Spatial Heterogeneity in the Sharing Economy: Uber's Impact on Hotel Price

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Abstract

This study investigates how Uber's market entry influences hotel prices across urban geographies, with a focus on heterogeneous impacts driven by proximity to city centres and public transit accessibility. Employing a staggered difference-in-differences (DiD) framework on granular zip code-level data spanning six major U.S. cities (2011–2015), we find that Uber's entry increases average hotel prices by 7.75%. The largest price increases arise in neighbourhoods with moderate but incomplete public transit access, rather than in the most distant or best transit locations. This pattern indicates that Uber acts as a complement to existing mobility infrastructure, increasing the effective accessibility of locations that were previously underserved. Demand and supply tests confirm that these pricing effects are demand driven rather than supply driven. The results highlight a previously overlooked cross sector linkage: ride-sharing can expand spatial hotel demand by reducing last-mile frictions. These findings underscore Uber's role not only as a transportation disruptor but also as an urban reallocator of economic activity, with implications for hospitality markets, platform regulation, and urban accessibility policy.

Keywords: Sharing Economy, Hotel Industry, Public Transportation, Market Entry, Price Changes
JEL Codes: R30, M31, R41, L11,L91

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1 Introduction

The rapid expansion of the sharing economy has reshaped the organisation of urban services and altered how consumers access transportation, accommodation, and other experience-based goods. The sharing economy, defined by the World Economic Forum as a system enabling individuals to redistribute under-utilised assets through digital platforms, has profoundly disrupted multiple industries. Uber (launched in 2011) and Airbnb have redefined mobility and accommodation markets. Uber's evolution from a luxury car service in San Francisco to the mass-market UberX rollout in 2012 exemplifies this transformation; by 2023, the platform served 93 million active users and 3.5 million drivers globally. Beyond their economic significance, these platforms raise broader questions about how digital intermediation reshapes urban space. While previous debates have focused on whether the sharing economy fosters innovation, enables more efficient resource allocation, or instead destabilises labour markets and regulatory frameworks (Martin, 2016), considerably less attention has been paid to its spatial consequences. In particular, the hospitality sector, whose performance is tightly linked to accessibility, proximity to amenities, and transportation costs, provides an important yet under-examined setting for understanding how platform enabled mobility may alter the geography of consumer demand. Despite the visibility of platforms like Uber, we still know relatively little about whether improved access to destinations changes the spatial distribution of lodging preferences within a city.

This paper investigates the impact of the sharing economy on incumbent service industries, with a particular focus on Uber's effect on hotel pricing. Prior work highlights urban accessibility as a key determinant of lodging demand (Lee et al., 2010), yet it remains unclear whether ride-sharing technologies reshape this spatial equilibrium. In traditional urban models, travellers face a clear trade-off between price and proximity: hotels located farther from major business districts or tourist hubs typically command lower rates due to higher travel times and weaker connectivity. The emergence of ride-hailing, however, introduces a potentially transformative shift by reducing both the cost and uncertainty associated with urban travel. We hypothesize that Uber's entry may relax transportation constraints and expand the effective choice set for travellers by improving access to locations beyond the central area. By enabling door-to-door mobility, ride-hailing reduces the time costs of travelling to outskirts neighbourhoods, thereby weakening the historical penalty associated with distance. The app-based matching technology further minimises search frictions by guaranteeing predictable wait times and eliminating the need for traditional street hailing. Together, these features may narrow the longstanding disadvantage faced by hotels in less accessible neighbourhoods and allow travellers to substitute toward a broader geographic set of accommodations. Whether this adjustment leads to a reallocation of demand, a flattening of spatial price gradients, or a complementary relationship between Uber and existing transit networks remains an open empirical question, one that this paper seeks to answer.

However, the effect of ride-hailing on the lodging market is unlikely to manifest as a simple spatial reallocation of demand from central to peripheral areas. Instead, a growing body of urban transportation research suggests that platforms like Uber may function primarily as *complements* to existing transit systems rather than as substitutes (Hall et al., 2018). Ride-hailing fills gaps in public transport coverage, mitigates last-mile problem, and provides flexible mobility in neighbourhoods where transit networks are present but insufficiently dense. In this setting, the magnitude and direction of Uber's impact depend not only on geographic distance from the city centre but also on the underlying quality of local transportation infrastructure.If Uber effectively strengthens last-mile connectivity, locations characterised by moderate yet incomplete transit access may experience disproportionately large gains in lodging demand and pricing power. These neighbourhoods stand to benefit most because the marginal improvement in mobility is greatest where transit options are available but do not provide seamless point-to-point travel. By contrast, areas with either very limited transit or highly efficient, multimodal systems may observe smaller effects: in the former, overall accessibility remains constrained despite Uber's presence, while in the latter, the incremental benefit of ride-hailing is limited. This heterogeneity underscores the need to distinguish between *physical distance* and *functional accessibility*, which reflects the combined influence of transit networks and platform-enabled mobility. This framework leads to the core research question: does improved mobility generated by ride-sharing platforms reshape the spatial pattern of hotel performance, and if so, along which margin is the effect most pronounced: physical distance or functional accessibility? Identifying whether geographic distance or functional accessibility drives heterogeneity is essential for understanding not only how travellers reorganise their lodging choices but also how digital transportation platforms interact with existing urban systems. Answering this question has important implications for understanding the spatial distribution of hotel prices and the broader competitive dynamics between the sharing economy and traditional urban service providers.

Understanding Uber's effect matters for two reasons. First, it clarifies whether emerging transportation services influence accommodation choices, thereby informing urban transportation planning. If ride-hailing effectively enlarges the set of feasible lodging locations for travellers, then transportation policies influence not only mobility patterns but also the spatial distribution of tourism activity and associated economic externalities. This connection is particularly relevant as cities increasingly integrate platform-based mobility into long-term planning frameworks, raising questions about how digital services should be regulated, priced, or incorporated into multimodal networks. Second, the interaction between transportation platforms and the hospitality sector remains under-examined in the literature, despite the hotel industry's dependence on access to urban amenities and customer mobility. Identifying whether ride-hailing expands the effective market reach of hotels has direct implications for both policy and industry strategy.

To address these questions, this article employs the Difference-in-Differences (DiD) framework to examine the causal effect across six major U.S. cities (New York City, San Diego, Los Angeles, Seattle, Boston, and Buffalo) between January 2011 and December 2015. The staggered introduction of Uber provides quasi-experimental variation in entry timing, allowing us to isolate the effect of Uber's presence on hotel prices and to study how this effect varies with geographic proximity to city centres and public transit accessibility. The analysis draws on monthly zipcode level panel that include various metrics such as average monthly hotel prices, revenue, occupancy rates, total room revenue, and census property and room counts. We further construct indicators of local amenity density and public transportation accessibility for each zip code, and identify the geographic centre of each city to measure distance-based heterogeneity. These data allow us to quantify both the traditional spatial penalty associated with distance and the variation in mobility conditions that may be relaxed by the introduction of ride-hailing services. To ensure credible identification, the empirical specification incorporates an extensive set of fixed effects, including zipcode fixed effects to absorb time-invariant spatial characteristics and year-month fixed effects to capture local macroeconomic conditions, seasonality, and specific temporal shocks. We further include time-varying controls that proxy for changes in local demand and supply conditions, and cluster standard errors at the appropriate geographic level to account for spatial correlation in unobserved shocks. Together, these elements support a research design capable of separating the causal effect of Uber's entry from broader trends in urban tourism, hotel investment, and neighbourhood development dynamics.

Our findings reveal three layered insights. First, the impact of Uber on hotel pricing does not vary systematically with physical distance from the city centre. Prices rise across virtually all distance bands, but the differences between central and more remote locations are small and generally not statistically significant. This pattern suggests that geographic distance is not the primary margin along which ride-hailing alters consumer behaviour. In other words, the traditional "distance penalty" does not meaningfully weaken in response to Uber's entry. Second, when centrality is defined in functional rather than geographic terms, a much clearer pattern emerges. Hotels in areas with moderate but incomplete public transit access experience the largest post-entry price increases, while both transit-poor and transit-rich locations display substantially smaller effects. This non-linear gradient is consistent with Uber acting as a complement to existing transportation infrastructure. Ride-hailing improves point-to-point mobility most strongly where transit networks exist but fail to provide seamless last-mile connectivity, thereby generating the greatest marginal improvement in accessibility in these "intermediate" areas. Third, analyses of occupancy and total demand confirm that the price effects are demand-driven. Uber's entry increases both room sales and revenue, particularly in moderately accessible areas, suggesting that the platform expands the effective market reach of hotels rather than simply reallocating existing demand. The combined evidence points to partial spatial convergence,not because peripheral locations inherently catch up to the centre, but because Uber reduces mobility frictions in previously underserved yet transit-adjacent neighbourhoods.

Our paper makes several contributions. First, while prior research has focused on intra-industry competition within the sharing economy, such as Uber's disruption of taxis (Berger et al., 2018) or Airbnb's substitution effects on hotels (Zervas et al., 2017),we provide evidence of a novel cross-industry linkage: ride-sharing platforms indirectly reshape hotel demand by alleviating transportation constraints. This analysis is the first to demonstrate the interdependence between ride-sharing and the hotel sector, implying that regulations targeting Uber could influence hotel performance. Second, this research advances the spatial pricing literature. While classic hedonic models emphasize the premium placed on proximity to amenities (Rosen, 1974; Lee, 2015), they typically treat transportation conditions as fixed. By using Uber's staggered entry as a quasi-natural experiment, we isolate the causal role of effective mobility in shaping hotel prices and demonstrate that accessibility is the relevant margin of spatial heterogeneity. In doing so, we extend the urban equilibrium framework to incorporate platform-enabled changes in transport costs..

2 Literature Review

Research on the economic impacts of Uber has expanded rapidly, covering labour market dynamics, industry competition, and spatial reconfiguration. In labour markets, Uber's gig-based model reshapes work patterns: studies document persistent gender pay gaps and changes in labour supply despite equal platform access (Angrist et al., 2021). In product markets, Uber has disrupted traditional taxi services, lowering driver wages (Berger et al., 2018), while its interaction with public transit appears largely complementary, often serving last-mile travel needs. Concerns remain, however, about Uber's contribution to traffic congestion (Tarduno, 2021). Beyond market effects, Uber generates broader social spillovers: in some regions, greater availability is linked to increased alcohol consumption among young adults (Teltser et al., 2021), whereas in others, such as Brazil, it has been associated with reduced traffic-related fatalities (Barreto et al., 2021). Overall, these studies underscore Uber's complex role as both a market disruptor and an enabler, highlighting the need to examine its indirect effects on lodging preferences through enhanced transportation accessibility—a topic that remains under explored.

Research on the sharing economy's impact on lodging has largely focused on short-term accommodation platforms, particularly Airbnb. Airbnb's entry has been associated with higher housing and rental prices across various locations (**?**Barron et al., 2021). Some cities have implemented ordinances requiring valid registration for home-sharing, which helped reduce housing and rental prices (Koster et al., 2021). However, in areas adjacent to banned zones, both the number of Airbnb listings and their revenue increased, while housing prices within and near these zones decreased (Valentin, 2021).

Studies examining Airbnb's effect on hotels provide further context. Airbnb has been shown to reduce hotel prices and revenues (Farronato and Fradkin, 2022; Zervas et al., 2017), prompting hotels to adjust pricing strategies (Li et al., 2022). Local regulations have also sought to manage the impact of the sharing economy (Bibler et al., 2021), highlighting that Airbnb's substitutability depends on local demand elasticity. While these studies focus on accommodation platforms, less is known about how transportation platforms like Uber—by reshaping mobility and accessibility—indirectly affect hotel pricing and demand.

Theoretical frameworks on spatial externalities offer insights into Uber's potential role. Vickrey (1963) demonstrated that businesses relocate to higher-rent areas only if reductions in transportation costs offset rent increases, emphasizing the importance of transport in location decisions. Hedonic pricing models posit that goods derive value from their characteristics (Rosen, 1974), and have been widely applied in tourism research to study hotel room prices and the impact of distance on rates (White and Mulligan, 2002; Zhang et al., 2011; Lee, 2015). Further, **?** and Conroy (2020) document the spatial concentration of peer-to-peer accommodations, underscoring how distance influences tourists' choices due to uneven lodging distribution. Because commuting costs correlate with distance, better transit availability or proximity to destinations reduces travel costs. Zhang et al. (2022) explored Uber's effect on the short-term rental market in Austin, showing its moderating role on Airbnb and hotel demand, and the varying effects of transit accessibility. Unlike prior work focusing on platform interactions, this article examines how ride-sharing platforms shape lodging preferences through transportation accessibility, extending the literature on the spatial economics of tourism markets.

The rest of this paper is organised as follows. Section 3 shows the mechanism of the research questions in this paper, showing the hotel price and demand change based on commuting distance and cost. Section 4 shows the data collection, the data resources and summary statistics for this research. Section 5 stated the empirical strategy. Section 6 elaborated the results of regressions and analysis. Section 7 is the conclusion.

3 Theory

In this section, we present a theoretical model to analyse how the exogenous entry of Uber influences hotel prices in both city centres and outskirts through changes in market equilibrium. The model guides our empirical analysis in terms of model specification, estimation strategies and interpretation of the results.

