Your Uber has Arrived: Ridesharing and the Redistribution of Economic Activity

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Abstract

This paper studies how improvements in local accessibility influence cities' distributions of economic activity. Exploiting UberX's entry interacted with a location's prior accessibility, I measure how local economic activity responds to changes in access. After ridesharing's entry, restaurant net creation doubles in previously inaccessible locations, from 5% to 10%. As these areas open up and become more attractive, the median house price rises by 4% and rents rise by 1%. I quantify the impacts of these changes on welfare using a spatial equilibrium framework. Resident welfare depends on the trade-off between accessibility and amenity benefits versus housing costs. In the post-period, all residents benefit from ridesharing's entry. Homeowners are willing to pay $1,060 per year for ridesharing's entry, as user costs fall. Renters are willing to pay $430, as they do not realize capital gains.

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1 Introduction

Transportation technology effects the spatial distribution of economic activity in cities. Knowing this, governments have spent hundreds of billions of public dollars investing in large infrastructure projects. As a result, highways, commuter rail, and subways have allowed cities to expand their spatial footprints, allocating more land to production in the center and residences in the suburbs. The goal of these projects is often to improve accessibility in cities. Recently, the private sector introduced a new transportation technology, in the form of ridesharing, that has the potential to reshape our cities.

This paper looks at how ridesharing impacts cities. Ridesharing services such as Uber and Lyft provide on-demand, point-to-point travel, and have the potential to reshape our cities by improving accessibility. Ridesharing services remove the fixed cost of owning a car, allow more flexible routes than public transit, and expand taxi services by hailing via online platform rather than physically searching for a ride. In contrast to changes in access due to large infrastructure projects, ridesharing arrives without planning or prior announcement from public officials. In addition, it arrives in every location within a city, instead of a along single new route. This variation affords clean, short-run estimation of the impact of access on economic activity.

In this paper, I explore how residents value this improvement in access introduced via ridesharing. As zipcodes become more accessible, customers can travel to them more easily. This enables firms to take advantage of lower rents in previously inaccessible areas, especially those firms sensitive to consumers' travel choices, such as restaurants, which are important urban consumption amenities. The improvements in access and amenities beg the question of whether more fundamental neighborhood changes, such as gentrification, are afoot. While the short run demographic responses show no evidence of displacement or residential resorting, transit-inaccessible zipcodes already see house price growth consistent with local redevelopment.

First, to measure UberX's impact on cities, I compare economic outcomes in accessible and inaccessible zipcodes within cities, pre- and post-ridesharing. I use variation in pre-period inaccessibility, which differs within cities and across zipcodes, interacted with the staggered entry of the UberX platform into cities in a difference-in-differences design.[1] This natural experiment measures how economic activity, specifically restaurants and housing costs, responds to differential improvements in access induced by ridesharing. The design is also expanded to an event-study setting to observe how these responses evolve over time.

The reduced-form results show that economic activity, as measured by restaurant net creation, house prices, and rents, increases relatively more in inaccessible zipcodes than in their accessible peers. After ridesharing's entry into a city, inaccessible zipcodes add 0.75 new restaurants per year more than their accessible peers. This doubles the restaurant net creation rate from 5% of stock in the pre-period to 10% in the post-period; suggesting the supply of local consumption amenities are highly elastic with respect to access. As previously inaccessible zipcodes enjoy improved access and new amenities, house prices rise by 4% and rents by 1% for the median zipcode. These results show no evidence of pre-trends, are not driven by general urbanization or gentrification, and are robust to a variety of sample definitions and inaccessibility metrics.

Second, to measure how residents value improvements in access, I write down a model for welfare in order. The spatial equilibrium model contains a demand system in which residents choose how much and where to consume private amenities (restaurants). The UberX natural experiment shocks travel times and costs. Resident utility increases as their zipcode of residence gains access and amenities, but declines as it realizes higher housing costs. This framework allows me to weigh travel times, amenities, and housing costs in a unified framework to estimate how the distribution of welfare changes over time by accessibility status.

After ridesharing, all residents gain more from improvements in access and amenities than they lose due to increasing housing costs. Homeowners actually see their user costs fall, and are willing to pay $1,060 for ridesharing's entry. Renters realize higher rents and do not benefit as much; they are nonetheless willing to pay $430 a year, or $36 a month for ridesharing and all of its associated benefits. Residents of accessible locations, both homeowners and renters, are willing to pay 0.5% more than their inaccessible peers. For

[1] UberX is a mobile app-based ridesharing platform in which a person can hail a vehicle via the app to come to their location.

homeowners, this is because they realize higher capital gains; even with lower house price growth, prices are initially more expensive in accessible locations. Renters in accessible locations are better off than their inaccessible peers as their rents do not rise as quickly.

Because this paper provides evidence that a short-run innovation in transportation technology can reshape cities without the need for major infrastructure projects, it complements the literature on access and economic activity. Generally, this literature finds that lowering transit costs leads to urban growth and decentralization. Reduced-form work showing that changes in access lead to dispersion of economic activity began with Baum-Snow (2007), who showed that highways lead to suburbanization. More recent work on transportation has exploited innovations independent of infrastructure, to measure the impact of taxi deregulation on congestion (Mangrum and Molnar, 2019), and the impact of congestion pricing on travel patterns (Kreindler, 2018). Bridging those two strains, the reduced-form section of this paper utilizes a modern change in technology independent of infrastructure to measure the impact of a transportation change on economic activity, rather than on travel or congestion.

The welfare section of the paper complements the empirical spatial equilibrium literature, which has traditionally used long-term variation in access from infrastructure changes (Heblich, Redding and Sturm, 2019; Monte et al., 2018; Tsivanidis, 2019). I adapt the demand structure introduced by Ahlfeldt et al. (2015), part of the empirical spatial equilibrium framework that brought theory on non-monocentric cities (Ogawa and Fujita, 1976; Rossi-Hansburg and Lucas, 2002), to a tractable empirical model. I modify the framework for the short-run setting, shutting down the labor supply response and introducing demand for consumption amenities to the consumer's problem.

In studying how innovations in transportation impact the distribution of consumption, this paper integrates the urban consumption literature and the access literature, which emphasizes the distributions of jobs and residences. Glaeser, Kolko and Saiz (2000) posit that cities add value not only in production, but also in consumption. Cities provide access to nontradable services such as lawyers or restaurants, which increasingly drive urbanization (Couture and Handbury, 2017). In addition, consumers value consumption density (Couture (2019)) and segregate their consumption based on spatial and social frictions (Davis et al., 2017). These papers rely on holding the commercial and transportation landscape fixed, allowing people to sort and move across the city's geography. In contrast, this paper uses a complementary form of variation; I shock travel times, changing the distribution of amenities, while holding residents fixed.

Finally, this paper joins a growing literature examining the Uber economy. Researchers have studied consumer welfare (Cohen et al., 2016), and the labor supply of Uber drivers (Chen et al., 2017; Hall and Krueger, 2016; Cook et al., 2018). In response to Uber's arrival, ambulance use has fallen (Moskatel and Slutsky, 2017), but traffic fatalities are on the rise (Barrios, Hochberg and Yi, 2018). Hall, Palsson and Price (2018) show that Uber can be a substitute or complement to a city's transportation network, depending on its extent. My paper furthers this finding; since Uber can substitute or complement current travel modes, residents have more travel flexibility and consume in new places, leading to aggregate increases in resident welfare.

2 Institutional Background and Data

Before exploring how ridesharing redistributes economics activity in cities, it is useful to understand how travel has changed since its introduction. This section uses travel survey data from the National Household Travel Survey to show that the share of trips taken by taxis or ridesharing is five times higher than in a world with only taxis. Furthermore, travel modes have become increasingly specialized; residents switch from public transit to ridesharing for social and recreational trips, and prefer public transit for work-related trips. Zooming in on New York City, which offers extensive trip-level data over many years, shows that take-up of ridesharing services in the outer boroughs is strongly correlated with increased restaurant growth and housing rents.

Taken together, the travel data support studying how restaurant net creation has changed in transit-inaccessible locations, as people switch from transit to ridesharing to consume. Moving from the NYC case study to the national sample requires data pre- and post-ridesharing in accessible and inaccessible locations for house prices, rents, and restaurant establishment counts for a set of U.S. cities.

2.1 Travel Patterns and the Introduction of Ridesharing

While the United States is often considered primarily a driving country, U.S. travelers have a variety of travel options. The **National Household Travel Survey** (NHTS) provides detailed trip descriptions for approximately 1 million trips every 8 years, with the most recent surveys in 2009 and 2017. Limiting the sample to trips taken in Core Based statistical areas (CBSAs) with at least 2 million residents in 2010 yields approximately 291k trips in 2009, and 282k trips in 2017. Analysis of the two recent NHTS waves gives us insight into how ridesharing is changing travel patterns in our biggest cities.

The NHTS classifies trips for work, social and recreational activities, shopping and other.[2] I define travel mode as driving private vehicle, taking public transit (including buses, subways, commuter rail, street car, light rail), or hailing a taxi. In 2009, all taxi trips can only be taken using the traditional taxi services, those one hails on the street or requests by calling the dispatch station. In 2017, this field was updated to include Uber and Lyft. Using the confidential NHTS data releases, one can determine whether a respondent's home is within a 5 mile radius of the CBSA's city center.[3]

From 2009 to 2017, more people travel to work with public transit, but travel for fun with ridesharing. Both public transit and ridesharing has increased at the expense of private vehicles, and this is especially true in city centers. Table 1 describes the transportation options observed in the NHTS trip data for 2009 and 2017. In 2009, 95% of travel used private cars, decreasing to 83% in city centers. In city centers, this declined to 71% after the introduction of ridesharing. Over the same period, people traveling to work rode more with public transit, increasing from 25% to 39% of trips from central origins.[4] For social and recreational trips, travelers switched from driving private cars, especially so in city centers, to using ridehailing, with these services growing from 2–10% of social and recreational trips.

Taken together, Table 2 and Figure 1 suggest travelers enjoy taking social and recreational trips via ridesharing. Driving trips prior to ridesharing see about one-fifth of trips devoted

[2] Analysis uses the "trippurp" variable. The more specific trip purpose variable, "whyto", which gives the travel purpose for a destination, independent of origin, changed the response options across the two waves, introducing error when tracking travel purposes over time.

[3] City centers are defined by querying the latitude and longitude of a city in Google Maps.

[4] 29/34 US. cities with at least 2 million people have subways or lightrail systems, as listed in Table E1.

both to work and to social and recreational activities. In central locations after ridesharing, driving trips are increasingly work-related. Public transit seems to have become especially work-related, with the work share growing from 36% in 2009 to 50% in 2017. The share of transit trips taken for fun has declined, especially so in city centers, from 24% to 14%. As driving and transit became more specialized for work trips, ridesharing trips have become increasingly socially driven; social trip shares for taxi/ridesharing trips increase from 13% to 46%. This revealed preference for ridesharing is not limited to areas with previous taxi experience. Looking to Figure 1, we see that the cities best served by public transit see a growth in centrally originated social trips using taxi or ridesharing services, from 5% to 17%, but also cities without as much transit reliance saw growth from 0.1% to 3%. These are also cities in which ridesharing entered later, so their take-up is in earlier stages.[5]

2.2 Case Study of the Impacts of Ridesharing: New York City

Not only did ridesharing introduce taxi services to cities lacking them in the pre-period, it also filled in gaps within even the best-served public transit and taxi city, New York City. While the yellow cab is one of the most recognizable symbols of the city, it is far from omnipresent outside of Manhattan. Poorer and minority areas have long had trouble hailing yellow cabs, to the extent that the city introduced green cabs in 2013 to provide more options to outer borough residents.[6] These areas are also much less densely served by the subway systems, making them overall harder to access and leave using public transit.

