	34.09***	26.65***

p-value < 0.0001 ***, < 0.01 **, < 0.05 *

Notes: In the OLS, I aggregate all trips into the "location-time" market, instead of doing OLS on the individual trip levels. Hence a much lower observation number. Here the OLS is simply the effect of location on the market share of UberPool for that specific market.

TABLE A4—OLS OF LOCATION ON UBERPOOL MARKET SHARE

I observe that if the routes are arriving at location 4, it has a higher share of UberPool almost throughout the day. (See A3) However, the same trend cannot be observed for departing from different locations. Even though the same pattern is not evident for departing from different locations, it is still worth endogenizing this spatial difference when calculating the consumer surplus. The summary statistics shown in A3 showed that in principle location does not change the price and travel time of Uber trips, meaning the impact should be exogenous. A simple OLS regression on what's affecting the UberPool market share further proves that the demand for UberPool is unique for Location 4. This can be served as a partial reason for the identification of spatial heterogeneity.

A2. Identification

In this subsection, I will show the patterns in the dataset to identify the heterogeneous preferences both within and across locations.

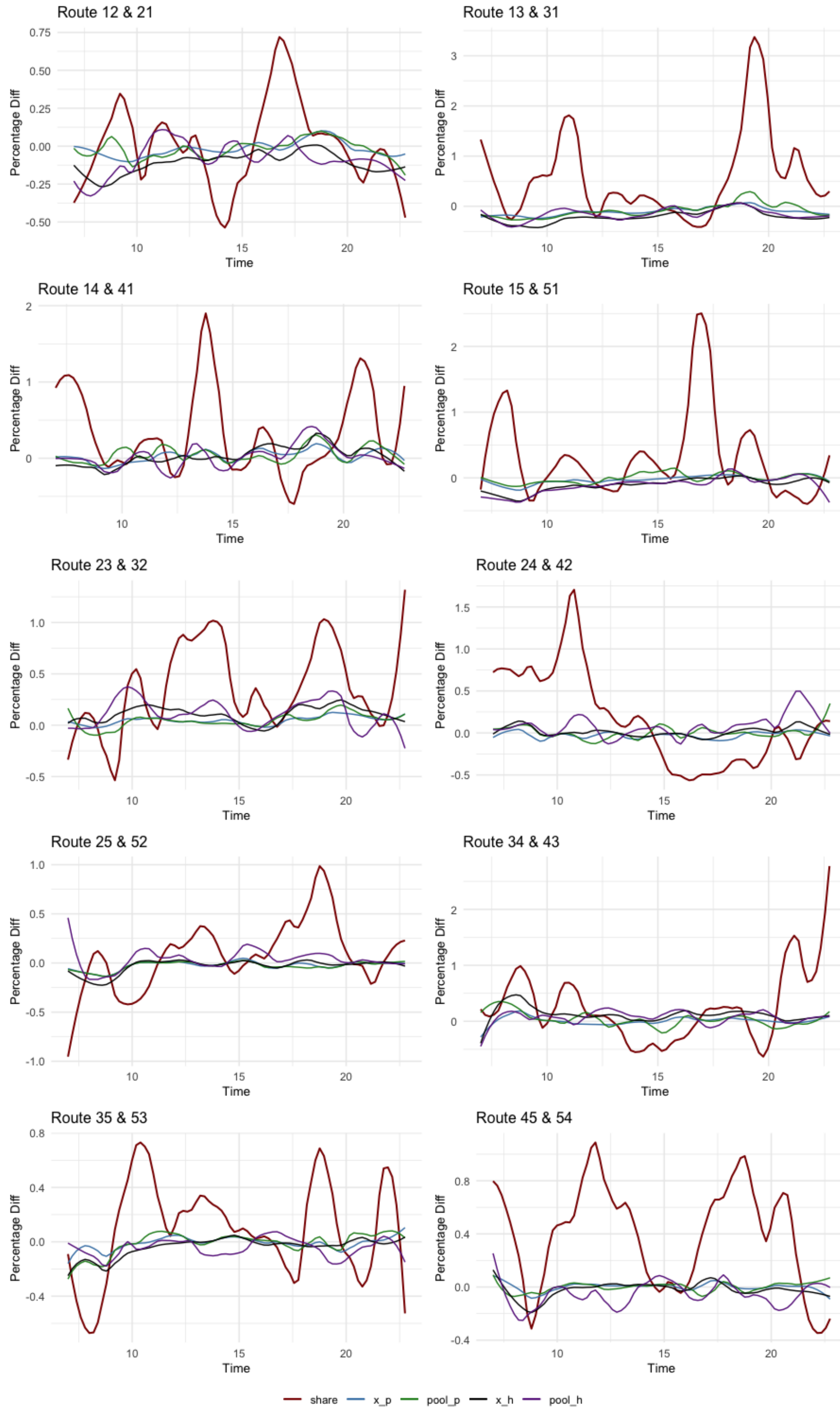


FIGURE A4. IDENTIFICATION OF CONSUMER HETEROGENEITY

In A4, of all the plots, there is a common trend that the market share of UberPool is always the one that is jumping around. For example, for routes 12 & 21, 13 & 31, and 15 & 51 around 17:00. The price and duration difference between both products are small ($< 10\%$ on average in terms of percentage), but the difference between the usage of UberPool is very high ($> 300\%$ for routes 13 & 31). If there is only one type of consumer, her preference will be the same (similar if with random coefficients) in terms of the product characteristic space. A smaller change in the product characteristics cannot induct such a large change in choices, and there should not exist such substitution patterns between such similar products.