There are two markets, the outskirts and central, $i = O, C$. Each market has a supply function that depends only on their own price: $Q^i_S(P^i)$, where the supply is increasing in the price: $\dfrac{dQ^i_S}{dP^i_S} > 0$. Each market has a demand function that depends on three things, the price within the market, P^i, the price of the other market, P^j, $j \neq i$, and the transportation cost, τ. Therefore demand is given by $Q^i_D(P^i, P^j, \tau)$. Demand is downwards sloping in own price, therefore $\dfrac{\partial Q^i_D}{\partial P^i} < 0$. As they are both hotels in the same city, the markets are substitutable, therefore we have that $\dfrac{\partial Q^i_D}{\partial P^j} > 0$ for $j \neq i$.[1] Own price effects dominate, therefore $\left|\dfrac{\partial Q^i_D}{\partial P^i}\right| > \left|\dfrac{\partial Q^i_D}{\partial P^j}\right|$. This assumption is made for two reasons. Firstly, intuitively the demand of the outskirts should be more sensitive to the price of the outskirts than the price of the central hotels. Secondly, this assumption ensures market equilibrium exists.[2]

Additionally, the outskirts demand is decreasing in the transport cost, $\dfrac{\partial Q^O_D}{\partial \tau} < 0$. This is consistent with the interpretation that consumers take the transportation costs into account when they consider a hotel on the outskirts. If this cost is reduced, it reduces the effective price of the outskirts hotels. Finally, we make the simplifying assumption that $\frac{\partial Q^C_D}{\partial \tau} = 0$. We note that this assumption could be easily relaxed leading to the same results, so long as the impact of transport costs on the outskirts demand was sufficiently higher than the impact of the central demand.

For any transportation cost τ, the market clears at a vector of prices given by

$$P^*(\tau) = \begin{bmatrix} P^{O,*}(\tau) \\ P^{C,*}(\tau) \end{bmatrix}$$

Specifically, this occurs when excess demand is 0 for each market:

$$\begin{bmatrix} Q^O_D(P^{O,\star}(\tau), P^{C,\star}(\tau), \tau) - Q^O_S(P^{O,*}(\tau)) \\ Q^C_D(P^{C,\star}(\tau), P^{O,\star}(\tau), \tau) - Q^C_S(P^{C,*}(\tau)) \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$

Reflecting the empirical evidence, we assume that $P^{*,O}(\tau) < P^{C,*}(\tau)$, for all transport costs τ. This reflects the fact that the demand is likely higher for central markets and more inelastic due to the location.[3]

[1]Note that this is the case for substitutes in *regular* demand. For inverse demand, substitutes would read as $\frac{\partial P^i_D}{\partial Q^j} < 0$ - in other words, an increase in the quantity of the other good reduces how much you would pay for an additional unit of the good. For regular demand, $\frac{\partial Q^i_D}{\partial P^j} > 0$ as an increase in the price of the good j makes good i look relatively more attractive, therefore increasing demand. The two conditions are dual.

[2]Note this requires that $\left|\dfrac{\partial Q^i_D}{\partial P^i} - \dfrac{\partial Q^i_S}{\partial P^i}\right| > \left|\dfrac{\partial Q^i_D}{\partial P^j}\right|$. As $\dfrac{\partial Q^i_D}{\partial P^i} < 0$ and $-\dfrac{\partial Q^i_S}{\partial P^i} < 0$ this is implied by the prior condition.

[3]We stay silent on supply, but one could imagine that supply would be lower in the central markets due to the additional

We will now show that with these assumptions we can get the following testable predictions:

1. The difference in prices is increasing in transportation costs: $\dfrac{d(P^{*,C} - P^{*,O})}{d\tau} > 0$. Therefore when transportation costs are reduced the difference in prices is reduced.

2. The price of the outskirts hotels is decreasing in the transportation costs: $\dfrac{dP^{*,O}}{d\tau} < 0$. Therefore when transportation costs are reduced the price of the outskirts hotels increases.

3. Additionally, the price of of the central hotels is also decreasing in the transportation costs: $\dfrac{dP^{*,C}}{d\tau} < 0$. Therefore when the transportation costs decrease the price of the central hotels should *also* increase.

To see this, consider the following initial equilibrium, depicted on the following figures:[4]

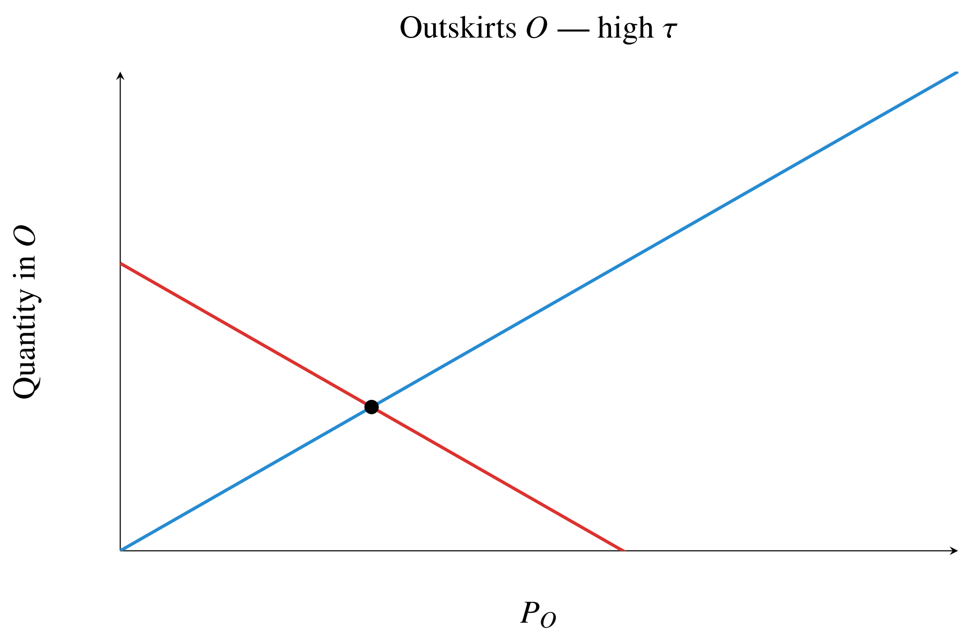

Figure 1: High τ: $D_O(Q) = 12 - 2P_O$, $S_O(Q) = 2P_O$; equilibrium at $(3, 6)$.

Starting from the second point surrounding the price of the outskirts hotels, if the transportation costs are reduced, this leads to to an increase in demand for any price level. In essence, demand shifts upwards. Therefore the price increases, as the intersection of supply and demand occurs at a higher point.

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costs involved.

[4]These figures are generated base on a model where $Q_S^C = \frac{P^C}{2}$, $Q_S^O = 2P^O$, $Q_D^C = 7 - \frac{3}{2}P^C + P^O$, and $Q_D^O = 14 - 2P^O + P^C - \tau$. $\tau = 7$ and $\tau = 0$ are considered.

Outskirts O — low τ

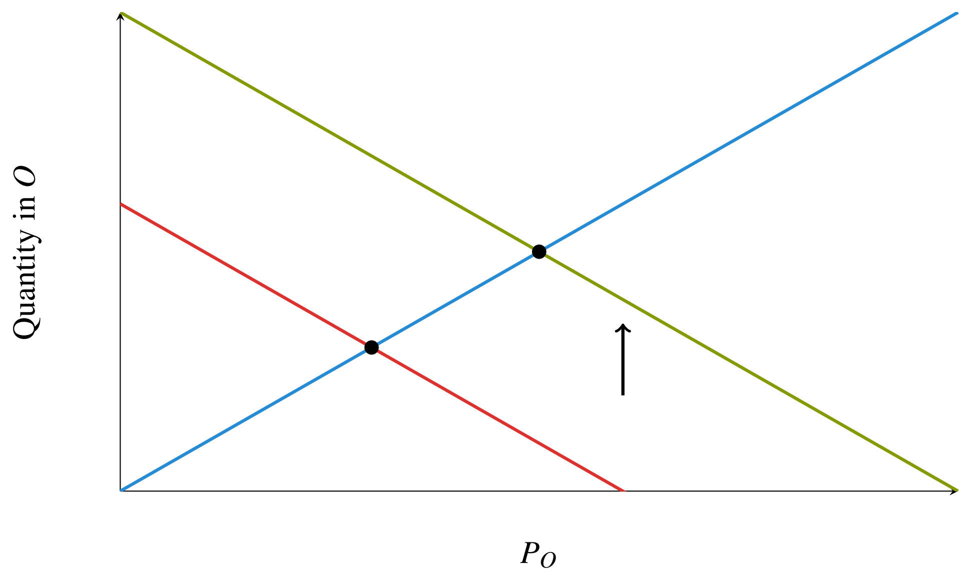


Figure 2: Low τ: $D_O(Q) = 20 - 2P_O$, $S_O(Q) = 2P_O$; equilibrium at $(5, 10)$.

However, the shift in price of the outskirts also has general equilibrium effects on the price of the central market. Specifically, when the price of the outskirts has increased, it makes the substitutable hotels (those that are central), look *relatively* cheaper.

Centre C — high τ

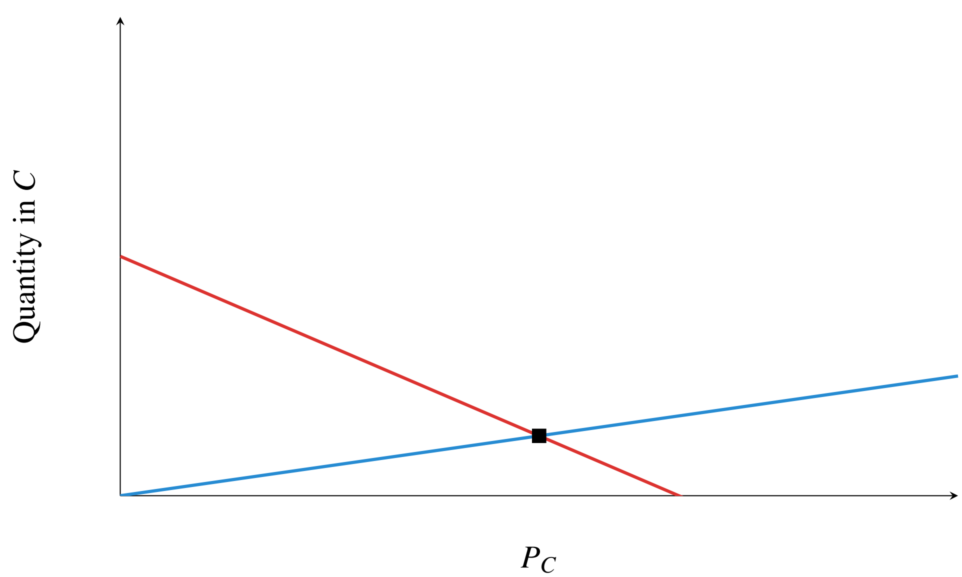


Figure 3: High τ: $D_C(Q) = 10 - 1.5P_C$, $S_C(Q) = 0.5P_C$; equilibrium at $(5, 2.5)$.

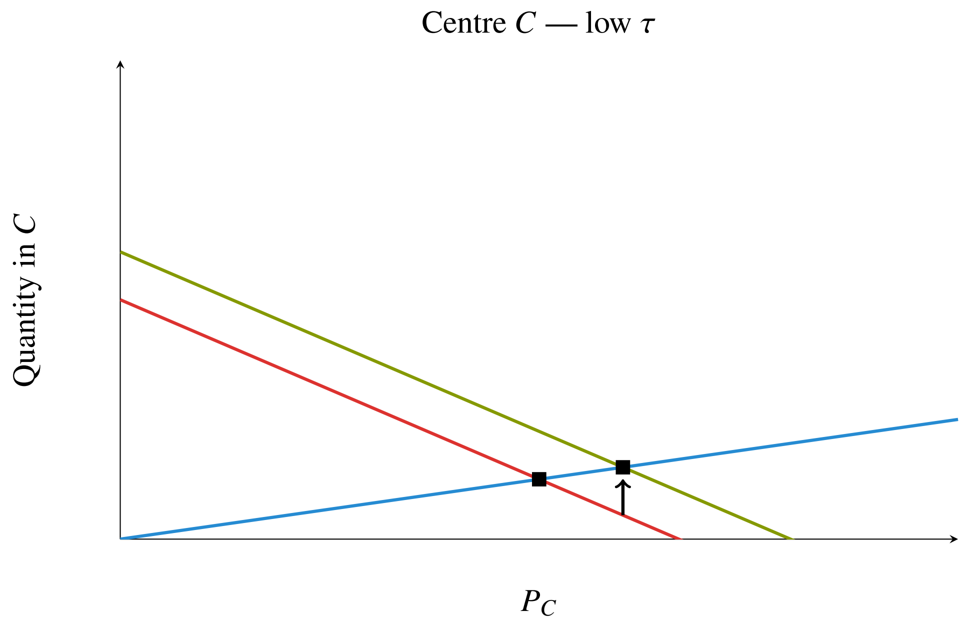


Figure 4: Low τ: $D_C(Q) = 12 - 1.5P_C$, $S_C(Q) = 0.5P_C$; equilibrium at $(6, 3)$. GE effect of price rising in outskirts hotel pushes central hotel demand upwards.

Therefore for any given *central* price, the demand rises, as the alternatives in the outskirts are more expensive. Note for this, we have assumed there is *no* direct effect of the transportation costs on the central demand. However, as own price effects dominate, the increase in price of the outskirts "catches up" to the central market, leading to our first prediction, that the difference in prices reduces when the transportation costs are reduced.