Using a combination of publicly available data from the **NYC Taxi & Limousine Commission** (TLC) as well as data acquired by Bialik, Flowers, Fischer-Baum and Mehta of the website FiveThirtyEight using a Freedom of Information Act (FOIA) request, one can construct the time series of trip origination locations by car travel mode: yellow cab, green cab, and Uber.[7][8][9] UberX entered NYC in September, 2012, Lyft entered in July, 2014, and

[5] Of the sample of the 34 largest U.S. CBSA's in 2010, San Francisco, New York City, Boston, Chicago, and Washington, DC represent, respectively, the first, second, third, fourth, and eight city-level UberX entry dates.

[6] Green cabs can pick up riders in the Bronx, Brooklyn, Queens and Staten Island, as well as in Manhattan above W 110^{th} St. and E 96^{th} St.

[7] Data available at `http://www.nyc.gov/html/tlc/html/about/trip_record_data.shtml`

[8] Data available at `https://github.com/fivethirtyeight/uber-tlc-foil-response/`

[9] I drop trips to or from the major airports as we are interested in how ridesharing impacts social and

UberPOOL, Uber's carpooling service, entered in January 2015. The FOAI'd data covers all Uber trips in NYC from April to September 2014, and from January to June 2015. Figure 2 shows how the take-up in ridesharing differs by borough. Panel (a) plots the Uber share of all pickups, by borough. Uber makes up a much greater share of the ridesharing market in outer boroughs, growing from 5 to nearly 40% of all trips by mid-2015. In contrast, Uber's market share in Manhattan grows at half the rate, still below 20% by mid-2015. Over the sample period, the total number of trips taken by any ridehailing service (yellow cab, green cab or Uber) in Manhattan fell by about 3%, while the number of trips originated in the outer boroughs rose by 69%, reflecting the differential improvement in access induced by ridesharing.

The NHTS data suggest many of these trips to outer boroughs may be to restaurants. Restaurants represent a particularly useful industry to study for two key reasons. First, restaurant contribute to the consumption value we derive from cities (Glaeser, Kolko, Saiz, 2000; Couture, 2018; Couture and Handbury, 2019; Davis et al., 2019). Second, due to their low start up costs, restaurants respond to changing local demand quickly, representing the green shoots of responsiveness to ridesharing. In 2017, the NHTS data show that trips to consume meals comprised 8% of all trips, and 54% of all social and recreational trips, up from 6% of trips in 2009 and 34% of all social and recreational trips. Given that we travel to restaurants often, explore a wide variety of restaurant cuisines, and start up costs are low relative to other industries, we would expect new restaurants to open up in locations previously hard to access using public transit.

The **County Business Patterns** provides zipcode level annual data on restaurants, among other industries. This data tracks the number of establishments by industry and employment size class.[10] After ridesharing's entry, we should observe more restaurants enter in previously hard-to-reach areas, so I construct a net creation variable as the change in the stock of restaurants over two years. For example, given a restaurant stock of 8 establishments in 2011, followed by 10 establishments in 2012, net creation equals 2 establishments. Because

recreational trips.

[10] I use data on full-service restaurants (NAICS code 722511) with between 10 and 100 employees. This ensures that I track destination-worthy restaurants, and not fast-casual establishments catering to work lunches, or coffee shops co-located with residences.

the data contains only count by zipcode, establishment size, industry and year, I am agnostic as to whether these establishments have relocated, newly opened, recently closed, grown or shrunk. Data is also collected for two placebo industries that should be less impacted by ridesharing. First, dentists, which represent a service we travel to. Second, dry cleaners, a service we consume close to home, which may move with gentrification. In both placebo industries, we have a low taste for variety, and so changes in travel options are less likely to induce us to explore new dry cleaners or restaurants.

Panel (b) in Figure 2 provides a quick check that net creation increases in inaccessible areas, and plots the growth in restaurants establishments in NYC by borough, using data from the County Business Patterns (6-digit NAICS 722511). Between UberX's entry in 2012 and the end of 2016, the outer boroughs increased their stock of restaurants by 70%, while Manhattan only increased its stock by 20%.

As the outer boroughs become more accessible and gain new restaurants, they become more desirable. To track how house prices and rents respond to ridesharing, I collect data on both. **House price data** comes from the CoreLogic Deeds Database, from 2000q1-2015q4. I construct zipcode level house price indices, normalized to 1 in 2000q1. Because of the potential for renovations associated with urbanization and gentrification over the sample period, I construct a hedonic index rather than a repeat-sales index. This method directly controls for a suite of housing characteristics. For each zipcode j, I construct the HPI_{jt} using the following specification:

$$ln(P_{kt}) = HPI_{jt}qtr_t + \delta Acres_{kt} + \gamma Sqft_{kt} + Built_{kt} + Bed_{kt} + Bath_{kt} + Garage_{kt} + \eta_{kt} \quad (1)$$

The hedonic specification regresses transaction k's log price, $ln(P_{kt})$, in zipcode j in quarter t, on quarter dummies, qtr_t, the number of acres and square feet in the home, and dummies for the year built, number of bedrooms, number of bathrooms, and whether the house has a garage. The estimates for HPI_{jt} provide the local house price index in zipcode j at time t. This yields a zipcode by quarter panel of house price indices.

Housing rent data comes from Zillow's *Zillow Rent Index* (ZRI) data for all homes, including single family, multifamily, condos and co-ops, at the zipcode level from 2010m1 through 2018m5. The ZRI provides an estimate of median market rent for each zipcode, smoothed and seasonally adjusted, denominated in dollars. Zillow does not reveal its proprietary index construction method. Figure 2(c) shows that ZRI, normalized to 1 in 2010m10, in the outer boroughs have grown 10% more than rents in Manhattan from the end of 2010 to 2018, during the expansion of ridesharing.

2.3 Moving from NYC to a National Set of Cities

Taken together, the NHTS and TLC data show that residents opt for ridesharing instead of public transit for social and recreational trips, and especially so in the boroughs of New York City least accessible via public transit. The CBP and ZRI data show that restaurants and rents have grown as the outer boroughs opened up due to ridesharing. Moving from the NYC case study to a national sample of 34 cities (those with at least 2 million residents in 2010) requires additional data on local accessibility. The inner/outer borough comparison is unique to New York City; not all cities have such intuitive cross-sectional variation in access. In Section 3, I develop a metric for a destination's accessibility, constructed from travel times and local population data.

Travel Times, my preferred proxy for the cost of travel, come from scraping the Google Maps Distance Matrix API, which provides travel duration for a variety of travel modes, given the latitude and longitude of the origin and destination. There are 7,276 zipcodes in the set of 34 CBSAs. I construct a travel matrix allowing travel between any two zipcodes *within* the same CBSA. This yields 2.4 million zipcode origin-destination pairs, or trips. To cut down on data costs, I assume travel times to be symmetric; $m_{ij} = m_{ji}$, where m_{ij} denotes travel time in minutes from origin i to destination j. Google provides average travel times, independent of traffic conditions, for driving and public transit modes.[11] Taking the difference between these two times yields the travel time wedge for a given trip ij. Finally, I also construct the geodesic distance between any two zipcodes for an infrastructure-invariant travel cost.

Population data comes from the American Community Survey (2011–2016) and the

[11] In ongoing work, I query Google Maps's website directly, and specify the departure time for each query. This allows me to pull real-time driving and public transit times, depending on time of day and day of week. This data contain $\approx$ 20 million queries, as a single trip is scraped multiple times.

2010 Census. I collect data on zipcode level population for use in constructing the accessibility metrics. I also collect data on median earnings and education. These data are used to control for time-varying demographic characteristics as well to test for residential sorting and gentrification around the introduction of ridesharing.

Additionally, the County Business Patterns, National Household Travel Survey, CoreLogic Deeds constructed HPI, and Zillow Rent index are collected for all zipcodes in the set of 34 cities.

3 Reduced-Form Research Design

3.1 Guiding Empirics with Model Intuition

I define an empirically tractable inaccessibility measure to provide cross-sectional variation across neighborhoods within cities. This measure is guided by theory laid out formally in Section 5. Here, I provide intuition linking the theory to the reduced-form inaccessibility measure, as well as two hypotheses testable in the data. The model yields expressions for the number of nontradable amenities (hereafter called "firms") in destination j, N_j, as well as the number of residents in origin i, R_i:

$$N_j = \sum_i \rho_{ij}^N \times R_i \times I_i \tag{2}$$

$$R_i = \sum_j \rho_{ij}^R \times N_j \tag{3}$$

Where ρ_{ij}^N is the probability of traveling between i and j, a measure of firms' access to residents; and ρ_{ij}^R is the probability of traveling between i and j, a measure of residents' access to firms. Equations 2 and 3 highlight that in equilibrium, residents wish to be close to amenities, and amenities wish to be close to residents.

These formulae yield two hypotheses we can test in the data. First, holding resident population and income ($R_i \times I_i$) fixed, an increase in firms' access to residents, ρ_{ij}^N, will increase the number of firms in destination j. The second hypothesis uses the fact that we can take the value of residential housing costs, q_i, out from the summation as follows:

$$R_i = \frac{1}{q_i^{\varepsilon\beta}} \sum_j \hat{\rho}_{ij}^R \times N_j \tag{4}$$

where $\hat{\rho}_{ij}^R$ is the remaining components of ρ_{ij}^R that remain in the summation. Equation 4 shows that, all else equal, in an environment where number of residents is fixed, an improvement in access to firms $(\hat{\rho}_{ij}^R)$ or a growth in the number of firms nearby (N_j), must be counterbalanced by rising housing costs. In short, there's no free lunch: one pays for restaurant access with higher rents.

3.2 An Empirical Definition of Inaccessibility

While the model used in Section 5 measures accessibility using data on times, incomes, housing costs, and population, as well as unobserved parameters and location characteristics, for the reduced-form estimation, the paper relies on a simpler metric. We can construct an empirically tractable market access metric in terms of observables: travel time, m_{ij}, the number residents, R_i, and the number of firms, N_j.

To provide cross-sectional variation in access to residents, I develop an index, m_j^N, that ranks zipcodes within each U.S. city by their population-weighted average travel time, in minutes. I do this for each travel metric discussed in section 2.3: public transit time, driving time, the wedge between times, and geodesic distance. Because the NHTS data suggests that residents in city centers switch from taking public transit in favor of ridesharing for social and recreational trips, for the main results, I let travel time equal public transit time. In additional analysis, I discuss other travel time options.

Figure 3 provides a visual example of how this index is constructed for various destination zipcodes within a city. In the example, zipcode A is the largest and closest to zipcodes B and C. T_{ij} denotes travel time between i and j. P_i denotes population in the origin zipcode. The populated-weighted average travel time to A is defined as $\widehat{T_A} = T_{BA} \times \frac{P_B}{P_B+P_C+P_D} + T_{CA} \times \frac{P_C}{P_B+P_C+P_D} + T_{DA} \times \frac{P_D}{P_B+P_C+P_D} = 6.52$, and to zipcode D as $\widehat{T_D} = T_{BD} \times \frac{P_B}{P_A+P_B+P_C} + T_{CD} \times \frac{P_C}{P_A+P_B+P_C} + T_{AD} \times \frac{P_A}{P_A+P_B+P_C} = 10.39$. Zipcode A is quicker to reach than zipcode D for the average city resident.