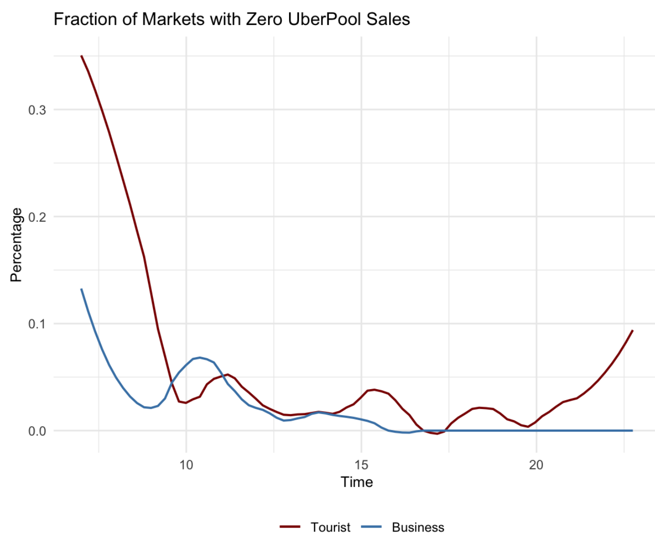


FIGURE A5. IDENTIFICATION OF SPATIAL HETEROGENEITY

In A5, tourist location has more percentage of markets with zero UberPool sales, which shows consumer types are more concentrated in the tourist location. A more concentrated consumer distribution can identify the pattern of spatial heterogeneity.

A3. Empirical Result

In this subsection, I attach the empirical result from GMM. The discussion of the result is recorded in detail in IV, with each less complicated model lacking a moment and/or parameter, showing the importance of including the moments and parameters in the benchmark model in Column IV.

	(I) Simple Logit	(II) Nested Logit	(III) Nested Logit	(IV) Nested Logit
Moments for SE	✓	✓	×	✓
Micromoments	✓	×	✓	✓
β_l^A	0.0011	3.3449	3.6516	2.5578
	(0.0038)	(9.9074)	(3.6845)	(0.9702)
β_h^A	-0.0698	-0.2491	-0.1516	-0.1857
	(0.0327)	(0.0642)	(0.0166)	(0.0119)
α^A	0.0001	0.0088	0.0747	0.0322
	(0.000032)	(0.0022)	(0.0053)	(0.0018)
β_l^B	6.544	1.2655	2.3766	0.5378
	(17.061)	(19.9382)	(6.2382)	(1.3245)
β_h^B	-0.0104	-0.0447	-0.1202	-0.0596
	(0.0018)	(0.1417)	(0.0414)	(0.0124)
α^B	0.0063	1.0535	0.8851	0.1429
	(0.000057)	(4.5844)	(0.6619)	(0.0531)
γ_B^A	0.2325	0.9905	0.8792	0.6887
	(0.0143)	(1.0498)	(0.0741)	(0.4986)
γ_T^A	0.9946	0.9944	0.9453	0.9916
	(2.5591)	(0.1491)	(0.0099)	(0.0128)
λ		0.0132	0.0217	0.0163
		(0.00062)	(0.001)	(0.00014)
N of Parameters	8	9	9	9
N of Moments	12	12	12	14

TABLE A5—EMPIRICAL ESTIMATION RESULT

A4. Counterfactual Results

In this subsection, I will attach two pictures showing the results of the counterfactual analysis. A6 is the counterfactual where only UberX is operated and sets the counterfactual price to either the previous UberX price(lower bound of the counterfactual CS) or the previous UberPool price(upper bound of the counterfactual CS).