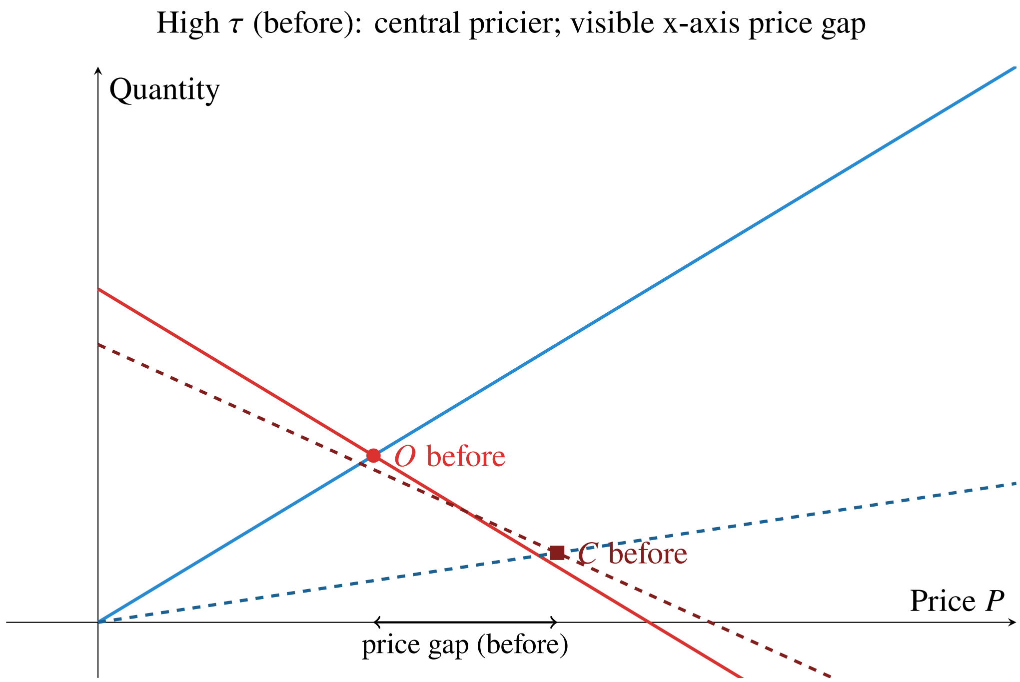


Figure 5: Before: $P_O = 3$ and $P_C = 5$; the x-axis price gap is 2.

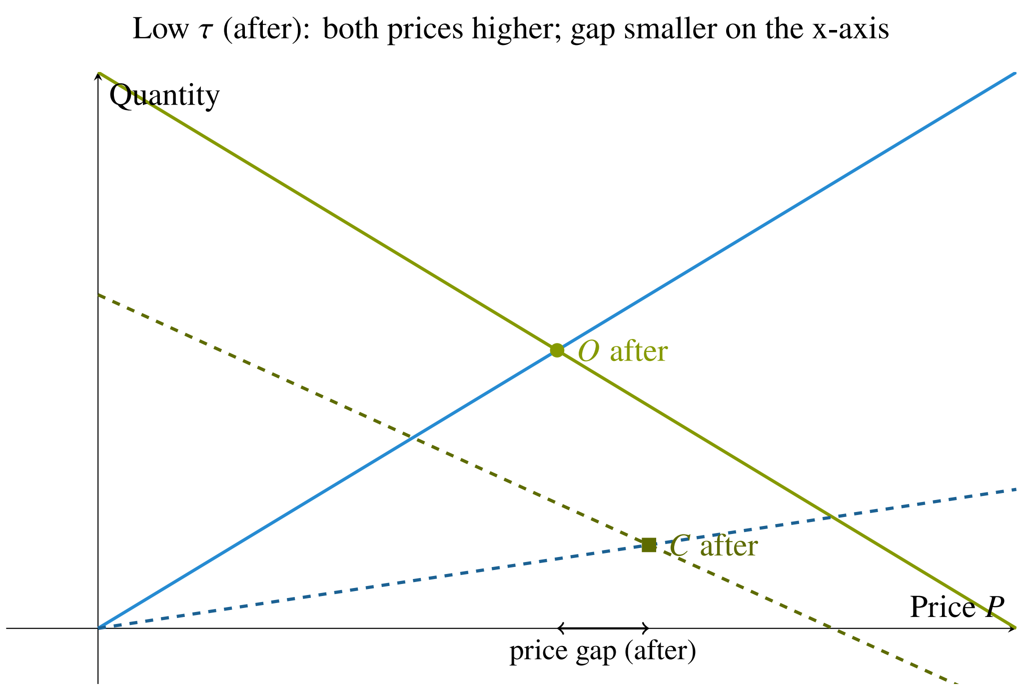


Figure 6: After: $P_O = 5$ and $P_C = 6$; the x-axis price gap is 1 (smaller than before).

4 Data

4.1 Background on Uber

UberX service was launched in New York city in July 2012, then expanded to other cities across US. Uber's app provides the ride-sharing services. Users can easily book the service on their Uber app via smartphone. The rider can enter their destination on the app and check the available options for vehicle size, price and estimated drop-off time, once it is confirmed, it is sent to a nearby Uber driver, who can choose to accept it. The rider can check the car's location on the app at anytime. Upon the driver's arrival, both the driver and the rider verify each other's names and the destination before starting the trip. They can also leave the reviews on the app. Uber provides the almost same services as taxis, but with easier way to hail which could save riders and drivers' time and enable the service to be more efficient. Uber drivers could independently decide when and where they want to work. Unlike the taxis, which are usually restricted by their licenses approved by local government(Berger et al., 2018), Uber drivers have more flexibility and thus Uber can help to compensate on some neglected areas. Overall, Uber is a low-cost substitute to the traditional taxis, and thus becoming very popular after its launch.

4.2 Data Collection

The data set for the main analysis spans 60 months from January 2011 to December 2015 in six cities in US, including New York City, Buffalo, Los Angeles, Boston, San Diego and Seattle. We collected the information of hotels at zip code level from professional hotel data collection company, which is the minimum aggregated level. I verified the zip code list by consulting the official websites of each city's government, which publish official zip code areas, and the U.S. Census Bureau, which lists the cities associated with each zip code. Other zip code level demographics are available on U.S. Census website as well.

A key component of our analysis is measuring the heterogeneous effects of distance and public transit accessibility. We collected road transportation distances and transit scores to quantify accessibility. The resulting dataset covers 71 zip codes across six U.S. cities over five years (January 2011–December 2015), yielding 4,260 observations and approximately 280 zip-code–level variables.

Hotel data. , a global database established in 1985 that collects comprehensive performance metrics for the hotel industry. Due to privacy restrictions preventing the identification of individual hotels, zip codes with fewer than three hotels are excluded. The main dependent variable is the monthly average daily rate (ADR), defined as the total room revenue divided by the number of rooms sold, calculated by dividing room revenue by rooms sold, ADR = Room Revenue/Rooms Sold, and the price is log-transformed in this analysis. The other hotel performance data we gathered from STR including: (1) Average rooms occupancy (Rooms Sold/Rooms available); (2) Average rooms revenue on all rooms, which is total room revenue divided by the total number of available rooms; (3) Rooms Supply: The number of rooms in a hotel or set of hotels multiplied by the number of days in a specified time period. Example: 100 rooms in subject hotel x 31 days in the month = Room Supply of 3,100 for the month; (4) Rooms Demand: The number of rooms sold in a specified time period (excludes complimentary rooms); (5) Rooms Revenue on sold rooms: Total room revenue generated from the guestroom rentals or sales; (6) Census Prop Count: Total number of existing hotels; (7) Census Room Count: Total number of existing hotel rooms;(8) Sample Prop Count: Total number of hotels submitting performance data to STR. (9) Sample Room Count: Total number of hotel rooms submitting performance data to STR.

Uber data. Uber initially offered a luxury service, Uber Black, providing vehicles for professional drivers. In 2012, the company launched UberX, allowing drivers to use their own vehicles to provide rides. This analysis focuses on UberX; all subsequent references to Uber refer specifically to UberX. Hall et al. (2018) provide publicly available data on Uber entry and exit dates, including all datasets and code used in their study. The Uber entry dates were collected from newspapers, official Uber releases, blogs, and social media posts. Uber first entered New York City in July 2012, followed by Los Angeles, Seattle, Boston, and San Diego in various months throughout 2013 and 2014.

Zip code census characteristics. For zip code characteristics data, we collected administrative data from U.S Census Bureau website[5] and at zip code level as well: (1) Housing data. The housing data contains the number of housing unit, housing price range, housing unit heating energy in categories (fuel, coal, gas etc.), the number of housing units with plumbing system and kitchen facilities, year of housing built and their vacancy status, the housing units of occupancy status, the number of rooms; (2) Labour related data, including number of Workers older than 16 years old, the earnings in the past 12 months, employment status (in labour force, employed and unemployment rate), number of workers in different career categories (agriculture, construction, manufacturing, wholesale trade, retail trade, transportation and warehousing, information, finance, professional, educational service, arts, public administration, armed forces, and other services except public administration), median household income and costs; (3) Census data. Total population, educational attainment rate, education enrolment rate, marital status, population by gender and race, and by age group. (4) Commuting. Number of workers in different commuting time, departure time and the transportation methods. (5) Others, including Gini index.

[5]See https://data.census.gov/

Distance data. To examine how hotel proximity to the city centre affects prices following Uber's entry, we collected distance data for each zip code relative to the city centre. The first step involved identifying the zip codes corresponding to the downtown area of each city. We aggregated population data and counts of restaurants, bars, and coffee shops within each zip code *i* to calculate local establishment density.

$$Density_i = \frac{Number\ of\ Restaurant,\ Bars\ and\ Cafe_i}{Population_i} \tag{1}$$

A prosperous zip code was defined based on the 10% highest density of these establishments. The zip code representing the city centre was defined as the area combining the highest establishment density with the economic and administrative centre of the city. Each zipcode was then matched to its nearest defined city centre area. The distances from each ZIP code to the city centre were measured as the driving distance by land transportation, obtained from the FreeDistanceTool website. [6]

Access to public transportation. To capture variation in transportation costs, we measure access to public transit, which may influence lodging choices (Ellinger, 1977). Public transit accessibility is proxied by the Transit Score from the Walk Score platform [7]. Transit Scores are reported at the neighbourhood level within each zip code. We matched neighbourhoods to zip codes using maps from Home.com and Statisticalatlas.com, and calculated the average Transit Score for each zip code to represent local public transit accessibility.

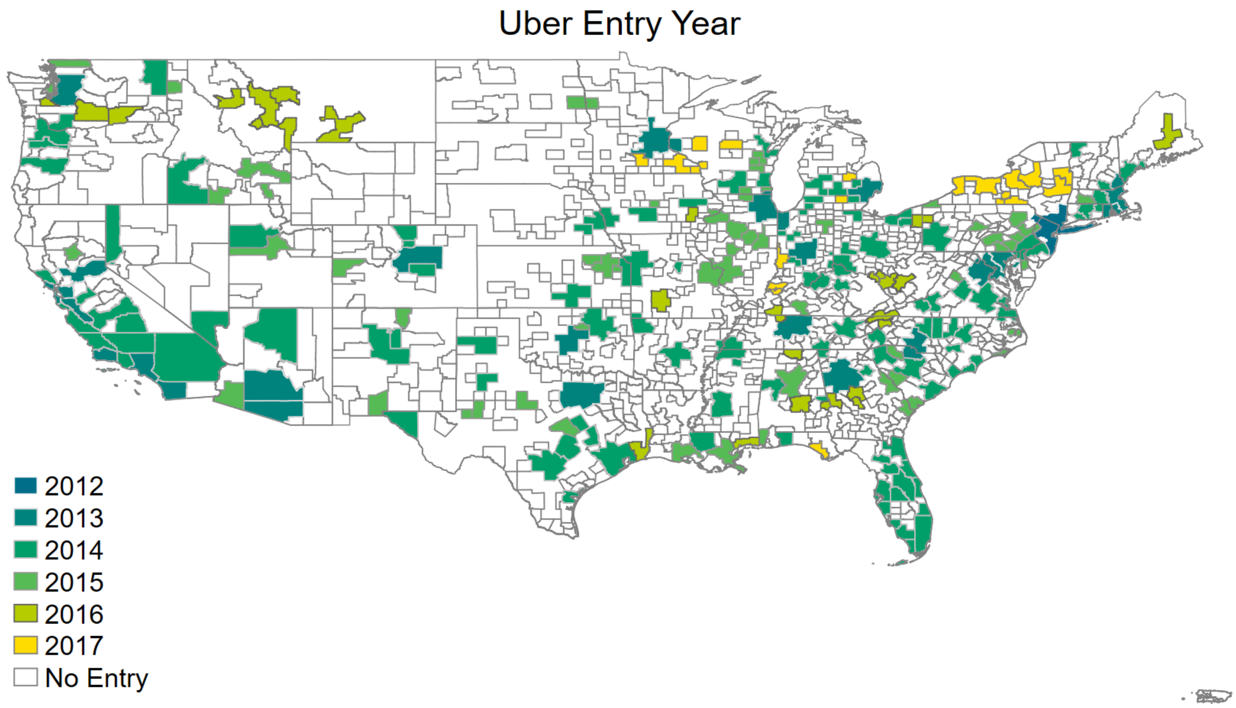
4.3 Summary Statistics

In Figure 7, the entry year is mapped at the MSA level. Uber first entered in New York, then it rapidly spread all over the whole country. By the end of 2017, Uber provides services in more than 200 MSA areas.

Figure 8 shows Uber's distribution in the US, showing the number of cities with Uber services in each state from 2012 to 2017. The shapefile of the United States is is based on the 2016 version of the Metropolitan Statistical Area (MSA) definition from official government sources. While New York State was the first state where UberX entered, California eventually surpassed it in having the maximum number of cities with Uber services. Texas and Florida followed closely as the states with the second-highest

[6] Data is avaliable at https://www.freemaptools.com/distance-between-usa-zip-codes.htm

[7] Transit Score is a patented measure of how well a location is served by public transit. Transit Score is based on data released in a standard format by public transit agencies.To calculate a Transit Score, the website assign a "usefulness" value to nearby transit routes based on the frequency, type of route (rail, bus, etc.), and distance to the nearest stop on the route. The "usefulness" of all nearby routes is summed and normalised to a score between 0 - 100.