Intuitively, the index measures a destination zipcode's access to its potential customer base. To construct the general index, I collapse the two-dimensional travel matrix discussed in Section 2.3 (the square matrix of origin-destination pairs ij with times m_{ij} in minutes) to a 1-dimensional index for the destination zipcodes, j. The collapse proceeds as follows. The sample is limited to destination zipcodes within 5 miles of a city's center, as defined by a Google search for "[City X] latitude and longitude". For each destination zipcode, average travel times, m_j^N, are calculated from all possible origin zipcodes within 5 miles of the destination zipcode (potentially 10 miles from the city center), called the set S_N, weighted by the origin zipcode's population:

$$m_j^N = \sum_{i \in S_N} R_i \times m_{ij} \tag{5}$$

Equation 6 shows the analogue from the residents' perspective. It measures residents' access to firms, m_i^R, by constructing the firm-weighted average public transit time within a 5 mile radius of origin i.

$$m_i^R = \sum_{j \in S_R} N_j \times m_{ij} \tag{6}$$

Once I have two continuous measures of firm and resident accessibility, m_j^N and m_i^R, I split the sample of zipcodes within each city into firm and resident accessible and inaccessible locations, summarized in Equations 7 and 8. Firm-inaccessible zipcodes are those for which m_j^N is longer than the median time it takes to get to a restaurant in 2010, $\bar{m}^N$. For example, if residents can reach 50% of the restaurants in 20 minutes, a zipcode taking the average resident 30 minutes to reach is restaurant-inaccessible. Resident-inaccessible zipcodes are those for which m_i^R is longer than the time it takes to get home from a restaurant for the median resident, $\bar{m}^R$. If half of residents can get home from restaurants within 20 minutes, a zipcode whose average travel time home from a restaurant is 30 minutes is resident-inaccessible.

$$Inaccess_j^N \equiv 1\{m_j^N > \bar{m}^N\} \tag{7}$$

$$Inaccess_i^R \equiv 1\{m_i^R > \bar{m}^R\} \tag{8}$$

Since these metrics depend on a city's public transit infrastructure, where residents live, and where firms exist in the pre-period, the cutoff for inaccessibility varies by city. Figure 4 shows how $\bar{m}^N$ varies for two cities in particular, Philadelphia and Houston. It takes the average Philadelphia resident $\bar{m}^N \approx 35$ minutes to travel to half of the city's restaurants, while in Houston the average Houstonian travels closer to 37 minutes to cover half of Houston's restaurants. This yields 6 accessible and 16 inaccessible zipcodes for Philadelphia, and 8 accessible and 10 inaccessible zipcodes for Houston within 5 miles of the cities' centers, anchored to the distribution of firms and residents prior to the introduction of ridesharing.

3.3 Defining the Post-Period using UberX Entry

After ridesharing, we expect inaccessible locations to gain relatively more from their improvement in access than areas previously easy to reach via public transit. As inaccessibility varies by city, so does ridesharing's entry, with each city having its own entry date, $Entry_c$. Temporal variation uses the staggered entry of UberX into into different cities, $Post_t$:

$$Post_t = 1\{t > Entry_c\} \tag{9}$$

Table 3 provides a list of the sample cities and their UberX entry year. For each of the 34 U.S. cities with at least 2 million residents in 2010, I search for UberX's entry date. Often times, Uber had a blog post announcing "[City X], your Uber is arriving now," though this was less common for earlier entries. When Uber did not provide the entry date itself, local news outlets provided the entry dates.

Temporal variation uses UberX as opposed to UberBlack, which entered first, as UberBlack relied on existing black car services and cost much more than UberX, as in Hall, Palsson and Price (2018). This meant it did not markedly expand ride-hailing quantities, and catered to those willing to pay higher fares. In addition, the paper uses Uber's entry dates instead of Lyft, or another ridesharing platform, as Uber has about 70% of the ridesharing market as of mid-2018 and was the first platform on the scene in most cities.[12]

Figure 5 shows both the temporal and geographic variation in entry. The map shows that UberX entered a variety of cities each year after 2012, without much evidence of gravity

[12] https://www.recode.net/2018/12/12/18134882/lyft-uber-ride-car-market-share

between cities. For example, entry did not jump from NYC to Philadelphia, entering in Dallas and Minneapolis in the meantime. This implies it would be difficult for residents and firms of a given city to predict entry based on their geographic peers.

3.4 Differences-in-Differences Design

In order to measure the costs and benefits associated with ridesharing's entry, we can study inaccessible and accessible locations within cities before and after UberX entry. Formally, I track restaurant net creation, house prices and rents over time in a differences-in-differences framework, as in Equation 10.

$$Y_{jt} = \beta Inaccess_j^N \times Post_t + year_t + zip_j + CBSA_j \times Post_t + \varepsilon_{jt} \tag{10}$$

The main analysis uses Y_{jt} as the net creation of establishments of a given industry in a zipcode: $\Delta\#(restaurants_{jt})$. For example, if zipcode j had 10 restaurants in 2010, and 12 restaurants in 2011, $\Delta\#(restaurants_{j,2011}) = 2$. Additional analysis sets Y_{jt} as the house price index or Zillow Rent Index normalized to the rent in the entry year. j indexes zipcodes, and t indexes years. The coefficient of interest, β, measures the differential impact that UberX's entry has on Y_{jt} in the inaccessible areas relative to the accessible areas per unit of time. In addition to zipcode and year fixed effects, the specification includes a CBSA-by-post indicator to control for time-varying cohort effects.

In order to obtain an estimate for pre-period Y_{jt} in inaccessible locations, I remove zipcode fixed effects and instead add dummies for inaccessibility, $Inaccess_j^N$, and treatment-by-city dummies, $Inaccess_j^N \times City_j$ to control for cohort-treatment fixed effects. The coefficient on $Inaccess_j^N$ yields the pre-period average Y_{jt}, useful to gauge the magnitude of the treatment effect.

$$\begin{aligned} Y_{jt} = Inaccess_j^N + Post_t + \beta Inaccess_j^N \times Post_t + CBSA_j \\ + CBSA_j \times Post_t + Inaccess_j^N \times CBSA_j + \varepsilon_{jt} \end{aligned} \tag{11}$$

Focusing on the main outcome of interest, restaurant net creation, validity of this research design requires three assumptions: first, the parallel trends assumption; second, exogeneity of UberX entry to within–city restaurant dispersion; and third, that these results are not driven by gentrification, urbanization, or other residential sorting that pulls restaurants to new locations instead of UberX entry pushing them farther out. Section 4 provides evidence to support each assumption.

4 Reduced-Form Results

4.1 Ridesharing's Entry Induces Restaurant Dispersion

Prior to ridesharing's entry, restaurant inaccessible zipcodes had on average 14 restaurants as shown in Table 4. Table 6 shows the results of the differences-in-differences analysis. Column (1) matches estimating Equation 10, and shows that after ridesharing's entry, inaccessible zipcodes create 0.74 net new restaurants more than their accessible peers in the same city. Column (2) adds time-varying demographic controls to assuage concerns of demographic drivers pulling restaurants towards inaccessible neighborhoods; the point estimate is stable at 0.73. Finally, column (3) removes the zip code fixed effects, instead controlling for city and city-by-inaccessibility, as in Equation 11. This enables one to back out a point estimate for pre-period restaurant net creation in inaccessible zipcodes. The results in column (3) are consistent with the other columns, with the impact of ridesharing's entry on inaccessible areas adding an additional 0.74 net new restaurants, relative to their accessible peers, and inaccessible zipcodes adding on average 0.72 restaurants per year in the pre-period. Column (3) shows that inaccessible locations are *doubling* their rate of restaurant net creation from 5% (0.72/14) in the pre-period to 10% (1.46/14) in the post-period.

4.1.1 Testing Parallel Trends

The parallel trends assumption requires that inaccessible and accessible locations would have similar trends in restaurant net creation or house price growth in the absence of ridesharing. Table 4 tests whether restaurant net creation, HPI and ZRI differ in accessible and inaccessible locations in the pre-period. Restaurant net creation is more than twice as high in accessible locations than inaccessible locations, and these locations have nearly twice the stock of establishments. As long as this net creation difference is stable in the pre-period, there is no violation in parallel trends, and β is unbiased and correctly identified.

The event study in Figure 6 provides a check for parallel trends. A violation of parallel trends would manifest as a nonzero slope different from zero in the years prior to UberX entry, while an exogeneity violation would show an uptick in the point estimate in the year or two prior to entry. The graphs plot the point estimates from Equation 12 for the three years pre- and post-UberX entry.

$$Y_{jt} = \sum_{k=-3}^{3} \beta_k Inaccess_j^N \times RelYear_k + year_t + zip_j + \varepsilon_{jt} \tag{12}$$

The left-hand panel plots the event study for annual restaurant net creation, $Y_{jt} = \Delta\#Restaurants_{jt}$, the right-hand panel plots restaurant net creation rate, $Y_{jt} = \frac{\#Restaurants_{jt} - \#Restaurants_{j,t=0}}{\#Restaurants_{j,t=0}}$. In order to construct a balanced panel with three years of data on either side, I limit the sample to 19/34 cities with full post-period data. The annual restaurant net creation graph shows no evidence of pre-trends, with all of the pre-period point estimates statistically indistinguishable from 0. In the post-period, two of the three years have point estimates bounded away from 0, and nearing 0.9. For the net creation rate graph, there is again no evidence of any pre-trend that would violate the parallel trends assumption. All of the pre-period point estimates are statistically indistinguishable from 0. By the end of the post-period, inaccessible zipcodes have added approximately 20% more of their restaurant stock relative to accessible zipcodes in the same city.

4.1.2 Testing Exogeneity of UberX Entry

Addressing the second assumption stated at the end of Section 3, we need to establish that Uber did not strategically enter cities after observing an expansion in restaurant amenities. Uber is not forthcoming in its reasons for entry, with little discussion on its city level blogs. Lief Johnson, Uber's Director of New Mobility, has said publicly that Uber considers first population size.[13] Other important variables include the availability and affordability of current public transit options in the city as a whole. Hall, Palsson and Price (2018), in

[13] https://motherboard.vice.com/en_us/article/vv734x/what-it-takes-to-lure-uber-to-your-small-town

testing whether Uber is a substitute or complement to public transit, show that the main determining factor in UberX's entry date is indeed a city's population size. Specifically, they find that when comparing any two cities in which UberX entered, the probability that UberX entered the larger city first is 68%. No other explanatory variable has even half the magnitude of impact as population. The authors conclude that UberX's entry decision is largely based on tackling large markets first, and is uncorrelated with variables relating to transit ridership.

In contrast to Hall, Palsson, and Price, identification in this paper's context requires that UberX entry be exogenous not to city-level characteristics, but to how characteristics differ *within* cities. Table 5 tests for whether UberX's entry month occurs earlier based on a variety of city-level characteristics in the year prior to entry. In the top univariate panel, we find that an additional million residents in the CBSA predicts that UberX enters 3 months earlier. We also see that UberX enters richer and more educated cities earlier, as well as those with many new restaurants. Looking *within* cities, in the bottom panel, we see that almost none of the differential characteristics predict UberX entry. Indeed, the point estimate on restaurant creation in inaccessible vs. accessible locations is identical and insignificant.

The event studies in Figure 6, also support exogeneity of UberX entry. Neither graph suggests restaurant dispersion in the pre-period, making it unlikely that Uber strategically entered with perfect timing in 19 separate cities upon observing dispersion.

4.1.3 Testing Gentrification and General Urbanization

The kinked time path of the point estimates in the event studies support the assumption that generalized urbanization or gentrification trends are not causing the dispersion in restaurants; however, to gauge how UberX interacts with gentrification and urbanization forces, we can analyze how industries less likely to be impacted by UberX respond to its introduction.[14] Table 9 tests two industries' responses to UberX entry, using the appropriate industry-specific $Inaccess_j^N$.

Column (1) presents the restaurant results from Table 6. Dry cleaners represent a common neighborhood good, which we are unlikely to switch after the introduction of ridesharing;

[14] Even if gentrification occurs linearly, UberX might be amplifying urbanization and gentrification

there is not much to be gained in variety by traveling to a new location. They also represent a good tied to gentrification, as dry cleaning services are normal and so should increase as a location becomes gentrified, and higher income. In the pre-period, dry cleaning inaccessible zipcodes had a 0% growth rate off of a stock 5 establishments. The point estimate in column (2) implies that these inaccessible zipcodes gain an additional 3% of their stock in the post-period. While restaurant-inaccessible locations gain an additional restaurant every 8 months, it will take an a dry cleaning inaccessible zip code 7 *years* for a new establishment to open. So while UberX may be interacting with gentrification, opening up areas to new neighborhood amenities, the rate is far below the impact on an industry directly effected by falling travel costs.