A7 is the counterfactual where UberPool is only allowed to be operated in the tourist

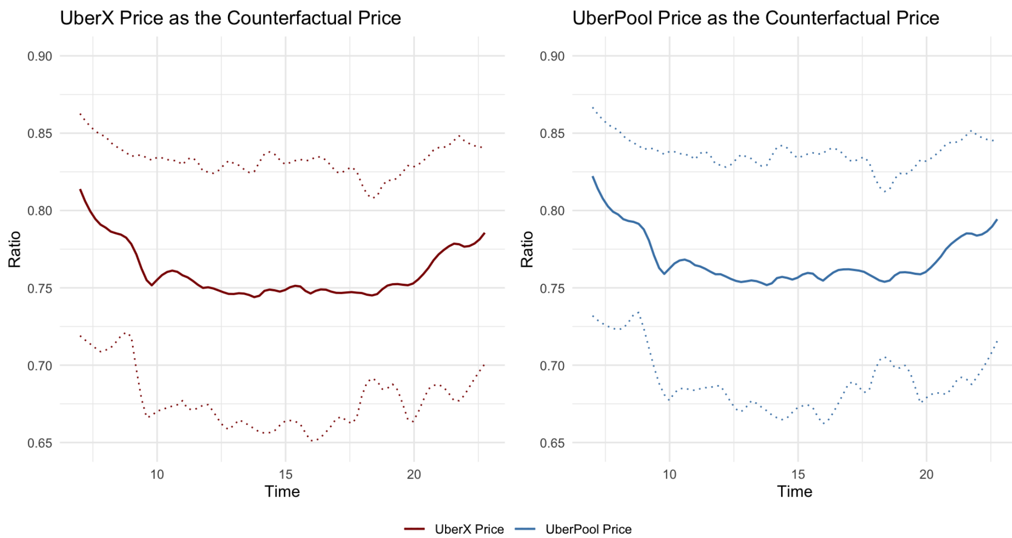


FIGURE A6. COUNTERFACTUAL: LOWER(L) AND UPPER(R) BOUNDS OF CS RATIO B/W ONLY UBERX AND UBERX AND UBERPOOL WITH 95% CI

location. A high jump in the CS compared to the results previously shows the significance of variety effect, even with very limited access to the new product.

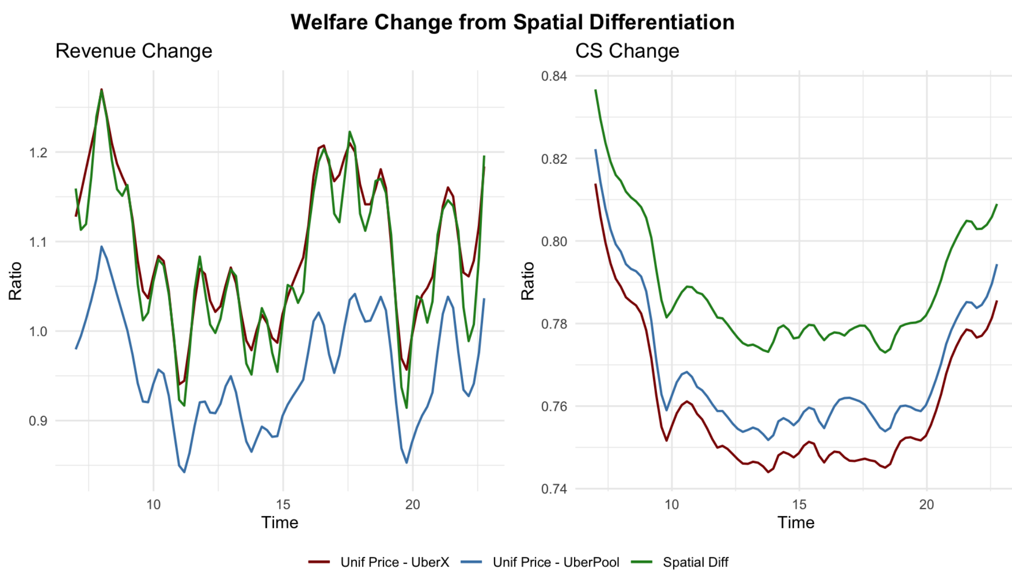


FIGURE A7. COUNTERFACTUAL: WELFARE CHANGE IF PRODUCT PROVIDED IS DIFFERENT AMONG LOCATIONS