Notes: The map only contains the mainland of US, the maps of Hawaii, Alaska and other islands are not plotted in this figure. Each colour represents different years that Uber entered in the area. The darkest colour means the earliest year that Uber entered.

Figure 7: The Uber first entry year in US from 2012 to 2017

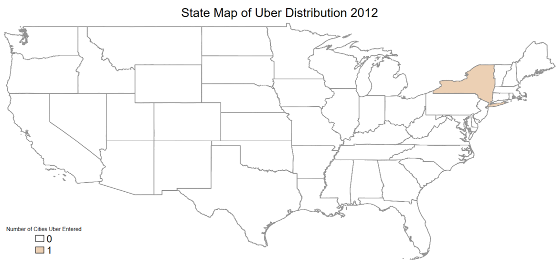
number of cities with Uber services. However, as of the end of 2017, Wyoming and South Dakota still did not have any Uber services available.

Table 4 in Appendix A presents summary statistics for the key variables used in this study, showing the overall observations across six cities. It reports the mean and standard deviation of each variable, including the average hotel room rate, as well as demographic data on age, education level, housing, and the number of individuals in different commuting time brackets. Additionally, the table provides the 25th, 50th, 75th, and 90th percentile values for each variable, offering a deeper understanding of the distribution of these measures.

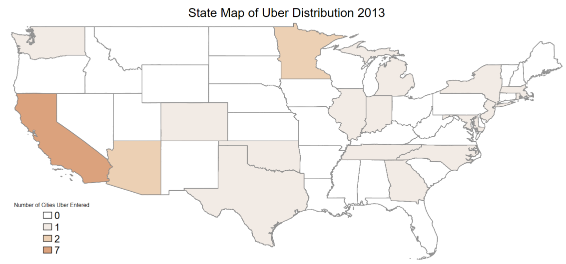
5 Empirical strategy

5.1 Effect of Uber on Hotel Prices

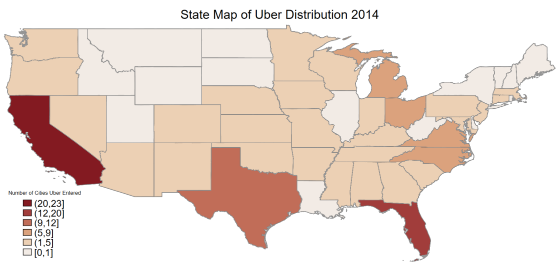
To explore the causal effect of Uber entry on hotel prices and the variations in hotel prices with distance, the main empirical framework to analyse is based on the difference-in-differences (DiD) model. Uber



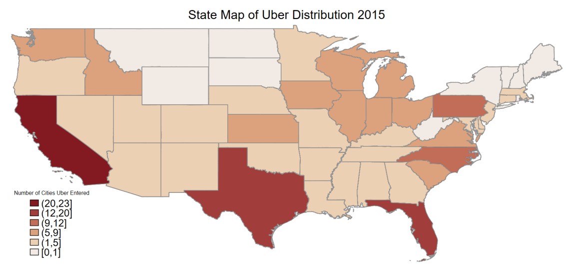
(a) 2012



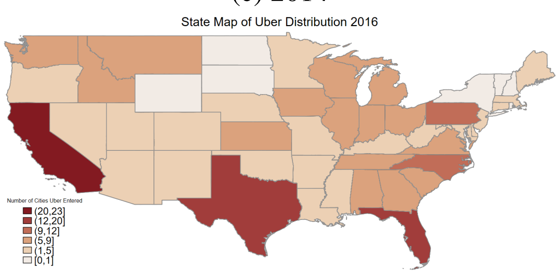
(b) 2013



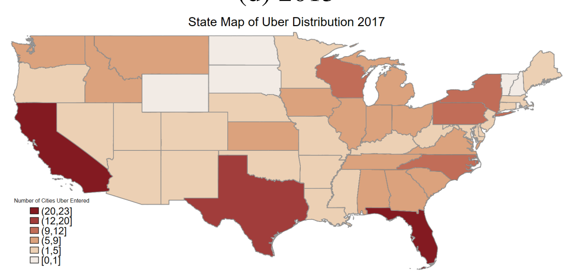
(c) 2014



(d) 2015



(e) 2016



(f) 2017

Figure 8: The Uber distribution from 2012 to 2017 in the US

entered into Buffalo after December 2015, making Buffalo city form the control group while the other five cities form the treatment group. Given that Uber entered different cities at different times, the DiD model incorporates time-varying factors as outlined by Beck et al. (2010). Specifically, this paper estimate the Uber's effect on hotel price by comparing the prices before and after Uber entered in a city. The identification strategy relies on the assumption that the treated group which has Uber service and non-treated group which has no Uber service had parallel trends before being treated and after, conditioned on treatment.

The estimation equation is as the following:

$$Price_{it} = \beta_1 Uber_{it} + \boldsymbol{\delta X}_{it} + \mu_i + \tau_t + \epsilon_{it} \tag{2}$$

where $Price_{it}$ is the average hotel prices of zipcode i at time t in log. $Uber_{it}$ equals to 1 if zipcode

i has Uber at time t and 0 otherwise. $\boldsymbol{X_{it}}$ includes time-varying control variables of each zipcode that may be related to hotel price at the zipcode level. β_1 measures the treatment effect of Uber, μ_i captures the zipcode fixed effect, and τ_t is the month fixed effect. We would expect that β_1 can show a positive relationship between Uber entry and hotel prices if people alter their lodging preferences from city centre to outskirts by using a comparatively cheaper transportation method.

To explore the heterogeneous effect by distance, we added the interaction of distance and treated effect. Therefore, the equation is expanded as following:

$$Price_{it} = \beta_1 Uber_{it} + \beta_2 Uber_{it} \cdot Distance_i + \boldsymbol{\delta X_{it}} + \mu_i + \tau_t + \epsilon_{it} \tag{3}$$

$Uber_{it}$ equals to 1 if zipcode i has Uber at time t and 0 otherwise. β_2 is the main coefficient we care which explains the different impact of distance on prices before and after Uber entered. All specifications above include zipcode fixed effect (μ_i) to account for the time-invariant factors that may be related to Uber's entry and time fixed effect (τ_t) to capture the factors related to time trend such as the economic development and policy changes.

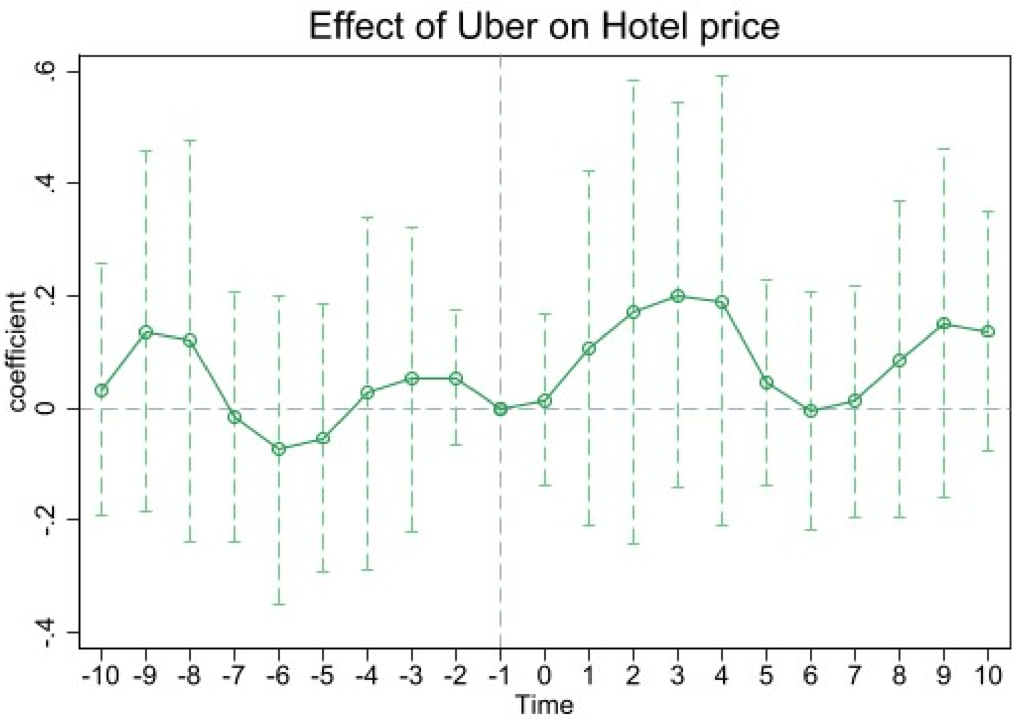
One threat for the DiD estimate here is the absence of unobserved factors that could be correlated with both Uber's entry and hotel prices. Hall et al. (2018) estimated the Uber's entry decision to US considering factors such as population density, education level, and income. Their findings suggest that Uber's entry decisions were primarily influenced by the population size of cities. This was further supported by statements from Uber executives, affirming that Uber's objective is to expand its presence to as many cities as possible, rather than being specifically tied to the local transportation or some other industries.

Another concern is if the city-level event could be influence hotel performance.While major city-level events (e.g., concerts, international exhibitions, or sporting events) may transiently affect hotel demand, our empirical design mitigate their confounding effects by exploring monthly-level data, which inherently smooths out short-term demand shocks lasting only days or weeks. Persistent effects of Uber's entry—unlike ephemeral event-driven fluctuations—would manifest as sustained monthly price changes, which our model is designed to capture.

6 Results

6.1 Hotel Price before and After Uber's Entry

Figure 9 shows the hotel price change with time before and after Uber's entry at 95% significance level. The hotel price increased after Uber entered into the market. The parallel trend shows the positive effect of Uber on hotel price, however there is a lagged trend of treatment effect.



Notes: the figure plots the coefficients and 95% confidence intervals. The zip code level variables are controlled, and the month fixed effect and zip code fixed effect are also controlled. Standard errors are clustered at city level.

Figure 9: Event Study: Effect of Uber on Hotel Price

Table 2 reports the estimation results of the difference-in-differences models specified in Eq. 2 and Eq. 3. The table presents changes in hotel prices before and after Uber's market entry, capturing the direct effect of Uber as well as its interaction with continuous measures of distance and transit accessibility. All five regressions include controls for zip codes, along with zip code and year–month fixed effects. The distance and transit score variables themselves are omitted as they both are cross-sectional and does not vary over time.

Column (1) reports the baseline treatment effect of Uber's entry, showing an overall 7.75% increase

Table 1: DiD Model: Hotel Price before and after Uber Entry

VARIABLES	Price	Price	Price	Price	Price
Uber	0.0775***		0.0787***		0.0306
	(0.0123)		(0.0165)		(0.0299)
Uber × Distance		0.00244	-0.000224		
		(0.00167)	(0.00193)		
Uber × TransitScore				0.000976***	0.000691
				(8.79e-05)	(0.000359)
Controls	✓	✓	✓	✓	✓
Year-Month Fixed Effect	✓	✓	✓	✓	✓
Fixed Effect	✓	✓	✓	✓	✓
Observations	4,150	4,150	4,150	4,150	4,150
R-squared	0.955	0.954	0.955	0.955	0.955

Robust standard errors in parentheses ***$p < 0.01$; **$p < 0.05$; *$p < 0.1$
Standard errors are clustered at MSA level

in hotel prices following Uber's introduction. Column (2) examines whether the distance of hotels from the city centre moderates this effect. The results suggest that hotel prices increase by 0.244% per unit of distance after the treatment, however, this effect is not statistically significant. Column (3) incorporates both the Uber treatment and its interaction with distance, revealing that while hotel prices tend to rise in more central areas, the marginal effect of greater distance from the city centre after Uber's entry remains statistically insignificant. Column (4) investigates the interaction between Uber and the continuous transit score variable, indicating a 0.09% increase in hotel prices with higher transit accessibility after Uber's entry. Finally, Column (5) compares areas with poor versus good transportation accessibility, finding no statistically significant differential effect of Uber's entry across these areas.

Although the interaction terms with the continuous distance and transit accessibility measures yield coefficients with the expected signs, the effects are not statistically significant. This suggests that the marginal treatment effect may not vary linearly with these continuous measures. A potential explanation is that the relationship between hotel performance and proximity or transit accessibility is non-linear, with meaningful variations only occurring at certain segments of the distribution (e.g., very central vs. peripheral locations).

To explore this possibility, I next examine the heterogeneity by grouping the continuous variables into categories. This approach allows me to test whether Uber's entry differentially affects hotels located in distinct distance bands or transit accessibility levels, which cannot be fully captured by a simple linear interaction term.

6.2 Heterogeneous Effect (Distance Groups / Transit Score)

The baseline results show that Uber's entry is associated with a significant increase in hotel prices; however, the interaction terms with the continuous distance and transit score measures do not provide evidence of a linear moderating effect. This suggests that the treatment effect may not vary smoothly along these continuous dimensions. Instead, the impact of Uber may differ discretely across locations—such as between central and peripheral areas or between neighbourhoods with high versus low transit accessibility.

To further investigate this possibility, this subsection examines heterogeneity in the treatment effect by grouping hotels along two dimensions: (i) distance to the city centre and (ii) transit score. We extend the baseline specification (Eq. 2) by interacting the treatment indicator with these distance and transit categories, while keeping all controls and fixed effects unchanged.