Column (3) in Table 9 shows the results for dentists, a nontradable service we travel to, but which we are unlikely to switch with the introduction of a new travel mode. This inelasticity comes from the high cost of switching one's dentist , which outweighs any gains from exploring a variety of dental service providers. Dentists then represent general nontradable services in a city, which should disperse with the city if the restaurant results are driven by urbanization instead of redistribution of trips in space induced by ridesharing. Column (3) finds no evidence of general nontradable services dispersion, with the point estimate for dentists and insignificant 0.11.

Finally, Appendix Figure F1 shows that resident demographic characteristics do not appear to respond to UberX entry in the first three years; populations remain stable, and new entrants seem neither higher income, nor differently educated.

4.1.4 Restaurant Results Robust to Different Travel Modes

The NHTS data indicate that residents switch from public transit to ridesharing for social and recreational trips, motivating construction of the $Inaccess_j^N$ metric using the matrix of public transit travel times between all origins and destinations in the set of cities; however, this is not the only travel metric useful to construct. I construct the $Inaccess_j^N$ variable similarly, only changing the origin-destination input matrix for a variety of other travel times: the wedge between transit and driving times, the geodesic distance, and the driving times. Each metric illuminates one more aspect of how residents change their travel patterns in light of improvements in accessibility. Table 7 shows the correlations between the binary treatment indicators, for example (Distance, Transit) shows the correlation between $Inaccess_j^N(transit)$ and $Inaccess_j^N(distance)$. None of the different metrics are perfectly correlated with each other, so they highlight different margins along which access has changed.

Table 8 shows the results of changing the inaccessibility metric in Equation 10. Column (1) is identical to column (1) in Table 6, and shows that the least transit accessible zipcodes add an additional 0.74 restaurants relative to transit accessible zipcodes. Column (2) uses the wedge, or the difference between driving and transit times, and shows that the areas with the highest discrepancy between the two add an additional 0.58 net new restaurants in the post-period. While highly correlated with the transit treatment, a zipcode with a 25 minute mean transit time and a 10 minute mean driving time is indexed similarly to one with a 40 minute mean transit time and a 25 minute mean driving time; both have a 15 minute wedge, but the first zipcode is more central to the city, pushing the point estimate downwards relative to the transit time metric. The difference between the wedge and transit results highlight that activity increases most in areas that see a large drop in travel time (large wedge), and are also farther from the transit lines.

Column (3) in Table 8 shows the results when using the geodesic distance origin-destination matrix to construct $Inaccess_j^N$. This column is infrastructure invariant across cities, allowing us to check whether reducing travel costs leads to restaurant dispersion, abstracting from road and transit networks. The point estimate falls to 0.51, but remains statistically significant, showing that places farther away from the city centers see an increase in restaurant activity.

Finally, column (4) provides a convenient placebo test of the natural experiment; simply put, a zipcode difficult to reach by car in the pre-period remains difficult to reach by car. The point estimate is less than a third as large as the transit results, and cannot be distinguished from zero, indicating UberX has had little to no impact in areas difficult to drive to. Additionally, interacting transit and driving inaccessible locations, Table E3 provides additional evidence that net creation is happening in strictly transit inaccessible locations.

4.1.5 Additional Robustness Checks

The results so far have explored a variety of controls, inaccessibility measures (including a placebo), and heterogeneous industries (including placebos) with the consistent finding that restaurants are dispersing in the age of ridesharing. These results do not show evidence of pre-trends or strategic UberX entry, remain across different access measures, do not hold for industries unlikely to be impacted by ridesharing, and remain robust to controlling for time-varying demographic controls. I perform a number of additional robustness checks.

Table E4 creates a zipcode-employement size category - year panel, in order to have more observations within a zipcode-year for estimating Equation 10 with **linear zipcode time trends**.[15] The results remain robust, with each zipcode-size category adding 0.25 restaurants per year, since there are three categories, this sums to the familiar 0.74 restaurants per zipcode per year. Adding time trends lowers the point estimate to 0.21, as shown in column (3) of Table E4, for a total impact of 0.63, in the ballpark of the main results.

The results are also robust to defining the city according to **different radii**, expanding the set of zipcode origin-destination pairs; the point estimate in Table E5 falls from 0.74^{***} at a city with a 5-mile radius to 0.14 with a 10-mile radius, with the point estimates statistically significant through a 9-mile radius.

Using a **dose-response design**, in which I interact m_j^N with $Post_t$, the point estimates in Table E6 imply that a zipcode with an additional minute of average transit travel time adds 0.02 more restaurants per year after UberX entry; for a zipcode that it takes, on average, 30 minutes to get to, this translates into 1 additional new restaurant every 2 years. I can also implement a **binned dose response design**, in which zipcodes are divided into quintiles based on the 20^{th}, 40^{th}, 60^{th}, 80^{th}, and 100^{th} percentiles of travel times to restaurants. The results, in Table E7, show that relative to the most accessible quintile, most of the restaurant creation happens in the 3^{rd} and 4^{th} quintiles, which go from adding $0.7^{***} - 1$ new establishments in the pre-period, to adding $1.3^{***} - 1.5^{***}$ in the post-period. In addition, the second quintile sees no impact due to ridesharing, so it does not seem

[15] The CBP zipcode level data is a panel of zipcodes, over NAICS codes, over employment size classes. The main results for restaurants sum over all employment classes with between 10 and 100 employees (restaurants with fewer employees comprise a small ($< 3\%$) share of employment in the industry, and add a lot of noise to the data as they open and close often.)

that establishments relocate from the accessible zipcodes to inaccessible, rather this is true establishment creation.

Finally, the results are robust to controlling for whether a city is one of the top 5 most **public transit reliant** cities, at least for commutes, as defined by the 2010 ACS commuting mode data from Table E2. Controlling for whether at least 10% of a city commutes via public transit in Table E8 drops the point estimate from 0.74^{***} to 0.64^{***}, with the top 5 most transit reliant showing an additional impact of 0.33.

The **Other App Adoption Appendix** discusses how ridesharing interacts with other platforms that might be contributing to the main findings. For example, Yelp and UberX amplify each other by providing information and access; however, the existence of these other online platforms cannot explain the kinked nature of the event studies, and their entry does not correspond with UberX's.

Finally, in the **Travel Appendix**, I check to make sure that travel patterns have dispersed into $Inaccess_j^N$ areas along with restaurant activity. I explore travel trends in New York City as well as national automotive vehicle emissions, both of which support the hypothesis that residents travel more via car than in the pre-period. The NYC results suggest this is due to taking trips to more transit inaccessible locations; even if residents take the same number of trips, this implies changing from transit to ridesharing. The emissions results find that inaccessible areas within cities see an increase in emissions of nearly 10%, averaged over nearly five years.

4.2 Implications for Residential Housing Costs

The direct effect of UberX entry is to make inaccessible locations easier to reach. Indirectly, as restaurants move into previously inaccessible locations, these zipcodes endogenously improve, and the increased desirability will be reflected in house prices, as hypothesized in section 3. Figures 7b and 7a show that rents for the average zipcode have increased by $\approx 3\%$ after 4 years, and the median house price has increased by nearly 10% after 2 years. [16], [17]

[16] Figure F9 shows some neighborhoods become superstars, with the mean house price growth topping 20% after 2 years.

[17] Due to data availability, one cannot track house prices as long as rents.

Three components drive the observed changes in house prices. First, these locations have become closer to the city with the introduction of ridesharing. Second, they benefit from amenities such as restaurants moving in. Third, homebuyers may expect these locations to improve further. Differentiating between a location's status as being restaurant-inaccessible, $Inaccess_j^N$, and resident-inaccessible, $Inaccess_j^R$, can help disentangle the impacts of improvements in access from improvements in amenities.

Both improvements in amenities and access contribute to higher house prices. Table 10 shows the impact of UberX entry on median house price indices in resident-, $Inaccess_j^R$, and restaurant-inaccessible, $Inaccess_j^N$, zipcodes.[18] The table shows meaningful HPI impacts from both the increase in amenities, column (1), as well as the increase in access, column (2). Column (1) shows that house prices for the median restaurant-inaccessible zipcode rose by 3% in the post-period. Column (2) shows that house prices for the median resident-inaccessible zipcode rose 3% in the post-period. Column (3) interacts both types of inaccessibility; restaurant-inaccessible only zipcodes see a 4% increase in HPI, resident-inaccessible only zipcodes realizes an increase of 2%, and should a zipcode be both resident- and restaurant-inaccessible, the gains to UberX entry total 3%. Taken together, the magnitudes of the impacts for endogenous amenity improvements and improvements in access are similar, but for the median zipcode, house prices increase nearly twice as fast with better amenities than with better access.

Table 11 presents the same analysis, but for the mean Zillow Rent Index (ZRI). The third row of column (1) shows that the average restaurant-inaccessible zipcode sees rents grow 1% per month more in the post-period, relative to accessible peers. The fifth row of column (2) shows that the average resident-inaccessible zipcode sees 0.4% rent growth, though this is indistinguishable from 0. Column (3) runs the horse race to distinguish the impact of access from the impact due amenities. The third row of column (3) states that restaurant-inaccessible zipcodes see an additional 1.6% rent growth, relative to accessible zipcodes. The fifth row states that resident-inaccessible zipcodes see an additional 1.8% rent growth. Column (3) shows that zipcodes which are both resident- and restaurant-inaccessible benefit

[18] House price results show median instead of mean impact due to large outliers in the right tail driving up average house price growth.

less from UberX entry, with the rent increase totaling 1%. Rents grow in zipcodes of both inaccessibility types in the post-period, and in contrast to the house price results, grow at similar rates.

Taken together, the restaurant and house price results show that ridesharing has had a meaningful impact already in reshaping our cities. Private amenities have begun to disperse in measurable ways, and house prices and rents have responded to the changing spatial distribution of access and consumption.

5 Resident Welfare in the Age of Ridesharing

The reduced-form estimates *measure* the impacts on of ridesharing on the spatial distribution of restaurants, travel and house prices. By framing these costs and benefits in a spatial model of consumer demand, one can *weigh* the dollar costs of increased house prices against the benefits of fewer minutes of travel and more restaurant amenities. All derivations are in the consumer theory appendix.

The model follows the demand structure developed by Ahlfeldt et al. in their 2015 paper, in which they develop an empirically tractable spatial equilibrium framework.[19] Zipcodes in cities contain economic activity, including firm and resident locations, and are linked by roadways and other transit infrastructure. In contrast to many of the papers in the spatial equilibrium literature, the model abstracts away from any labor supply response, motivated by the NHTS data suggesting residents do not commute to work via ridesharing. This removes the joint location problem or where to live and work, fixing both locations exogenous to the model. An additional adaptation fixes housing supply, since housing markets are highly inelastic in the short term. This fixes the number of residents in a given location. Residents choose how much housing, tradable goods, and nontradable amenities to consume, as well as where to consume nontradable amenities, conditional on their residential location. Aggregating up consumers' demand for nontradables across all potential origins yields a local demand function for nontradable amenities in each destination. Nontradable amenity

[19] By nesting this demand structure in the full equilibrium model, we can later perform counterfactual experiments.

producers then clear the markets by matching demand.

Resident utility is a function of data and parameters. By estimating the local demand function, we recover parameters necessary to estimate welfare. In combination with data on income, travel times, and housing, one can construct a welfare money metric for a given origin-destination pair. Finally, I calculate residents' willingness to pay for UberX entry, and observe whether homeowners or renters benefit more from entry.

5.1 Residents' Demand for Nontradables

The goal of the resident's problem is to determine local demand in each location within a city for three goods: a nontradable amenity we must travel to, n_i, a tradable good, c_i, and housing, h_i. Destinations are indexed by j, and residences are indexed by i.

A resident maximizes her utility over consuming housing, tradable goods and nontradable amenities, subject to an endowed income constraint:

$$\max_{n_i,c_i,h_i} \quad \left(\frac{h_i}{\beta}\right)^{\beta}\left(\frac{c_i}{\alpha}\right)^{\alpha}\left(\frac{n_i}{1-\beta-\alpha}\right)^{1-\beta-\alpha}\frac{z_{ij}}{e^{\tau m_{ij}}} \tag{13}$$

$$\text{s.t.} \quad I_i = q_i h_i + p c_i + n_i \tag{14}$$

Utility is Cobb-Douglas, with an idiosyncratic preference term, z_{ij}, Frechet distributed, $F(z_{ij}) = e^{-T_i E_j z_{ij}^{-\varepsilon}}$, which governs where the nontradable amenity is eventually consumed. E_j is the average amenity value of destination j, similar to a destination fixed-effect; T_i is E_j's origin counterpart. ε governs substitutability between locations for the nontradable amenity. Residents trade off travel against uniqueness when choosing where to consume. For example, restaurants will have high ε, and so we will be willing to travel long distances to a particularly attractive restaurant. Dry cleaners, on the other hand, are not very differentiated, so the cost of travel is not justifiable and we will observe these to be clustered by residences. m_{ij} is a distance term, in minutes, between locations i and j. τ is a scaling parameter that raises or lowers m_{ij}, and can be thought of as the opportunity cost of travel time. I_i is the endowed income for a resident in location i. q_i is the local price of housing.[20] p is the price of tradable

[20]The model normalizes the price of nontradable services, the object of interest, rather than the price for the outside good, housing, for three reasons. First, is data availability. Extensive margin changes for amenity

goods, which does not vary in space.

Maximizing utility leads to the following Marshallian demands:

$$n_i = (1 - \beta - \alpha) I_i \tag{15}$$

$$h_i = \frac{\beta I_i}{q_i} \tag{16}$$

$$c_i = \frac{\alpha I_i}{p} \tag{17}$$

Intuitively, consumers allocate a share of their income to nontradable services, and a share to housing, which depends inversely on the price of housing. Plugging in these Marshallian demands into the utility function, we can derive the indirect utility for the resident in location i traveling to location j:

$$V_{ij} = \left(\frac{h_i}{\beta}\right)^{\beta} \left(\frac{c_i}{\alpha}\right)^{\alpha} \left(\frac{n_i}{1 - \beta - \alpha}\right)^{1-\alpha-\beta} \frac{z_{ij}}{e^{\tau m_{ij}}} = \left(\frac{I_i}{q_i}\right)^{\beta} \left(\frac{I_i}{p}\right)^{\alpha} (I_i)^{1-\beta-\alpha} \frac{z_{ij}}{e^{\tau m_{ij}}} = \frac{I_i z_{ij}}{q_i^{\beta} p^{\alpha} e^{\tau m_{ij}}} \tag{18}$$

Utility along route ij depends on the income and house prices in the origin location, the price of tradables, the idiosyncratic shock, and the time it takes to travel between the origin and destination.

5.1.1 Deriving the Local Demand Estimating Equation

Given that z_{ij} is Frechet distributed, V_{ij} is also Frechet distributed. Let the probability of taking trip ij to consume nontradable amenities be ρ_{ij}^{N}, then

demand, establishment flow, and local housing rents are observable, while intensive margin changes for amenity demand, prices, are unobservable. Second, rental payments are much larger as a proportion of consumer budgets than amenity prices. Third, the price impacts from the introduction of ridesharing are less clear than on housing or restaurant net creation. On the one hand, the introduction of ridesharing brings establishments closer to each other, increasing competition, lowering local market share, and putting downward pressure on prices until less productive establishments exit. On the other hand, ridesharing brings establishments close to customers, increasing the demand for their services, pushing prices up and encouraging entry. The net effect in the data shows that the increase in demand wins out; more establishments have been added and rents have increased, but the implications for price are ambiguous. It is not within the current scope of this framework to model local competition along with the increase in access, so the model focuses on the extensive margin problem, with establishment entry being tied to local rents and access.

$$\rho_{ij}^N = \frac{E_j(e^{\tau m_{ij}})^{-\varepsilon}}{\sum_s E_s(e^{\tau m_{is}})^{-\varepsilon}} \tag{19}$$

ρ_{ij}^N is the probability that a resident in location i travels to consume nontradables in destination j; it is akin to a firm's access to consumers. For nontradable amenity demand in location j, N_j^d , we sum over all possible origin location's travel probabilities, ρ_{ij}^N, weighted by the number of residents in the origin locations, R_i, and how large their wallets are, I_i.[21]

$$\begin{aligned} N_j^d &= \sum_i \rho_{ij}^N \times R_i \times I_i \\ &= E_j \sum_i \frac{R_i I_i (e^{\tau m_{ij}})^{-\varepsilon}}{\sum_s E_s(e^{\tau m_{is}})^{-\varepsilon}} \end{aligned} \tag{20}$$

Intuitively, the term in the summation can be thought of as a market access term: how many residents, R_i, are available to travel from all potential origin zipcdoes, i, to destination zipcode j, weighted by the travel distance, $e^{\tau m_{ij}}$, between i and j in city c. As distance between i and j grows, $(e^{\tau m_{ij}})^{-\varepsilon}$ decreases; the farther apart are two locations, the less likely income will flow from i to j.

Producers of nontradable amenities scale up production according to local demand, N_j^d, so that the nontradables market clears: $N_j^s = N_j^d = N_j$. As discussed in developing the empirical inaccessibility metrics, local demand depends on the probability of taking trip ij, weighted by how many residents and how much income travels along that route. The number of residents, R_i, is exogenous to the model as there is no new residential building, and buildings cannot be converted between the commercial and residential sectors.

5.2 Constructing A Money Metric for Welfare

In order to compare residents' welfare before and after UberX entry, one can take expectations over the utility in Equation 18 to find the expected utility of living in location i:

[21] In this setting, the number of residents, R_i, in an origin is taken as fixed and exogenous to the model; however, in the standard spatial equilibrium framework, firms care about access to consumers, while consumers care about access to firms. Consumers then have an associated trip share, $\rho_{ij}^N = \frac{T_i I_i^\varepsilon (e^{\tau m_{ij}} q_i^\beta)^{-\varepsilon}}{\sum_r T_r I_r^\varepsilon (e^{\tau m_{rj}} q_r^\beta)^{-\varepsilon}}$. This allows for endogenous resident location, $R_i = \sum_j \rho_{ij}^R \times N_j$, depending on N_j.

$$E(V_{ij}) = E\left(\frac{I_i z_{ij}(\varepsilon)}{q_i^{\beta} p^{\alpha} e^{\tau m_{ij}}}\right) = \frac{I_i \Gamma\left(\frac{\varepsilon-1}{\varepsilon}\right)}{q_i^{\beta} p^{\alpha}} \frac{E_j^{\frac{1}{\varepsilon}}}{e^{\tau m_{ij}}} \tag{21}$$

To create a money metric, note that we can log-linearize the utility function along a route ij,

$$ln(V_{ij}) = ln(I_i) + ln(\Gamma\left(\frac{\varepsilon-1}{\varepsilon}\right)) + \frac{1}{\varepsilon} ln(E_j) - \beta ln(q_i) - \alpha ln(p) - \hat{\tau} m_{ij} \tag{22}$$

Equation 22 puts utility and its components in terms of elasticities; for example, a 1% change in housing costs decreases utility along route ij by β%. Equation 23 holds utility fixed, so that we can find the amount of income needed to balance the changes in q_i, p, E_j, $\hat{\tau}$, and m_{ij}, that is, to bring a resident to utility of 0:

$$ln(I_i) = \beta ln(q_i) + \alpha ln(p) + \tau m_{ij} - \frac{1}{\varepsilon}\ln(E_j) - ln(\Gamma\left(\frac{\varepsilon-1}{\varepsilon}\right)) \tag{23}$$

To calculate the willingness-to-pay for UberX entry, we can compare the income needed to reach 0 utility in the pre- and post-periods:

$$WTP_{ij} = I_i^{pre} - I_i^{post} \tag{24}$$

Intuitively, if a resident needs fewer dollars to reach a utility level of 0 in the post-period than in the pre-period, he or she is willing to pay money for UberX entry. The difference in compensation is the willingness-to-pay.

WTP_{ij} relies on a variety of estimated and calibrated inputs. In order to recover (time-varying) destination quality, E_j, and the opportunity cost of travel time, τ, one estimates the local demand function in Equation 20. Rents and travel times, q_i and m_{ij}, are equilibrium outcomes not solved for in the model. I estimate $\hat{q}_j$ and $\hat{m_{ij}}$ using the UberX natural experiment in the reduced-form section in order to recover the exogenous component of house price change and travel time change.[22] I calibrate $\varepsilon = 8$, which is among the higher range of elasticities of substitution for amenities, but in line with those estimated for the

[22] When predicting $\hat{q}_j$ and $\hat{m_{ij}}$, I use the continuous variable m_j^N instead of the discreet $Inaccess_j^N$ interacted with $Post_t$ as this is closer to ρ_{ij}^N, which is a continuous measure of access.

restaurant industry (Couture, (2016); Atkin et al. (2018); Einav et al. (2019); Su (2018); Couture et al. (2019)). Finally, $\beta = 0.3$, and $\alpha = 0.6$ consistent with literature on the share of housing and tradables expenditure shares in overall consumption. Finally, p is taken as the city-specific non-housing CPI from the Bureau of Labor Statistics.

5.2.1 Recovering τ and E_j

Log-linearizing Equation 20 allows estimation via nonlinear least squares (NLS) to recover the combined Frechet - travel cost parameter, $\varepsilon\tau$, as well as the non-observable zipcode level characteristics, E_j:

$$ln(n_j^c) = \kappa^c + ln\left(\sum_{i \in c} R_i^c (e^{\tau m_{ij}^c})^{-\varepsilon}\right) + ln(E_j^c) \tag{25}$$

j indexes destination zipcodes within a city, c, with i indexing origin zipcodes. $\kappa^c = \sum_{s \in c} E_s (e^{\tau m_{is}^c})^{-\varepsilon}$ is a city-level fixed effect, as the term in the denominator of Equation 20 does not vary across zipcodes within a city.

Taking the model to the data, N_j is the annual zipcode level establishment count for restaurants, from the Census' County Business Patterns. R_i is zipcode level population, from the annual American Community Survey. m_{ij} comes from travel times scraped from Google Maps, in combination with survey data from the NHTS, details of construction follow in the NHTS Appendix. The parameters of interest are $\varepsilon\tau$, and E_j.

Estimation is performed using either pre-period or post-period data to estimate $\hat{\varepsilon\tau}_{pre}$ and $\hat{\varepsilon\tau}_{post}$ separately. Table 12 has the results of the estimation, showing that the cost of travel has fallen by half from $\hat{\tau}_{pre} = 0.02$ to $\hat{\tau}_{pre} = 0.01$, reflecting the increased ease of travel by private, flexible, and cheap ridesharing options. These results are in line with previous estimates from Tsivanidis (2019), who finds $\tau = 0.012$, and Ahlfeldt et al. (2015) who find $\tau = 0.01$.

5.2.2 Estimating q_i for Renters and Homeowners

The reduced-form results show that house prices rise differentially in inaccessible areas in the post-period. This will have different implications for renters and homeowners. Renters will see the cost of living in a location rise, while homeowners will see their user costs fall as their equity rises. This necessitates two different version of q_i. Since q_i is an equilibrium outcome, we need to isolate the UberX specific component of changes in q_i. For renters, I regress rents in dollars, using the ZRI, on the continuous treatment variable, m_j^N, which measures average travel time to location i, interacted with $Post_t$:

$$ZRI_{it} = \lambda m_j^N \times Post_t + year_t + zip_i + \epsilon_{it} \tag{26}$$

This yields the UberX implied portion of monthly rent increases. To get annual rent expenditure, q_i^{ZRI}, I multiply the predicted $(Z\hat{R}I_{it})$ by 12. For homeowners, I regress HPI_i constructed using the CoreLogic data on the same treatment and post variables:

$$HPI_{it} = \lambda m_j^N \times Post_t + year_t + zip_i + \epsilon_{it} \tag{27}$$

This yields the UberX implied portion of house price index increases. To get an annual housing cost in dollar terms, I first multiply $H\hat{P}I_{it}$ by the value of a housing transaction in 2010, the first year in my sample. The provides the exogenous changes in house price, q_i^{HP}, as opposed to index, over the sample. Finally, the annual carrying cost of a home can be measured in its user cost:

$$UC_i = (1 - \tau_I) r q_i^{HP} + (1 - \tau_I)\tau_p q_i^{HP} + (\mu + \delta + \gamma) q_i^{HP} - \pi^e q_i^{HP} \tag{28}$$

Where τ_I is the resident's income tax bracket, τ_p is local property taxes, μ is maintenance cost, δ is depreciation costs, γ is the risk premium, and π^e is expected nominal capital gains.[23] When a house appreciates in value, the mortgage and maintenance costs remain fixed, but the tax burden and expected capital gains increase:

$$UC_{it} = ((1 - \tau_I) r + \mu + \delta + \gamma) q_{i0}^{HP} + ((1 - \tau_I)\tau_p - \pi^e) q_{it}^{HP} \tag{29}$$

Equation 29 shows how, as q_{it}^{HP} increases, as long as $(1 - \tau_I)\tau_p < \pi^e$, user costs will fall.[24] This implies we can expect homeowners to see falling housing costs, compared to renters who experience rising housing costs.