We divide hotels into four distance groups based on evenly distributed sample sizes: Distance 1 ($\leq$ 1 mile), Distance 2 (1–5 miles), Distance 3 (5–10 miles), and Distance 4 ($\geq$ 16 10 miles). We also classify hotels into five transit-score groups following WalkScore.com[8]: Transit 1 ($\geq$ 90, "world-class transit"), Transit 2 (70–89, "excellent transit"), Transit 3 (50–69, "many options"), Transit 4 (25–49, "few options"), and Transit 5 (0–24, "minimal transit"). Figure 10 plots the density of each transit score range. In the sample of this research, most of the hotels are in zip code with best level of public transportation accessibility. Only 11.27% of samples located in the area with poor public transportation. And the range 2, which corresponds to the 69 $\sim$ 89 interval of the transit score, has the second lowest hotel density.

Table 2 presents the estimation results for the moderating effect of distance in Panel A and the moderating effect of public transportation accessibility in Panel B. The results show the Uber's entry significantly influenced the hotel performance with notable differences observed across various distance categories. In each panel, the first column reports the classification of each group, the second column reports the group-specific DiD estimate (the "pure" treatment effect for that category compared before treatment), and the third column reports the difference in the treatment effect relative to the reference group (Group 1). Thus, coefficients in the third column provide formal tests for whether the treatment effect varies across categories.

Specifically, Hotels located within one mile of the central area (Group 1) experience an average price increase of 8.5% after Uber's entry ($p<0.01$). The group-specific effect remains positive and sizeable for hotels located 1–5 miles away (8.1%), 5–10 miles away (6.5%), and 10–16 miles away (7.8%). The third column shows that the differences relative to Group 1 are small and statistically insignificant throughout. Combined with the continuous interaction results from the baseline, Panel A suggests that physical distance from the city center, on its own, is not the key margin along which the impact of ride-hailing

[8]The transit score is a proprietary metric that assesses the accessibility of public transportation in a given area. This score is derived from standardised data provided by public transit authorities. The methodology of calculating Transit Score is to evaluate the convenience of nearby transit routes by considering factors such as frequency, mode of transportation (e.g., bus, rail), and proximity to the nearest transit stop. The combined "usefulness" of all nearby routes is then aggregated and scaled to produce a score ranging from 0 to 100. The provided transit score is divided into five ranges by the website to identify the accessibility of public transportation.

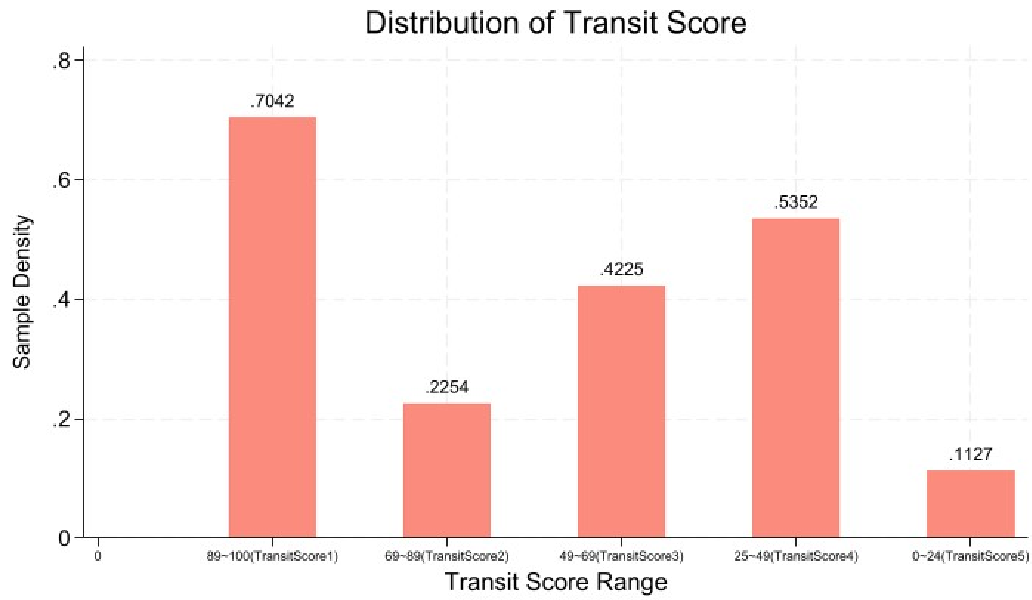


Figure 10: Transit Score Density

varies. The treatment effect appears broadly similar across space when distance is measured purely in geographic terms.

Panel B repeats the exercise using Transit Score categories as a measure of functional accessibility. Hotels located within area with world class transit system (Group 1) experience an average price increase of 8.71% after Uber's entry ($p<0.01$). The group-specific effect remains positive and sizeable for hotels located in area with excellent transit (Group 2, 11.7%), some transit(Group 3, 7.62%), and few transit (Group 4, 5.9%). The results for last group with minimal transit did not see significant increase.

Here, a clearer pattern emerges. Hotels in the highest-accessibility group (Transit Score 89–100, Group 1) experience an average price increase of 8.7 percent after Uber's entry. The effect is significantly larger, about 11.7 percent for hotels in the second-highest category (Transit Score 69–89, Group 2), and the difference relative to Group 1 is approximately 3 %. For the remaining three categories with lower Transit Scores, the group-specific treatment effects are smaller and, in most cases, not statistically distinguishable from the effect in the highest-access group.

Thus, when centrality is defined in terms of transit-based accessibility rather than physical distance, we find evidence of meaningful heterogeneity: Uber's entry has its strongest impact in locations that are reasonably well connected by public transportation but not at the very top of the accessibility distribution, while areas with poor transit infrastructure benefit substantially less. This pattern is consistent with the idea that ride-hailing services are most valuable where they can complement for existing transit

Table 2: DiD Model: Heterogenous Effect

VARIABLES	Panel A: Distance			Panel B: Transit Score		
	Category	Δ Price (Pre–Post)	Rel. to Centre	Category	Δ Price (Pre–Post)	Rel. to Centre
Group 1	<1 mile	0.0848***	Ref.	(89 -100)	0.0871***	Ref.
		(0.0168)			(0.00651)	
Group 2	1-5 miles	0.0811***	-0.00373	(69 -89)	0.117***	0.0299**
		(0.0145)	(0.0147)		(0.0127)	0.0101
Group 3	5-10 miles	0.0646***	-0.0202	(49 -69)	0.0762**	-0.0110
		(0.0152)	(0.0145)		(0.0204)	(0.0177)
Group 4	10-16 miles	0.0784**	-0.00637	(25 -49)	0.0590**	-0.0281
		(0.0197)	(0.0225)		(0.0222)	(0.0245)
Group 5	–	–	–	(0 -24)	0.0196	-0.0676***
					(0.0151)	(0.0137)
Controls		✓	✓		✓	✓
Seasonality		✓	✓		✓	✓
Fixed Effect		✓	✓		✓	✓
Observations		4,150	4,150		4,150	4,150
R-squared		0.955	0.955		0.955	0.955

Robust standard errors in parentheses $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.
Standard errors are clustered at MSA level

options, improving last-mile connectivity and expanding the effective market size for hotels in those neighbourhoods.

Taken together, the evidence from the continuous interaction models and the grouped specifications points to a clear conclusion that the relevant margin of heterogeneity is functional accessibility rather than physical distance alone. Uber does not simply "rescue" geographically remote locations; instead, its impact is strongest where some transit infrastructure is already in place and can be leveraged through improved connectivity. In terms of urban form, Uber appears to reshape effective accessibility more than it reshapes geographic space.

One interpretation of the heterogeneous price responses is that Uber relaxes a demand-side constraint by making certain locations more accessible to travellers. Under this mechanism, we would expect to observe increases in room demand alongside price increases. The next section evaluates this implication directly.

Table 3: Uber's Effect on Hotel Occupancy and Demand

	(A) Distance Groups		(B) Transit Score Groups	
	Δ Uber Effect	Rel. to Centre	Δ Uber Effect	Rel. to Group 1
Panel 1: Occupancy				
Group 1 (<1 mi / 89–100)	0.045***	Ref.	0.052***	Ref.
	(0.00565)		(0.00767)	
Group 2 (1–5mi / 69–89)	0.050**	+0.005	0.082***	+0.030**
	(0.0156)	(0.0113)	(0.0178)	(0.0126)
Group 3 (5–10mi / 49–69)	0.048***	+0.003	0.040**	-0.012
	(0.0100)	(0.0118)	(0.0123)	(0.00922)
Group 4 (10–16mi / 25–49)	0.079***	+0.034**	0.052***	-0.028
	(0.00872)	(0.00978)	(0.00567)	(0.0106)
Group 5 (0–24)	–	–	0.042***	-0.011
			(0.00503)	(0.00782)
Panel 2: Demand				
Group 1 (<1 mi / 89–100)	0.061***	Ref.	0.072***	Ref.
	(0.00843)		(0.0109)	
Group 2 (1–5mi / 69–89)	0.070**	+0.009	0.114***	+0.042*
	(0.0230)	(0.0166)	(0.0240)	(0.0170)
Group 3 (5–10mi / 49–69)	0.069***	+0.008	0.054**	-0.018
	(0.0146)	(0.0166)	(0.0194)	(0.0148)
Group 4 (10–16mi / 25–49)	0.117***	+0.056***	0.079***	-0.025
	(0.0107)	(0.0113)	(0.00844)	(0.0146)
Group 5 (0–24)	–	–	0.059***	-0.013
			(0.00795)	(0.0118)
Controls	✓	✓	✓	✓
Zipcode FE	✓	✓	✓	✓
Year-Month FE	✓	✓	✓	✓
Observations	4,150	4,150	4,150	4,150

Robust standard errors in parentheses $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$
Standard errors are clustered at MSA level

6.3 Demand-Driven Price Effects

The price effects documented above are consistent with a channel in which Uber expands the effective market for hotels by reducing travel frictions and increasing accessibility. If this interpretation is correct, the changes in price should be accompanied by increases in hotel occupancy and aggregate demand. Table 3 reports the results from specifications parallel to those used in the price analysis, but using occupancy rates and log room sold as the dependent variables. As expected in the short-run hotel market, we find no detectable change in room supply (Appendix A), ruling out supply-side adjustments as an alternative explanation

Panel 1 shows that Uber's entry increases hotel occupancy rate across all distance and transit categories. Uber the physical distance specification, hotels within one mile of the city centre experience a 4.5% increase in occupancy, with similarly sized effects for hotels located 1–10 miles away (around 5.0%), While the difference relative to the centre is not statistically significant. The only substantial deviation from this pattern occurs in the 10–16 mile band, where occupancy rises by 7.9%, and the difference relative to the centre is statistically significant (+3.4%). However, the overall pattern remains broadly flat across distance groups, consistent with the earlier finding that geographic distance alone is not the primary margin of heterogeneity.

In contrast, the transit score results in Panel 1 reveal a much clearer pattern. Hotels in the second-highest transit category (Transit Score 69–89) experience an 8.2% increase in occupancy, which is approximately 3% higher than hotels in the highest-transit locations. Effects decline for lower transit categories and are statistically insignificant relative to the benchmark. This shows the price results and reinforces the view that functional accessibility, not physical radius, is the dimension along which Uber disproportionately increases hotel use.

Panel 2 reports the estimates using log rooms sold as the dependent variable. The effects are positive across all distance categories and generally similar in magnitude to those observed for occupancy. Hotels within one mile of the city centre experience an estimated 6.1% increase in room demand following Uber's entry, with comparable effects for hotels located 1–10 miles from the centre. The effect is somewhat larger for hotels in the 10–16 mile band (11.7%). Though the difference relative to the central group is only statistically significant for category 4.The heterogeneity across transit categories is substantially sharper. Demand increases by 11.4 % in areas with Transit Scores of 69–89—more than 4 % above the highest-transit category—and the difference is significant. Below this range, the treatment effect declines and becomes statistically indistinguishable from the benchmark group.

The contrast between physical distance and transit accessibility provides additional insight into how Uber affects hotel performance. Under the distance specification, the treatment effect on prices is relatively homogeneous across space, with no group displaying a statistically significant difference relative to hotels located within one mile of the centre. However, the quantity margin measured through occupancy and total demand strongly across all distance bands. Even in locations where prices do not adjust, occupancy increases by 3.4% and total rooms sold increase by 5.6%. This pattern suggests that when heterogeneity is defined geographically, Uber's impact operates primarily through an extensive margin: the platform expands the number of hotel stays rather than altering relative prices across space.

In contrast, when urban structure is captured through Transit Score categories, both price and quantity margins vary meaningfully across groups. Hotels in the second-highest transit category experience significantly larger increases in occupancy and demand (roughly 3% above the benchmark), and these demand gains translate into measurable price increases. Below this range, the effects become statistically insignificant from the benchmark. This suggests that Uber may not be generating substantial new travel activity in these locations, whereas in transit accessible areas, it facilitates additional travel and supports higher willingness to pay.

The results refine the interpretation of the price effects. Uber consistently increases hotel demand across space, but the way this demand translates into prices depends on how proximity is defined. When distance is measured geographically, demand rises in both central and peripheral areas, yet prices do not diverge, suggesting that Uber expands the market without generating differential pricing power across distance bands. In contrast, when proximity is defined in terms of functional accessibility, both demand and prices increase more in moderately connected areas.

The transit-based estimates also indicate partial price convergence across space. Hotels in the second-highest Transit Score category experience significantly larger price increases than those in the highest-accessibility group, narrowing the initial price gap between the two areas. This pattern suggests that Uber reduces the effective centrality premium by improving access in locations that were previously less transit-connected. In other words, ride-hailing compresses the spatial price gradient not by lowering prices in central locations, but by allowing moderately accessible areas to catch up.

Before Uber's entry, hotels in less accessible locations faced inherent demand constraints due to limited transportation options. While central hotels benefited from dense transit networks, many peripheral or transit-poor areas remained difficult to reach, limiting both occupancy and pricing power. The introduction of Uber relaxes these constraints by providing a flexible and relatively low cost mobility option that improves last-mile connectivity. Rather than simply shifting demand from the city centre to the outskirts, Uber expands the effective choice set for travellers, particularly in neighbourhoods where transit options are present but incomplete. As a result, locations that were previously reachable only with difficulty may now become viable lodging alternatives, driving increases in both demand and price. Taken together, the evidence indicates that Uber's primary effect is demand expansion, and that the relevant spatial margin is accessibility rather than physical distance. Ride-hailing services reshape the effective geography of urban hotel markets not by changing how far locations are, but by changing how easy they are to reach.

6.4 Robustness Check

To ensure that the main results are not sensitive to modelling choices or sample composition, we conduct a series of robustness checks. For the baseline specification, we test alternative sample windows and include higher-level fixed effects, with results remaining consistent with the main estimates. For the distance-interaction and transit-score specifications, we perform placebo tests by randomly generating city-centre locations, confirming that the observed heterogeneity is not driven by arbitrary city-centre selection. We also examine the robustness of spatial price convergence by testing alternative definitions of central and suburban hotels, finding that the convergence patterns remain largely unchanged. Detailed results for all robustness analyses are reported in Appendix Tables 5, 6, and 7. Overall, these checks reinforce the credibility of our findings, indicating that the effects of Uber entry on hotel prices and spatial price convergence are robust to alternative specifications.

7 Conclusions

This paper exploits the staggered entry of Uber across U.S. cities as a quasi-natural experiment to examine how ride-hailing technologies reshape outcomes in the hotel industry. Using a multi-city panel of zip code–level hotel data, the analysis reveals that Uber's entry leads to an average increase of 7.75% in hotel prices. Importantly, the effect is not primarily driven by geographic remoteness from the city centre. Instead, the strongest price responses occur in locations with moderate levels of public transit access, while hotels in the best accessible areas experience smaller changes. These findings suggest that Uber does not simply eliminate distance frictions, but instead complements existing mobility infrastructure, expanding effective demand most in neighbourhoods where transit connectivity is incomplete.

The demand and supply analysis reinforces this interpretation. Uber's entry significantly increases both hotel occupancy and total room demand, particularly in areas where baseline transit access is neither extremely high nor extremely low. Rather than inducing a simple shift in lodging choices from central to peripheral locations, ride-hailing appears to broaden the spatial distribution of hotel demand by improving last-mile connectivity and enabling travellers to access a wider range of accommodations. In this sense, Uber narrows the economic distance between neighbourhoods not by reducing miles, but by reducing the cost of movement.

These findings contribute to the growing literature on the economic spillovers of the sharing economy. While recent years have seen increased attention to the impact of the sharing economy on established industries, particularly concerning platforms like Uber and Airbnb, much of the prior research has focused on their individual effects within their respective industries. For instance, previous studies have examined how Uber affects public transit or taxi services (Berger et al., 2018) or Airbnb's effects on hotels and housing (Zervas et al., 2017). This study highlights a cross platform interaction channel, whereby ride-hailing influences the performance of the lodging sector. Complementing Zhang et al. (2022), who first documented interactions between sharing platforms, this paper demonstrates that Uber can expand demand for hotels rather than merely reallocating it within the industry.

The results also carry implications for regulation. Restrictions on ride-hailing are often motivated by concerns about competition with incumbent transport providers. However, if Uber facilitates greater demand for hotels in partially accessible areas, limiting its operations may unintentionally reinforce spatial inequities by disproportionately reducing demand outside the urban core. Policymakers evaluating platform regulation should therefore consider not only impacts within the transport sector, but also broader spillovers to local service industries.

This paper also has some limitations worth noting. First, the hotel data is gathered at the zip code level because of the privacy agreement between hotel companies and data collection organisations. More precise results might might be achievable if individual hotel data were accessible. Second, further investigation into hotel price elasticity could enhance the reliability of the empirical results. Building a price and demand model in subsequent research steps could address this limitation.

References

Angrist, J. D., Caldwell, S., and Hall, J. V. (2021). Uber versus taxi: A driver's eye view. *American Economic Journal: Applied Economics*, 13(3):272–308.

Barreto, Y., Neto, R. D. M. S., and Carazza, L. (2021). Uber and traffic safety: Evidence from brazilian cities. *Journal of Urban Economics*, 123:103347.

Barron, K., Kung, E., and Proserpio, D. (2021). The effect of home-sharing on house prices and rents: Evidence from airbnb. *Marketing Science*, 40(1):23–47.

Beck, T., Levine, R., and Levkov, A. (2010). Big bad banks? the winners and losers from bank deregulation in the united states. *The Journal of Finance*, 65(5):1637–1667.

Berger, T., Chen, C., and Frey, C. B. (2018). Drivers of disruption? estimating the uber effect. *European Economic Review*, 110:197–210.

Bibler, A. J., Teltser, K. F., and Tremblay, M. J. (2021). Inferring tax compliance from pass-through: Evidence from airbnb tax enforcement agreements. *Review of Economics and Statistics*, 103(4):636–651.

Conroy, S. J.and Toma, N. G. G. P. (2020). The effect of the las vegas strip on hotel prices: A hedonic approach. *Tourism Economics*, 26(4):622–639.

Ellinger, R. (1977). Industrial location behavior and spatial evolution. *The Journal of Industrial Economics*, 25:295–312.

Farronato, C. and Fradkin, A. (2022). The welfare effects of peer entry: the case of airbnb and the accommodation industry. *American Economic Review*, 112(6):1782–1817.

Hall, J., C., P., and Price, J. (2018). Is uber a substitute or complement for public transit? *Journal of Urban Economics*, 108:36–50.

Koster, H. R., Van Ommeren, J., and Volkhausen, N. (2021). Short-term rentals and the housing market: Quasi-experimental evidence from airbnb in los angeles. *Journal of Urban Economics*, 124:103356.

Lee, K. W., Kim, H. B., Kim, H. S., and Lee, D. S. (2010). The determinants of factors in fit guests' perception of hotel location. *Journal of Hospitality and Tourism Management*, 17(1):167–174.

Lee, S. K. (2015). Quality differentiation and conditional spatial price competition among hotels. *Tourism Management*, 46:114–122.

Li, H., Kim, Y., and Srinivasan, K. (2022). Market shifts in the sharing economy: The impact of airbnb on housing rentals. *Management Science*, 68(11):8015–8044.

Martin, C. J. (2016). The sharing economy: A pathway to sustainability or a nightmarish form of neoliberal capitalism? *Ecological economics*, 121:149–159.

Rosen, S. (1974). Hedonic prices and implicit markets: product differentiation in pure competition. *Journal of political economy*, 82(1):34–55.

Tarduno, M. (2021). The congestion costs of uber and lyft. *Journal of Urban Economics*, 110:103318.

Teltser, K., Lennon, C., and Burgdorf, J. (2021). Do ridesharing services increase alcohol consumption? *Journal of Health Economics*, 77:102451.

Valentin, M. (2021). Regulating short-term rental housing: Evidence from new orleans. *Real Estate Economics*, 49(1):152–186.

Vickrey, W. S. (1963). Pricing in urban and suburban transport. *The American Economic Review*, 53(2):452–465.

White, P. J. and Mulligan, G. F. (2002). Hedonic estimates of lodging rates in the four corners region. *The Professional Geographer*, 54(4):533–543.

Zervas, G., Proserpio, D., and Byers, J. W. (2017). The rise of the sharing economy: Estimating the impact of airbnb on the hotel industry. *Journal of marketing research*, 54(5):687–705.

Zhang, H., Zhang, J.and Lu, S., and Cheng, S.and Zhang, J. (2011). Modeling hotel room price with geographically weighted regression. *International Journal of Hospitality Management*, 30(4):1036–1043.

Zhang, S., Lee, D., Singh, P., and Mukhopadhyay, T. (2022). Demand interactions in sharing economies: Evidence from a natural experiment involving airbnb and uber/lyft. *Journal of Marketing Research*, 59(2):374–391.

Appendix

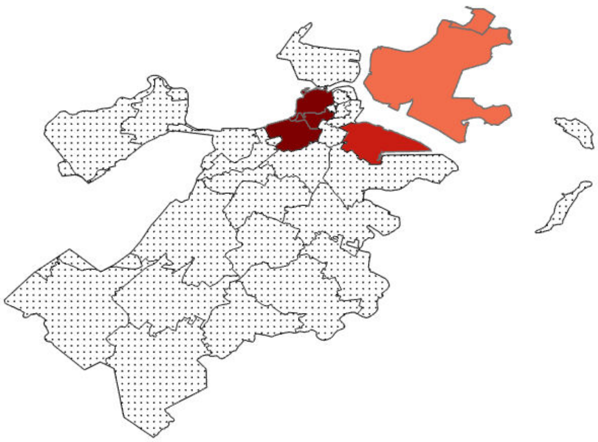
A Data Construction and Variable Definitions

A.1 Summary Statistics

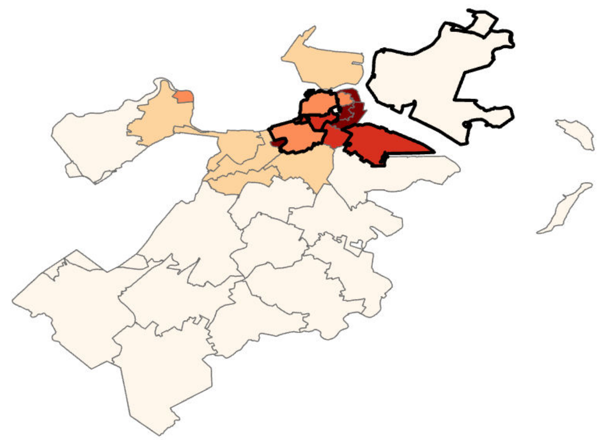
Table 4: Summary Statistics

VARIABLES	N	mean	sd	min	max	p25	p50	p75	p99
Occupancy	4,210	77.01	11.88	32.10	99.40	69.49	79.20	86.50	94.46
Average Revenue	4,210	140.1	79.58	20.18	473.0	80.89	118.9	189.9	390.2
Rooms Supply	4,210	79,972	105,056	8,176	569,811	22,382	37,292	76,950	503,471
Rooms Demand	4,210	64,357	89,666	3,207	517,111	16,030	29,470	59,877	443,073
Total number of hotels	4,260	10.53	9.032	3	46	5	6	14	43
20-24 year old	4,212	0.0912	0.0489	0	0.326	0.0620	0.0790	0.106	0.294
25-29 year old	4,212	0.114	0.0478	0	0.263	0.0800	0.102	0.148	0.246
30-34 year old	4,212	0.0951	0.0320	0	0.218	0.0670	0.0920	0.120	0.173
60-64 year old	4,212	0.0515	0.0131	0	0.0970	0.0430	0.0520	0.0600	0.0850
80-84 year old	4,212	0.0192	0.00890	0	0.0460	0.0140	0.0170	0.0250	0.0420
Total housing unit	4,260	15,959	8,944	0	40,991	10,181	13,925	21,415	39,823
Median earnings	4,200	45,956	18,571	11,438	95,716	30,371	43,576	57,670	86,193
Yearly salary of workers(>100000)	4,200	0.259	0.160	0.0180	0.579	0.110	0.270	0.401	0.542
Mean earnings(dollars)	4,200	90,911	38,910	33,515	197,108	56,122	85,088	120,332	181,142
Less than high school graduate	4,212	0.0875	0.0761	0	0.295	0.0270	0.0590	0.147	0.251
High school graduate	4,212	0.204	0.0939	0	0.523	0.131	0.201	0.271	0.459
College(no degree)	4,212	0.153	0.0572	0	0.286	0.0980	0.149	0.198	0.269
Bachelors degree	4,212	0.293	0.110	0	0.481	0.191	0.327	0.380	0.473
Graduate or professional degree	4,212	0.231	0.130	0	0.487	0.100	0.237	0.347	0.479
Occupied housing units	4,260	14,197	7,796	0	33,348	8,887	12,551	19,094	32,610
Median household income (dollars)	4,200	73,084	25,498	22,648	132,969	50,881	71,018	94,495	127,968
Total Workers(16 years and over)	4,260	17,215	9,471	0	42,377	11,110	15,471	23,257	40,366
(Occupation)Public administration	4,260	625.4	560.2	0	3,092	231	490	879	2,899
Vacant housing units	4,260	1,762	1,632	0	8,852	732	1,254	2,169	8,044
Housing units with Complete plumbing facilities	4,260	15,803	8,844	0	40,232	10,033	13,896	21,196	38,992
Householder(Asian alone)	4,260	1,814	2,089	0	13,314	613	1,301	2,370	13,064
Householder(Black or African American alone)	4,260	2,939	6,753	0	58,690	637	1,507	2,930	54,359
Householder(American Indian and Alaska alone)	4,260	148.7	140.9	0	811	42	119	206	676
Renter occupied housing units	4,260	8,469	5,611	0	28,824	4,998	7,083	11,343	28,106
Housing for rent	4,260	372.6	312.7	0	1,497	173	297	453	1,412
Housing value (250000-299999)	4,260	320.9	452.2	0	2,367	51	121	359	1,916
Housing value (>1000000)	4,260	1,076	1,435	0	5,575	57	340	1,602	5,431
Housing with vehicle avaliable(>3 vehicles)	4,260	801.5	892.4	0	4,302	49	450	1,216	3,584