[23] This form of user cost assumes one can borrow and lend at the same rate.

[24] I calibrate user costs using the following parameters: $\tau_I = 0.36$, $r = 0.045$, $\mu + \delta = 0.04$, $\gamma = 0.02$, $\tau_p = 0.01$, and $\pi^e = 0.03$

5.3 Calculating the Dollar Value of UberX Entry

With the estimated parameters, exogenous rents and house prices, and calibrated parameters in hand, we can calculate the compensation needed for residents to reach a utility of 0 before and after UberX entry. When UberX enters a city, it directly changes travel times, m_{ij}, as residents switch from transit to driving, as well as travel costs, $\hat{\tau}$. As residents, restaurants, and housing markets respond, house prices and destination zipcodes' values endogenously respond. Tables 13 and 14 show the willingness to pay for UberX entry holding each of these components fixed to their pre-period levels. This allows one to decompose the willingness-to-pay by travel times and costs, housing costs, and amenities.

The first row of Table 13 shows the annual pre-period dollar compensation needed to bring a resident to 0 utility, by whether the resident lives in an inaccessible or accessible location.[25] In the pre-period, accessible homeowners need \$7,814 in compensation, while inaccessible homeowners need \$6,485. The second row documents how compensation changes when travel costs, τ, fall, holding all else fixed. Now, accessible homeowners need \$6,996 in compensation, and inaccessible homeowners need \$5,783. Had they been given their pre-period compensations, they would have positive utilities of \$818 and \$702, respectively. By bringing them back down to their original utilities of 0, this reflects a WTP_i of \$818 and \$702. The third row varies travel costs and times. This actually lowers willingness-to-pay, as the distribution of travel times no longer matches the distributions of amenities or prices; in effect, times have decreased to places with poor amenities and increased to places with many amenities. Willingness-to-pay increases markedly in row 4, reflecting that homeowners have seen large gains to their equity position in the ridesharing era as user costs fall. Finally, after allowing amenities to resort, destination quality improves and homeowners' willingness-to-pay increases again, to \$945–\$1178 depending on accessibility status. This translates to a monthly WTP for ridesharing of \$79–\$98. Inaccessible homeowners are willing to pay 14.6% of their pre-period compensation for UberX entry. Accessible homeowners are willing to pay 15.1% of their pre-period compensation for UberX entry, showing that while homeowners in both locations are better off, accessible homeowners have benefited by 0.6% more. While

[25] Since each origin is connected to 12 destination, the numbers in Tables 13 and 14 multiplies the per-route WTP_{ij} by 12 to get the total WTP_i conditional on living in i.

house prices grew faster in inaccessible locations, they are still higher in levels in the accessible locations; slower growth off a higher base yields more capital gains in dollars.

Table 14 shows the same welfare exercise for renters. In the pre-period, accessible renters needed \$6,565 in compensation, while inaccessible renters needed \$5,899. After travel costs fall, accessible and inaccessible renters are willing to pay about \$665. This time, the fourth row shows that allowing for housing costs to change decreases the willingness-to-pay substantially, falling from \$666 and \$665 for accessible and inaccessible renters to \$275 and \$250. In contrast to homeowners, who experience lower user costs as house prices rise through gains in equity, renters take only the price hit. Allowing amenities to adjust in the post-period balances out some of the rent burden, as renters enjoy access to better destinations, increasing willingness-to-pay with the full model to \$467 and \$394 for accessible and inaccessible renters. This translates to a monthly WTP of \$33–\$39. In all, renters in inaccessible locations are willing to pay 6.7% of their pre-period compensation, while renters in accessible locations are willing to pay 7.1%, showing that renters in accessible locations realize higher welfare gains than their inaccessible peers. This is because they enjoy increases in access and amenities, without as much increase in rents.

While all residents gain from UberX entry, the homeowners are the welfare winners in this exercise. The average homeowner is willing to pay \$1,060 for UberX entry, while the average renter is willing to pay \$430, only 40% as much. As rents and house prices continue to rise, the wedge between renter and homeowner WTP may continue to grow, eventually leading to renter displacement if housing supply does not adjust to put downward pressure on prices.

6 Conclusion

This paper contributes to our understanding of accessibility and consumption and provides evidence that the spatial distribution of consumption has responded to ridesharing's entry. By exploiting the staggered entry of UberX crossed with the pre-existing distribution of access within cities, the paper explains how ridesharing has begun reshaping our cities. I find that ridesharing has already meaningfully impacted restaurant dispersion, house prices, and resident welfare by expanding the set of desirable and accessible zipcodes in cities. Restaurant net creation in inaccessible locations doubles in the post-period, as local demand changes in space. As these inaccessible areas become more desirable, house prices rise by 4%, reflecting their improved access and amenities.

Embedding these reduced-form findings in a spatial demand structure provides a means to weigh the benefits of improved access and amenities against the cost of rising house prices. I find that homeowners are willing to pay nearly 2.5 times as much for UberX entry than renters, as they can capture equity gains from increases in house prices, while renters only see higher costs. Residents in both inaccessible and accessible locations see welfare gains, but both renters and homeowners see marginally higher welfare gains in accessible areas.

These findings contribute to our understanding of neighborhood dynamics and gentrification in a variety of ways. First, we can observe in real time which economic agents respond to changes in neighborhood accessibility. In contrast to much of the research on how transportation reshapes cities, which primarily compares two equilibria, one prior to the change in infrastructure and one often decades later, the quick entry of ridesharing independent of urban planning allows researchers to study the impacts in real time. There is no need to wait for full roll-out or adjustment. This paper suggests that amenities most sensitive to changes in travel respond first, followed by house prices. Time will tell whether other industries follow as these areas continue to improve, or whether residents begin to resort, changing local labor supply.

The paper also signals that further work is needed to understand whether ridesharing's introduction will induce more gentrification or revitalization in previously inaccessible locations. While rents and house prices have risen in the post-period, these annual increases are well within the bounds allowed by rent-stabilization policies. Furthermore, the lack of evidence of neighborhood sorting thus far suggests that housing costs have not become burdensome enough for residents to be displaced. In the medium to long term, whether inaccessible neighborhoods revitalize or gentrify will depend on their local housing and commercial real estate supply elasticities, as well as the ease of conversion between the two sectors, suggesting that local zoning restrictions will play a large role in the eventual character of the inaccessible zipcodes.

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Tables

Table 1: NHTS Trip Shares by Mode

	All Origins		Central Origins	
	2009	2017	2009	2017
	All Trips			
% driving	95	94	82	71
% transit	5	5	17	25
% taxi/ridesharing	0	1	2	4
	Work Trips			
% driving	90	89	73	59
% transit	10	10	25	39
% taxi/ridesharing	0	1	1	2
	Social & Recreational Trips			
% driving	94	93	81	70
% transit	5	5	18	20
% taxi/ridesharing	1	2	**2**	**10**

Notes: This table shows the trip shares by purpose over modes in the 2009 and 2017 NHTS confidential trip files. Sample covers 31 U.S. CBSAs with at least 2 million residents in 2010. All trips originate at home, to maintain cross-wave comparability of 2009 and 2017 data. Central Origins are defined as those trips from home with a home census tract identified as laying within a 5 mile radius of the city center.

Table 2: NHTS Trip Shares by Purpose

	All Origins		Central Origins	
	2009	2017	2009	2017
	All Trips			
% Work	19	23	20	32
% Social	17	17	19	17
	Driving Trips			
% Work	18	21	20	26
% Social	17	17	18	18
	Transit Trips			
% Work	33	46	36	50
% Social	16	13	24	14
	Taxi/Ridesharing Trips			
% Work	11	19	16	24
% Social	23	34	**13**	**46**

Notes: This table shows the trip shares by type of travel mode over trip purpose in the 2009 and 2017 NHTS confidential trip files. Trip purposes not included in table are "other" and "shopping". Sample covers 31 U.S. CBSAs with at least 2 million residents in 2010. All trips originate at home, to maintain cross-wave comparability of 2009 and 2017 data. Central Origins are defined as those trips from home with a home census tract identified as laying within a 5 mile radius of the city center.

Table 3: UberX Entry Year

Entry Year	Cities	City Names
2012	2	New York, San Francisco
2013	16	Atlanta, Baltimore, Boston, Charlotte, Chicago, Dallas, Denver, Detroit, Los Angeles, Minneapolis, Phoenix, Sacramento, San Diego, Santa Barbara, Tucson, Washington DC
2014	14	Cincinnati, Colorado Springs, Houston, Kansas City, Miami, Orlando, Philadelphia, Pittsburgh, Portland, Raleigh, Riverside, San Antonio, Tampa
2015	2	Las Vegas, St. Louis

Notes: This table lists cities' UberX entry years. When possible, entry year is determined by Uber's city-specific blog post announcing expansion of services to the city. If not available, local news sources provide UberX launch dates.

Table 4: Balance Table for Outcome Variables

	$\boldsymbol{Inaccess_j^N = 0}$	$\boldsymbol{Inaccess_j^N = 1}$	$\boldsymbol{Difference}$
		Y_{jt}	
Δ(# Restaurants)	1.43	0.67	0.76***
	(0.15)	(0.07)	(0.15)
HPI	1.74	1.72	0.02
	(0.02)	(0.02)	(0.03)
ZRI	0.95	0.96	-0.004***
	(0.00)	(0.00)	(0.00)
		Related Descriptives	
#Restaurants	26	14	12***
	(1.01)	(0.52)	(1.02)
House Price ($1000's)	645	432	213***
	(53)	(47)	(78)
Rents ($)	1,620	1,525	95***
	(8.35)	(8.03)	(13)

Table 5: UberX Entry Uncorrelated with *Within* City Characteristics

	population	earnings	fraction bachelor's degree	restaurant net creation
			City Wide	
β	-3.23**	-0.47**	-0.44**	-0.11***
			Within City	
β_{access}	-5.6	-0.25	-0.02	-0.17
$\beta_{inaccess}$	-16.6	-0.06	-0.44**	-0.17
Obs.	34	34	34	34

Note: This tables regresses UberX entry month, on city level characteristics for the 34 cities in the sample in the top panel, $Month_c = \beta X_c + \varepsilon_c$. The bottom panel regresses entry month on within-city characteristics for the same cities, $Month_c = \beta^{Access} X_c^{Access} + \beta^{Inaccess} X_c^{Inaccess} + \varepsilon_c$.

Table 6: Restaurant Net Creation Results

	(1)	(2)	(3)
$\text{Post}_t \times Inaccess_j^N$	0.744***	0.728***	0.738***
	(0.223)	(0.247)	(0.212)
Post_t	0.00710	0.364	0.280
	(0.316)	(0.346)	(0.395)
Inaccess_j^N			0.723*
			(0.432)
R-Squared	0.253	0.270	0.168
Observations	3336	3026	3341
Year FE	X	X	X
Zip FE	X	X	
$\text{Inc}_{jt}, Edu_{jt}, Pop_{jt}$		X	
CBSA FE			X
CBSA X Inaccess.			X
CBSA X Post			X

Notes: This table shows the estimates from $Y_{jt} = \beta Inaccess_j^N \times Post_t + year_t + zip_j + \varepsilon_{jt}$, in column (1). Column (2) contains time-varying demographic controls. Column (3) removes zipcode fixed effects and introduces inaccessible-by-time, inaccessible-by-city and city-by-post dummies. Standard errors clustered by $City_c \times Post_{ct}$ in parentheses.
Significance: *** p<0.01, ** p<0.05, * p<0.1.