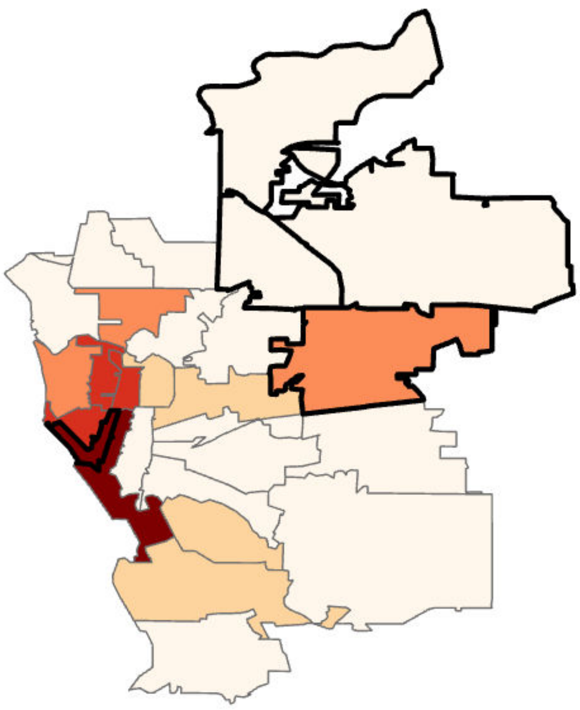
A.2 Spatial Distribution of Amenities and Transit Scores



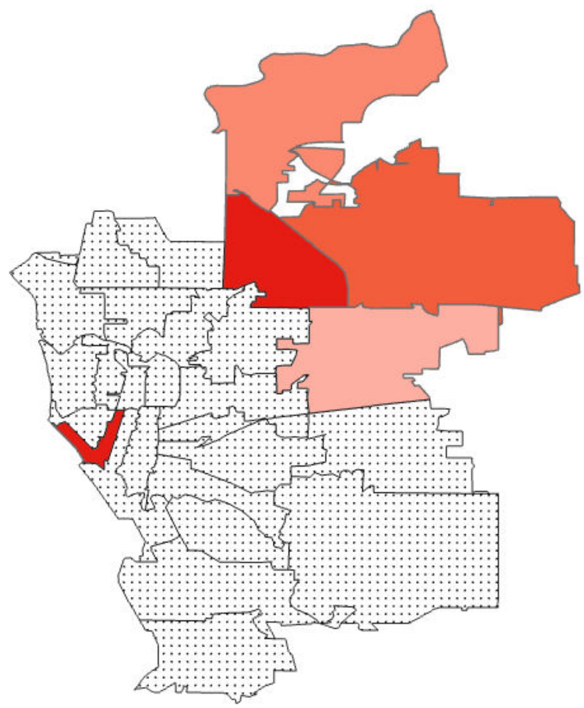
(a) Boston Amenities Density heatmap



(b) Boston Transit Score heatmap

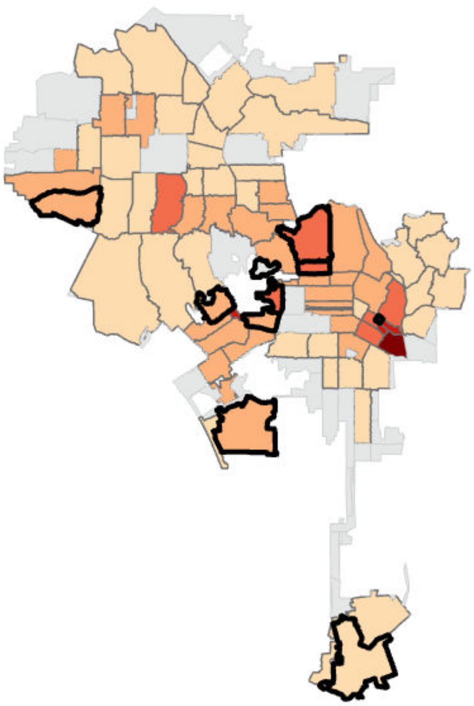


(c) Buffalo Amenities Density heatmap

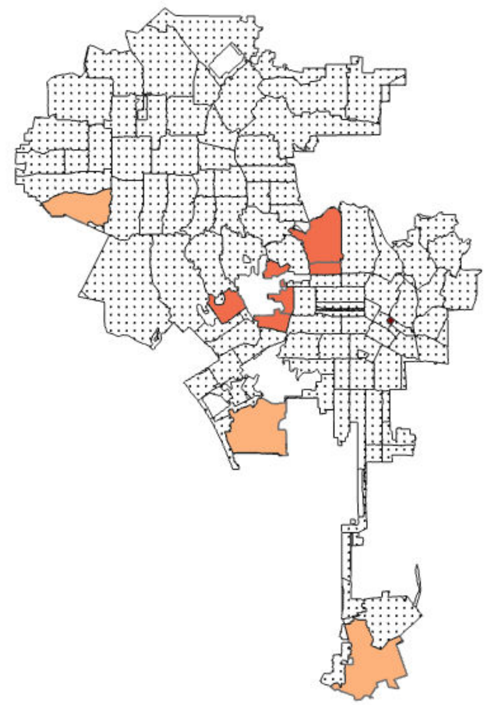


(d) Buffalo Transit Score heatmap

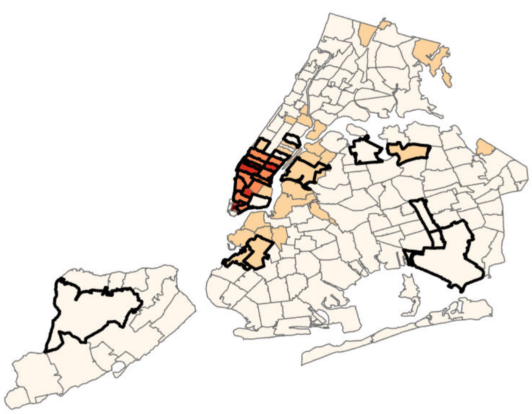
Figure 11: Spatial Distribution of Distance to City Centre and Transit Accessibility (Part 1)



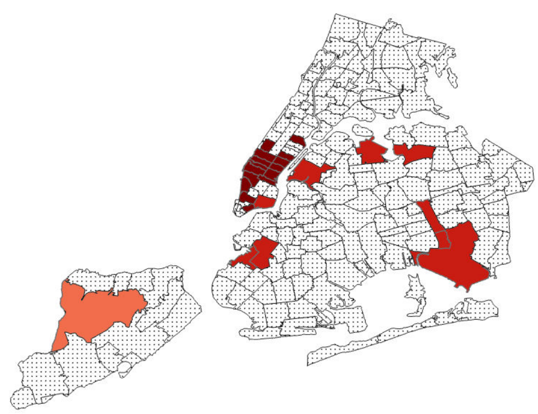
(e) Los Angeles Amenities Density heatmap



(f) Los Angeles Transit heatmap

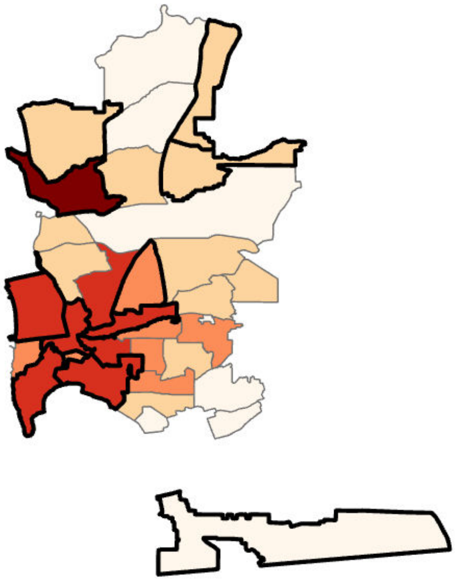


(g) New York Amenities Density heatmap

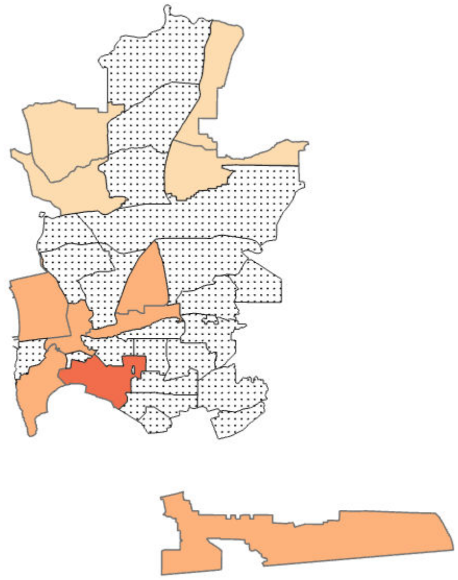


(h) New York Transit Score heatmap

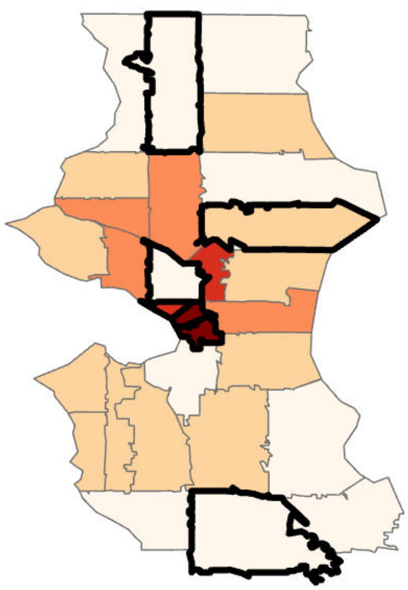
Figure 11: Spatial Distribution of Distance to City Centre and Transit Accessibility (Part 2)



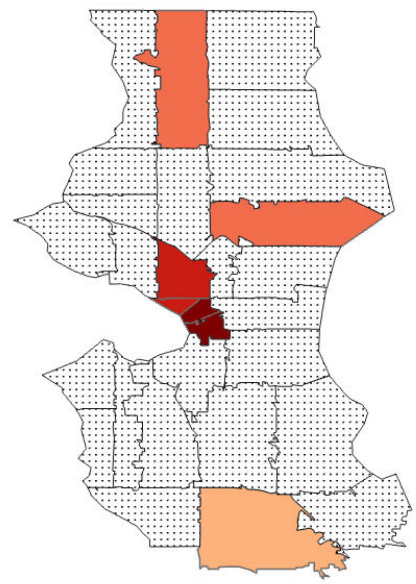
(i) San Diego Amenities Density heatmap



(j) San Diego Transit Score heatmap



(k) Seattle Amenities Density heatmap



(l) Seattle Transit Score heatmap

Notes:This figure displays the spatial distribution of zip code–level amenities (left panels) and public transit accessibility (right panels) for each city. Amenity density is measured as the density of local available restaurants, cafe and bars within each zip code. Distances are computed using road travel between each zip code centroid and the identified central areas of the city. Transit accessibility is derived from publicly available transit network data and normalised to a 0–100 scale. Darker shading indicates higher amenity density or greater transit accessibility. These maps are descriptive.

Figure 11: Spatial Distribution of Distance to City Centre and Transit Accessibility (Part 3)

B Theory Framework and Proof

Proof. We have that

$$\frac{dP^*}{d\tau} = \begin{bmatrix} \dfrac{dP^{O,\star}}{d\tau} \\[2ex] \dfrac{dP^{S,\star}}{d\tau} \end{bmatrix}$$

Using our expression for excess demand, knowing that it must be 0 in equilibrium, and diffrentiating with respect to τ, we find that:

$$\begin{bmatrix} \dfrac{dP^{O,\star}}{d\tau}\left[\dfrac{\partial Q_D^O}{\partial P^O} - \dfrac{dQ_S^O}{dP^O}\right] + \dfrac{dP^{C,\star}}{d\tau}\dfrac{\partial Q_D^O}{\partial P^C} + \dfrac{\partial Q_D^O}{\partial \tau} \\[3ex] \dfrac{dP^{C,\star}}{d\tau}\left[\dfrac{\partial Q_D^C}{\partial P^C} - \dfrac{dQ_S^C}{dP^{C,\star}}\right] + \dfrac{dP^{O,\star}}{d\tau}\dfrac{\partial Q_D^C}{\partial P^O} + \underbrace{\dfrac{\partial Q_D^C}{\partial \tau}}_{=0} \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$

$$\begin{bmatrix} \dfrac{dP^{O,\star}}{d\tau}\left[\dfrac{\partial Q_D^O}{\partial P^O} - \dfrac{dQ_S^O}{dP^{O,\star}}\right] + \dfrac{dP^{C,\star}}{d\tau}\dfrac{\partial Q_D^O}{\partial P^C} + \dfrac{\partial Q_D^O}{\partial \tau} \\[3ex] \dfrac{dP^{C,\star}}{d\tau}\left[\dfrac{\partial Q_D^C}{\partial P^C} - \dfrac{dQ_S^C}{dP^C}\right] + \dfrac{dP^{O,\star}}{d\tau}\dfrac{\partial Q_D^C}{\partial P^O} \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$

$$\begin{bmatrix} \dfrac{dP^{O,\star}}{d\tau}\left[\dfrac{\partial Q_D^O}{\partial P^O} - \dfrac{dQ_S^O}{dP^O}\right] + \dfrac{dP^{C,\star}}{d\tau}\dfrac{\partial Q_D^O}{\partial P^C} \\[3ex] \dfrac{dP^{C,\star}}{d\tau}\left[\dfrac{\partial Q_D^C}{\partial P^C} - \dfrac{dQ_S^C}{dP^C}\right] + \dfrac{dP^{O,\star}}{d\tau}\dfrac{\partial Q_D^C}{\partial P^O} \end{bmatrix} = \begin{bmatrix} -\dfrac{Q_D^O}{\partial \tau} \\[3ex] 0 \end{bmatrix}$$

$$\begin{bmatrix} \dfrac{dP^{O,\star}}{d\tau} \\[3ex] \dfrac{dP^{C,\star}}{d\tau} \end{bmatrix} \underbrace{\begin{bmatrix} \dfrac{\partial Q_D^O}{\partial P^O} - \dfrac{dQ_S^O}{dP^O}, & \dfrac{\partial Q_D^O}{\partial P^C} \\[3ex] \dfrac{\partial Q_D^C}{\partial P^O}, & \dfrac{\partial Q_D^C}{\partial P^C} - \dfrac{dQ_S^C}{dP^C} \end{bmatrix}}_{:=J} = \begin{bmatrix} -\dfrac{Q_D^O}{\partial \tau} \\[3ex] 0 \end{bmatrix}$$