Table 7: Correlation between Different Inaccessibility Metrics

	Transit	Distance	Wedge	Driving
Transit	1			
Distance	0.34	1		
Wedge	0.84	0.29	1	
Driving	0.13	0.18	0.00	1

Notes: This table shows the correlation between different $Inaccess_j^N$ metrics, depending on the input origin-destination travel times matrix, in which travel time is one of: transit travel time, geodesic distance, wedge (transit - driving) in travel time, and driving travel time.

Table 8: Restaurant Net Creation by Inaccessibility Metric

	(1) Transit	(2) Wedge	(3) Distance	(4) Drive
$\text{Post}_t \times Inaccess_j^N$	0.744***	0.580**	0.507***	0.202
	(0.223)	(0.259)	(0.155)	(0.213)
Post_t	0.00710	0.154	0.268	0.385
	(0.316)	(0.305)	(0.307)	(0.360)
R-Squared	0.253	0.252	0.252	0.251
Observations	3336	3336	3336	3341
Year FE	X	X	X	X
Zip FE	X	X	X	X

Notes: This table shows the estimates from $Y_{jt} = \beta Inaccess_j^N \times Post_t + year_t + zip_j + \varepsilon_{jt}$, with different metrics for constructing $Inaccess_j^N$. All columns contain the same specification as in column (1) of Table 6. Standard errors clustered by $City_c \times Post_{ct}$ in parentheses.
Significance: *** p<0.01, ** p<0.05, * p<0.1.

Table 9: Industry Net Creation Heterogeneity

	(1) Restaurants	(2) Dry Cleaners	(3) Dentists
$\text{Post}_t \times Inaccess_j^N$	0.744***	0.143**	0.109
	(0.0189)	(0.223)	(0.119)
Post_t	0.007	-0.107	0.0240
	(0.316)	(0.140)	(0.213)
R-Squared	0.253	0.143	0.171
Observations	3336	2504	3108
Year FE	X	X	X
Zip FE	X	X	X

Notes: This table shows the estimates from $Y_{jt} = \beta Inaccess_j^N \times Post_t + year_t + zip_j + \varepsilon_{jt}$, with different industries for Y_{jt}. All columns contain the same specification as in column (1) of Table 6, and use the public transit metric for inaccessibility. Standard errors clustered by $City_c \times Post_{ct}$ in parentheses.
Significance: *** p<0.01, ** p<0.05, * p<0.1.

Table 10: UberX Impact on HPI

	(1) Median	(2) Median	(3) Median
Post_t	-0.0594***	-0.0495***	-0.0662***
	(0.0207)	(0.0137)	(0.0239)
Inaccess_j^N	0.675***		2.797**
	(0.0344)		(1.318)
$\text{Inaccess}_j^N \times Post_t$	0.0310***		0.0387***
	(0.00623)		(0.0116)
Inaccess_j^R		0.684***	-2.136
		(0.0264)	(1.318)
$\text{Inaccess}_j^R \times Post_t$		0.0191***	0.0219**
		(0.00670)	(0.0106)
$\text{Inaccess}_j^N \times Inaccess_j^R \times Post_t$			-0.0291*
			(0.0151)
Observations	9926	9926	9926
Year FE	X	X	X
Zip FE	X	X	X

Notes: This table shows the quantile regression estimates from $HPI_{jt} = \beta_1 Inaccess_j^N \times Post_t + \beta_2 Inaccess_j^R \times Post_t + \beta_3 Inaccess_j^N \times Inaccess_j^R \times Post_t + year_t + zip_j + \varepsilon_{jt}$.
Standard errors clustered by $City_c \times Post_{ct}$ in parentheses.
Significance: *** p<0.01, ** p<0.05, * p<0.1.

Table 11: UberX Impact on ZRI

	(1) Mean	(2) Mean	(3) Mean
Post_t	0.00564	0.0102	0.00436
	(0.0237)	(0.0236)	(0.0238)
Inaccess_j^N	0.161***		-0.00106
	(0.0297)		(0.00326)
$\text{Inaccess}_j^N \times Post_t$	0.00962*		0.0157**
	(0.00499)		(0.00601)
Inaccess_j^R		0.165***	0.162***
		(0.0312)	(0.0300)
$\text{Inaccess}_j^R \times Post_t$		0.00379	0.0183**
		(0.00510)	(0.00792)
$\text{Inaccess}_j^N \times Inaccess_j^R \times Post_t$			-0.0244***
			(0.00911)
R-Squared	0.774	0.774	0.775
Observations	39321	39321	39321
Year FE	X	X	X
Zip FE	X	X	X

Notes: This table shows the estimates from $ZRI_{jt} = \beta_1 Inaccess_j^N \times Post_t + \beta_2 Inaccess_j^R \times Post_t + \beta_3 Inaccess_j^N \times Inaccess_j^R \times Post_t + year_t + zip_j + \varepsilon_{jt}$.
Standard errors clustered by $City_c \times Post_{ct}$ in parentheses.
Significance: *** p<0.01, ** p<0.05, * p<0.1.

Table 12: Model Parameters

Parameter	*source* Estimation	Calibration	Value
$\widehat{\varepsilon\tau}_{pre}$	✓		0.17***
$\widehat{\varepsilon\tau}_{post}$	✓		0.11***
β		✓	0.30
ε		✓	8.00
$\hat{\tau}_{pre}$			0.02
$\hat{\tau}_{post}$			0.01

Notes: Calibrated parameters taken from literature, estimated parameters obtained via estimating the travel equation, $ln(n_j^c) = \kappa^c + ln\left(\sum_{i\in c} I_i^c(e^{-\varepsilon\tau m_{ij}^c})\right) + ln(E_j^c)$, using nonlinear least squares for either pooled pre-period or pooled post-period data.

Significance: *** p<0.01, ** p<0.05, * p<0.1.

Table 13: Compensation ($'s) for Mean Homeowner, $t = -1$ to $t = +2$

Varied	$I_i^{Access^N}$	$I_i^{Inaccess^N}$	$WTP_i^{Access^N}$	$WTP_i^{Inaccess^N}$
Pre–period	7,814	6,485		
Cost: $\hat{\tau}$	6,996	5,783	818	702
Times & cost: $\hat{m}_{ij}, \hat{\tau}$	7,251	6,051	563	434
Times, cost, house prices: $\hat{m}_{ij}, \hat{\tau}, \hat{q}_i$	6,848	5,696	966	789
Full Model: $\hat{m}_{ij}, \hat{\tau}, \hat{q}_i, \hat{E}_j$	6,639	5,540	1178	945

Notes: This table shows that mean compensation and compensation change for resident homeowners, by residential location restaurant-inaccessibility status.

Table 14: Compensation ($'s) for Mean Renter, $t = -1$ to $t = +2$

Varied	$I_i^{Access^N}$	$I_i^{Inaccess^N}$	$WTP_i^{Access^N}$	$WTP_i^{Inaccess^N}$
Pre–period	6,565	5,899		
Cost: $\hat{\tau}$	5,899	5,590	666	665
Times & cost: $\hat{m}_{ij}, \hat{\tau}$	6,031	5,750	534	505
Times, cost, house prices: $\hat{m}_{ij}, \hat{\tau}, \hat{q}_i$	6,290	6,005	275	250
Full Model: $\hat{m}_{ij}, \hat{\tau}, \hat{q}_i, \hat{E}_j$	6,098	5,861	467	394

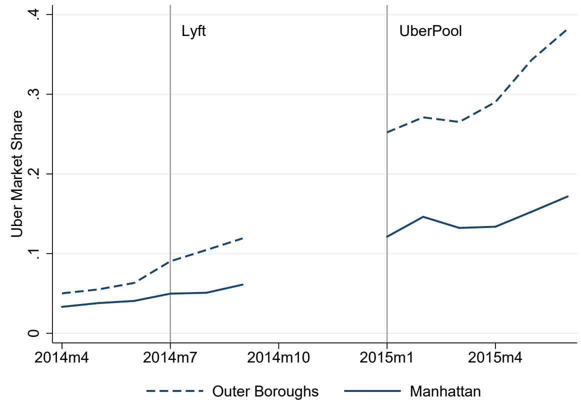
Notes: This table shows that mean compensation and compensation change for resident renters, by residential location restaurant-inaccessibility status.

Figures

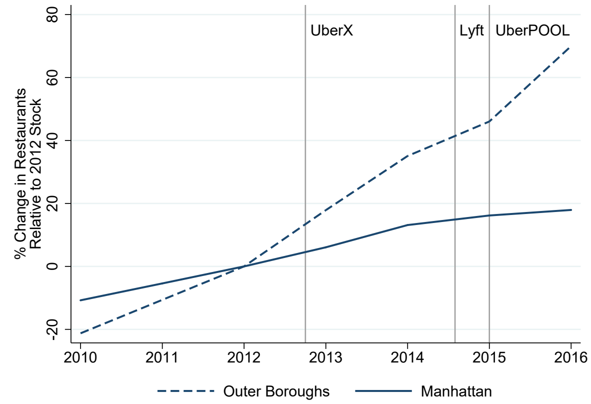
Figure 1: Share of Social & Recreational Trips by Taxi or Ridesharing, Central Origins

Notes: This table shows the share of social and recreational trips originating within 5 miles of a city center by taxi in the 2009 and 2017 NHTS confidential trip files, for public transit heavy cities (New York City, San Francisco, Washington, DC, Boston, and Chicago) vs. other cities. All trips originate at home, to maintain cross-wave comparability of 2009 and 2017 data. Central Origins are defined as those trips from home with a home census tract identified as laying within a 5 mile radius of the city center.

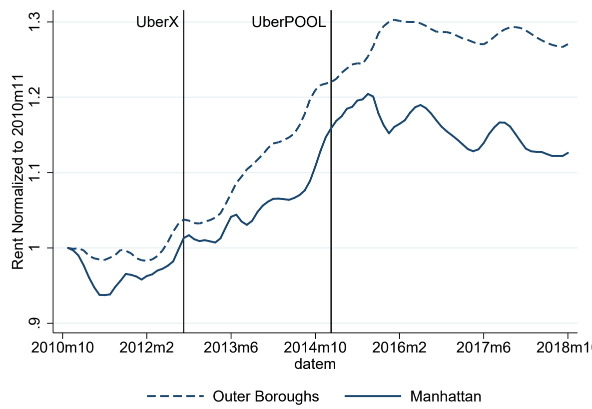
Figure 2: New York City and the Impact of UberX