Note by our assumption that own price effects dominate, J is invertible. We have that:

$$J^{-1} = \frac{1}{\left(\frac{\partial Q_D^O}{\partial P^O} - \frac{dQ_S^O}{dP^O}\right)\left(\frac{\partial Q_D^C}{\partial P^C} - \frac{dQ_S^C}{dP^C}\right) - \left(\frac{\partial Q_D^O}{\partial P^C}\right)\left(\frac{\partial Q_D^C}{\partial P^O}\right)} \begin{bmatrix} \left(\frac{\partial Q_D^C}{\partial P^C} - \frac{dQ_S^C}{dP^C}\right) & -\frac{\partial Q_D^O}{\partial P^C} \\ -\frac{\partial Q_D^C}{\partial P^O} & \left(\frac{\partial Q_D^O}{\partial P^O} - \frac{dQ_S^O}{dP^O}\right) \end{bmatrix}.$$

Therefore we find that:

$$\begin{bmatrix} \frac{dP^{O,\star}}{d\tau} \\ \frac{dP^{C,\star}}{d\tau} \end{bmatrix} = J^{-1} \begin{bmatrix} -\frac{Q_D^O}{\partial \tau} \\ 0 \end{bmatrix}$$

This provides us with the following derivatives:

$$\frac{dP^{O,\star}}{d\tau} = -\frac{\left(\frac{\partial Q_D^C}{\partial P^C} - \frac{dQ_S^C}{dP^C}\right)\frac{\partial Q_D^O}{\partial \tau}}{\left(\frac{\partial Q_D^O}{\partial P^O} - \frac{dQ_S^O}{dP^O}\right)\left(\frac{\partial Q_D^C}{\partial P^C} - \frac{dQ_S^C}{dP^C}\right) - \left(\frac{\partial Q_D^O}{\partial P^C}\right)\left(\frac{\partial Q_D^C}{\partial P^O}\right)}$$

Note that $\frac{\partial Q_D^C}{\partial P^C} < 0$, $\frac{\partial Q_S^C}{\partial P^C} > 0$ (therefore $-\frac{\partial Q_S^C}{\partial P^C} < 0$), and $\frac{\partial Q_D^O}{\partial \tau} < 0$. As our regularity assumption we have that the denominator is positive. Therefore we conclude that $\frac{dP^{O,*}}{d\tau} < 0$. Concluding that as transport costs increase the outskirts price decreases.

As for the other derivative:

$$\frac{dP^{C,\star}}{d\tau} = \frac{\left(\frac{\partial Q_D^C}{\partial P^O}\right)\frac{\partial Q_D^O}{\partial \tau}}{\left(\frac{\partial Q_D^O}{\partial P^O} - \frac{dQ_S^O}{dP^O}\right)\left(\frac{\partial Q_D^C}{\partial P^C} - \frac{dQ_S^C}{dP^C}\right) - \left(\frac{\partial Q_D^O}{\partial P^C}\right)\left(\frac{\partial Q_D^C}{\partial P^O}\right)}$$

As $\frac{\partial Q_D^C}{\partial P^O} > 0$ (as they are substitutes) and $\frac{\partial Q_D^O}{\partial \tau} < 0$, we conclude that $\frac{dP^{C,*}}{d\tau} < 0$, concluding that as the transport costs increase the central price decreases.

$$
\begin{aligned}
\frac{d(P^{C,\star}-P^{O,\star})}{d\tau} &= \frac{dP^{C,\star}}{d\tau}-\frac{dP^{O,\star}}{d\tau} \\
&= \frac{\left(\dfrac{\partial Q_D^C}{\partial P^C}-\dfrac{dQ_S^C}{dP^C}+\dfrac{\partial Q_D^C}{\partial P^O}\right)\dfrac{\partial Q_D^O}{\partial \tau}}{\left(\dfrac{\partial Q_D^O}{\partial P^O}-\dfrac{dQ_S^O}{dP^O}\right)\left(\dfrac{\partial Q_D^C}{\partial P^C}-\dfrac{dQ_S^C}{dP^C}\right)-\left(\dfrac{\partial Q_D^O}{\partial P^C}\right)\left(\dfrac{\partial Q_D^C}{\partial P^O}\right)}
\end{aligned}
$$

As $\dfrac{\partial Q_S^C}{\partial P^C}<0$ and $\dfrac{\partial Q_D^C}{\partial P^C}+\dfrac{\partial Q_D^C}{\partial P^O}<0$ due to the assumption own price effects dominate, we conclude that $\dfrac{d|P^{C,*}-P^{O,*}|}{d\tau}>0$, therefore as the transportation cost decreases, the difference reduces, as $P^{C,*}(\tau)-P^{O,*}(\tau)>0$. ■

C Robustness Check

C.1 Robustness check for baseline

We perform several robustness checks to assess the sensitivity of our baseline estimates. First, to ensure that our results are not driven by city-level time-invariant shocks, we augment the specification by including additional MSA fixed effects alongside zipcode and seasonal fixed effects while clustering standard errors at the zipcode level. The estimated coefficients remain positive and statistically significant, indicating that our findings are robust to higher-level fixed effects (Appendix Table 5). Second, to verify that our results are not driven by anticipatory or lagged effects, we re-estimate the model after dropping one year of observations before and after Uber's entry. The coefficients are virtually unchanged and remain statistically significant, suggesting that our main results are not sensitive to the choice of the estimation window (Appendix Table 5).

Table 5: Robustness Check

VARIABLES	Price	Price
Uber	0.0801***	0.0972***
	(0.00899)	(0.00886)
Controls	✓	✓
Seasonality	✓	✓
Fixed Effect	✓	✓
Observations	3,317	4,150
R-squared	0.955	0.951

Robust standard errors in parentheses $***p < 0.01$; $**p < 0.05$; $*p < 0.1$
Standard errors are clustered at MSA level

C.2 Robustness Check for Heterogeneity

C.2.1 Alternative cut-offs

This section examines the robustness of the heterogeneous treatment effects to alternative classifications of distance and transit accessibility. The purpose is to verify that the spatial patterns documented in the main text are not driven by specific binning choices. Panel A of Table 6 re-estimates the heterogeneous specification using a coarser three-group partition of physical distance (<3 miles, 3–10 miles, >10 miles).

The price responses remain positive across all groups. Hotels located less than 3 miles from the centre exhibit the largest treatment effect (8.34%), followed by those in the 3–10 mile band (6.82%). Farthest hotels show the effect about 6.82%. The estimated differences compare to city centre area remain insignificant, confirming that the Uber's effect across distance gradient is not sensitive to alternative cut-offs.

Table 6: Robustness Check: Heterogenous Effect

VARIABLES	Panel A: Distance			Panel B: Transit Score		
	Category	Δ Price (Pre–Post)	Rel. to Centre	Category	Δ Price (Pre–Post)	Rel. to Centre
Group 1	<3 mile	0.0834***	Ref.	(75 -100)	0.0486*	Ref.
		(0.0146)	(0.0146)		(0.0196)	
Group 2	3-10 miles	0.0682***	-0.0152	(50 -75)	0.0672***	0.0186
		(0.0140)	(0.0122)		(0.0118)	(0.0183)
Group 3	>10 miles	0.0787**	-0.00473	(25-50)	0.103***	0.0549*
		(0.0198)	(0.0248)		(0.00726)	(0.0226)
Group 4	–	–	–	(<25)	0.0842***	0.0356
					(0.0119)	(0.0194)
Controls		✓	✓		✓	✓
Seasonality		✓	✓		✓	✓
Fixed Effect		✓	✓		✓	✓
Observations		4,150	4,150		4,150	4,150
R-squared		0.955	0.955		0.955	0.955

Robust standard errors in parentheses $***p < 0.01$; $**p < 0.05$; $*p < 0.1$.
Standard errors are clustered at MSA level

Panel B implements a four-category scheme based on quartiles of the transit-score distribution. The resulting pattern is consistent with the main specification. All groups exhibit positive and statistically significant post-entry price increases. The smallest effect appears in the highest-access quartile (75–100), with an estimated increase of 4.86%. Locations in the lowest access quartile (<25) display a moderate but significant response (8.42%). The largest relative difference arises in the 25–50 range, where the treatment effect exceeds that of the best connected areas by 5.49%. This pattern reinforces the main finding that Uber generates the greatest marginal value in neighbourhoods with moderate transit accessibility, rather than in areas with either excellent or very limited public transportation.

Across both alternative distance and transit specifications, the heterogeneous treatment effects remain stable in sign, magnitude, and economic interpretation. Although the internal ordering across intermediate categories shifts modestly with coarser partitions, the core spatial contrasts are unchanged: moderately connected neighbourhoods consistently exhibit larger price increases than central or best transit areas. These robustness checks demonstrate that the heterogeneous effects are not sensitive to the choice of bin cut-offs and confirm that the spatial pattern identified in the main text reflects a systematic underlying mechanism rather than an artifact of discretization.

C.2.2 Walkability-Based Heterogeneity (Null Result)

Table 7: Heterogeous Effect across Walkability

VARIABLES	Price	Price
Uber	0.0858***	Ref
	(0.0109)	
Uber × Group 1	0.0892***	0.00345
	(0.0173)	(0.00751)
Uber × Group 1	0.0757***	-0.0100
	(0.0136)	(0.0171)
Uber × Group 1	0.0491	-0.0367
	(0.0266)	(0.0311)
Controls	✓	✓
Seasonality	✓	✓
Fixed Effect	✓	✓
Observations	4,150	4,150
R-squared	0.955	0.955

Robust standard errors in parentheses $***p < 0.01$; $**p < 0.05$; $*p < 0.1$
Standard errors are clustered at MSA level

I use Walk Score as a measure of general neighbourhood quality and amenity accessibility. Since Walk Score captures spatial amenities which is not related to transport, testing heterogeneity along this dimension allows us to evaluate whether the treatment effects are confounded by broader zipcode characteristics unrelated to transportation access.

Walk Score assigns points based on proximity to destinations across multiple categories (e.g., grocery stores, restaurants, schools, parks). Amenities located within a 5-minute walk (approximately 0.25 miles) receive full points, with scores declining as distance increases. The index incorporates environment features that influence walkability, including population density, block length, and intersection density, which proxy for pedestrian orientation and street network connectivity. The walk score ranges from 0 to

100, with higher values indicating greater walkability and easier access to daily amenities. According to walk score official website, walk score is divided into five categories, walk score 1 ($\geq$ 90, "Walker's Paradise"), walk score 2 (70–89, "Very Walkable"), walk score 3 (50–69, "Somewhat Walkable"), walk score 4 (25–49, "Car-Dependent"), and walk score 5 (0–24, "Car-Dependent").

Appendix Table 7 examines this heterogeneity. Treatment effects show no systematic variation across walkability groups compared to the highest walkability areas.This null result indicates that the distance gradient documented in the main analysis is unlikely to be driven by zipcode quality and instead reflects transportation accessibility differences.

C.3 Ruling Out Supply-Side Channels

Table 8: Uber's Effect on Hotel Supply across

	(A) Distance Groups		**(B) Transit Score Groups**	
	Δ Uber Effect	Rel. to Centre	Δ Uber Effect	Rel. to Group 1
Group 1 (<1 mi / 89–100)	-0.0337	Ref.	-0.00772	Ref.
	(0.0174)		(0.0161)	
Group 2 (1–5mi / 69–89)	-0.00486	0.0289	-0.0224	-0.0147
	(0.0327)	(0.0235)	(0.0224)	(0.0116)
Group 3 (5–10mi / 49–69)	-0.0294	0.00430	-0.0567*	-0.0490
	(0.0268)	(0.0236)	(0.0234)	(0.0251)
Group 4 (10–16mi / 25–49)	-0.0442*	-0.0104	-0.0397	-0.0320
	(0.0195)	(0.0139)	(0.0233)	(0.0174)
Group 5 (0–24)	–	–	0.000385	0.00811
			(0.0146)	(0.0179)
Controls	✓	✓	✓	✓
Zipcode FE	✓	✓	✓	✓
Year-Month FE	✓	✓	✓	✓
Observations	4,150	4,150	4,150	4,150

Robust standard errors in parentheses $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$
Standard errors are clustered at MSA level

Table 8 reports the effect of Uber's entry on hotel room supply using the same specification as the demand regression. Consistent with the short-run rigidity of hotel capacity, I did not find significant effect on supply across any distance or transit group. These results rule out supply adjustments as an alternative explanation for the main findings and reinforce the interpretation that Uber's entry operates primarily through a demand-driven mechanism.