(a) Uber's Market Share of Trips by Borough

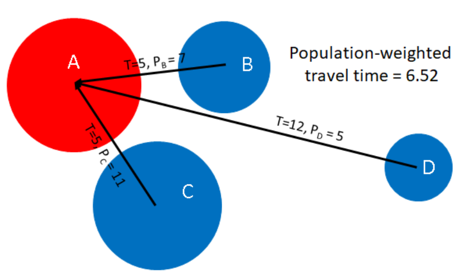


(b) Restaurant Growth by Borough

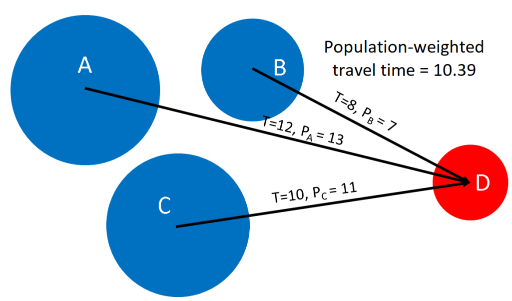


(c) Rent Growth by Borough

Figure 3: Destination Zipcode Travel Index



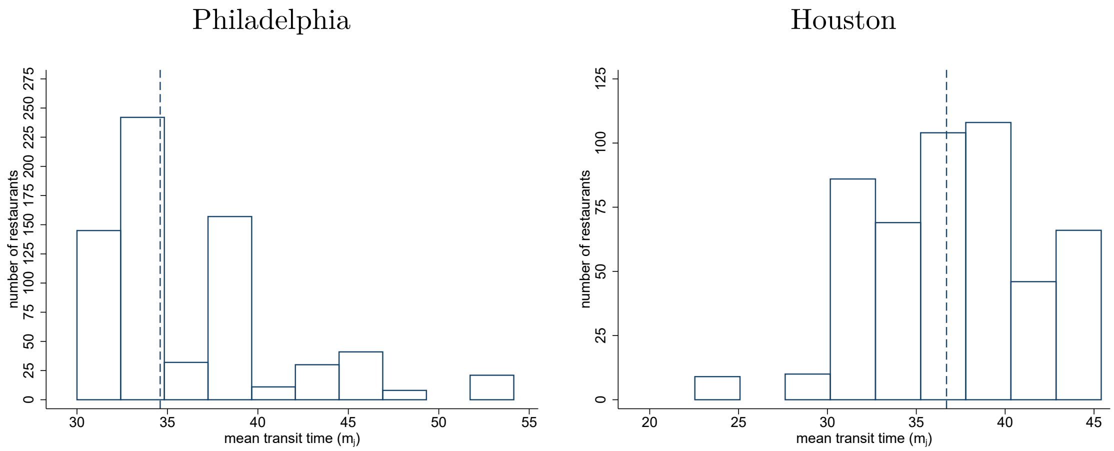
(a) Zipcode A



(b) Zipcode D

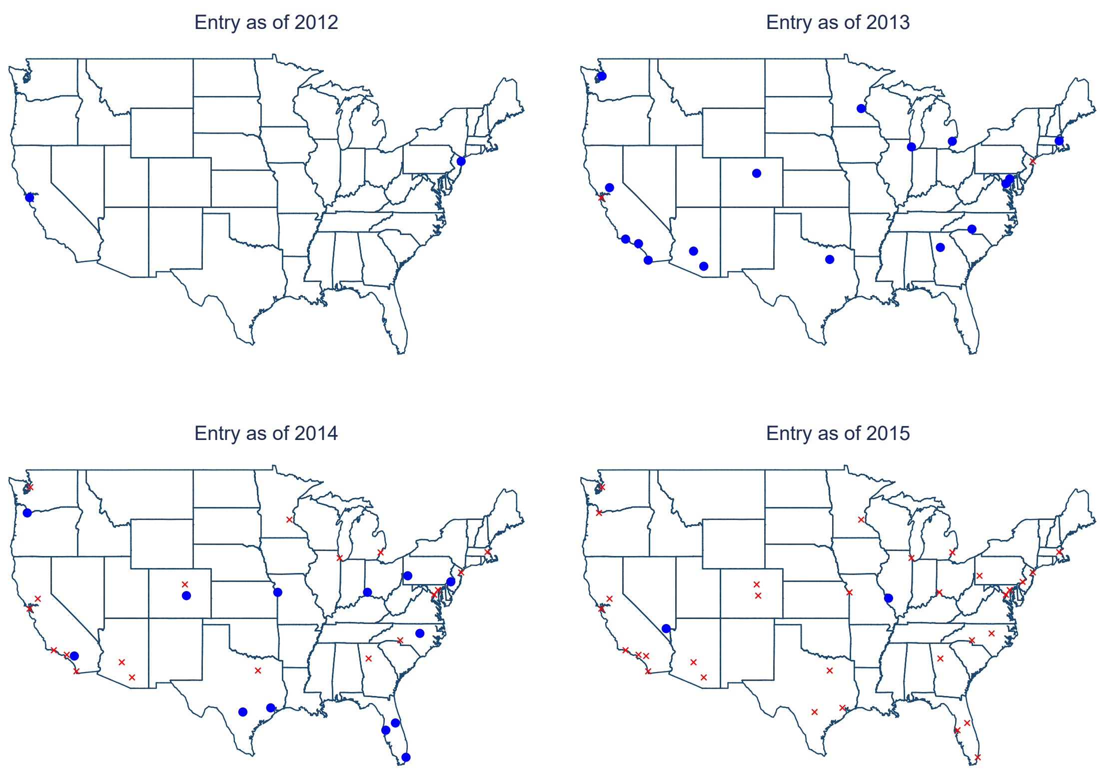
Notes: Panel (a) calculates the weighted average travel time from zipcodes B, C, and D traveling to zipcode A. Panel (b) calculates the weighted average travel time from zipcodes A, B, and C to zipcode D. Because the zipcodes differ in their populations, weighted average travel times differ between A and D.

Figure 4: Firm Inaccessibility Varies by City



Notes: The left panel plots the distribution of restaurants (left vertical axis) by m_j^N for Philadelphia. The vertical gray line is the public transit time to cover half of all restaurants, $\bar{m}^N$. The right panel shows the same information for Houston.

Figure 5: Temporal Variation in UberX Entry

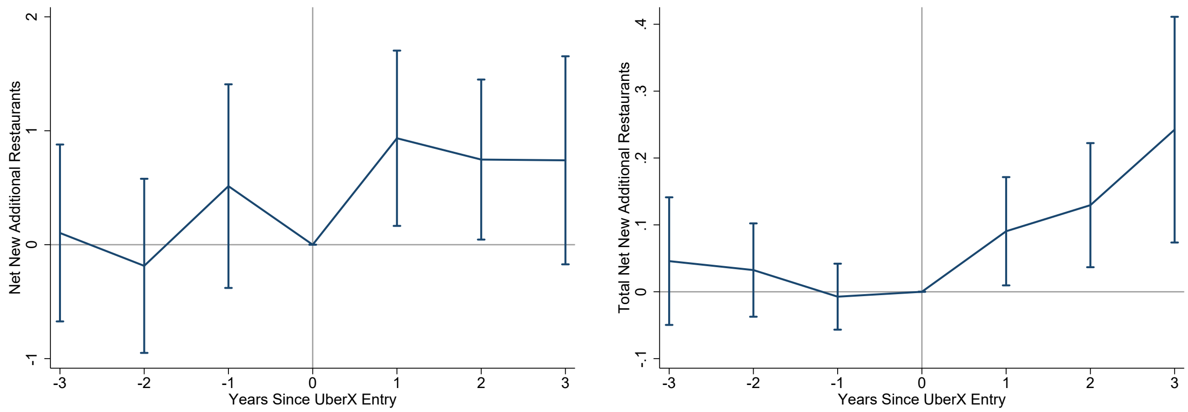


Notes: The four maps plot the cities in which UberX enters for each year between 2012 and 2015. Blue circles denote current year is the entry year, red x's denote that UberX had already entered the city in a previous year.

Figure 6: Testing Parallel Trends: Annual Restaurant Net Creation and Net Creation Rate

(a) Annual Net Creation

(b) Net Creation Rate

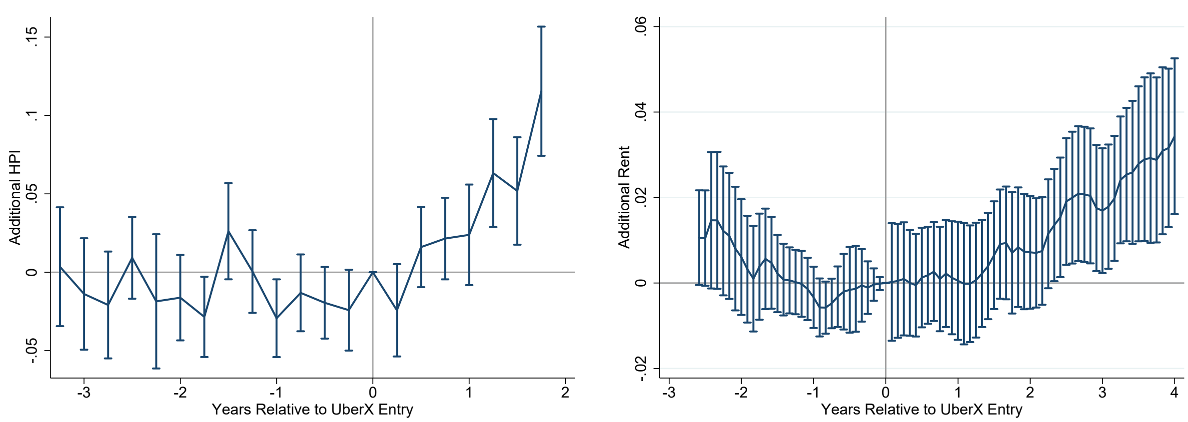


Notes: The figure plots $Y_{jt} = \sum_{k=-3}^{3} \beta_k Inaccess_j^N \times RelYear_k + year_t + zip_j + \varepsilon_{jt}$. Y_{jt} is net restaurant creation in panel (a), and net creation rate in panel (b). Sample includes 19/34 cities to capture 3 years of post data in balanced panel. Standard errors clustered by $City_c \times Post_{ct}$, 95% confidence intervals shown.

Figure 7: UberX Impact on HPI and ZRI in Inaccessible Areas

(a) HPI (median)

(b) ZRI (mean)



Notes: Panel (a)shows the β_t estimated from $ZRI_{jt} = Year_t + \sum_{\tau=-4}^{\tau=5}\{\beta_\tau Inaccess_j \times Year_\tau\} + City_j \times Year_t + \zeta_j + \varepsilon_{jt}$. Panel (b) shows the β_t estimated from a quantile regression for $HPI_{jt} = Year_t + \sum_{\tau=-4}^{\tau=3}\{\beta_\tau Inaccess_j \times Year_\tau\} + City_c \times Year_t + \zeta_j + \varepsilon_{jt}$. ZRI uses monthly data, while HPI uses quarterly.

Robust standard errors shown for HPI. Standard errors clustered by $City_c \times Post_{ct}$ for ZRI. 95% confidence intervals shown.

A Other App Adoption

As a final robustness check, it is important to consider other sources of variation in restaurant expansion over the time period. As shown in Davis et al. (2018), Yelp has become a considerable source of restaurant information over the same time period as UberX's entries, although without the sudden availability associated with a stark entry date. As such, disentangling information from access is a difficult endeavor. Ideally, one would include time-varying city-wide controls for Yelp's presence in the main specification, to control for a cities' changing information set. Controlling for Yelp's presence at a more localized level runs into issues of simultaneity bias, as the two on-line platforms likely amplify the impact of the other in the post period. For example, we may be more likely to travel to a far flung restaurant because we learned about it on-line (Yelp amplifying UberX). On the other hand, we may be more likely to review a new restaurant in a far flung location once access has improved (UberX amplifying Yelp).

As per Yelp's updated terms of service, one "may not modify, reproduce, distribute, create derivative works or adaptations of, publicly display or in any way exploit any of the Yelp Content in whole or in part except as expressly authorized by us." This limits my ability to pull data from the site; however, Yelp has released a dataset of nearly 6 million reviews for use by the general public. The data contains reviews, user information, and business information for four of the 34 cities in the sample: Las Vegas, Phoenix, Pittsburgh and Charlotte. Unfortunately, there is only one year of post data from Las Vegas, making that city less useful for analysis. Figure F2 shows the share of yelp reviews in inaccessible areas for Pittsburgh, Charlotte and Phoenix three years around UberX's entry. While there does seem to be an increase in the share in the post period, three cities' worth of data is not enough to do analysis similar to that in Equation 10. The small data size in combination with the caveats that Yelp data can be manipulated by the reviewed establishments, which often pay to solicit good reviews or remove bad ones, make the data a less than optimal measure of information flow.

Motivated by the Yelp data concerns, we can look for economic rather than statistical methods to test the information story. Consider two cities, one whose restaurant scene is tightly concentrated in the center of the city, city A, and another whose restaurant scene is more dispersed about the city, city B. Residents of city A know a lot about the restaurant scene in their city; since it is restricted to a small area, it is easy to walk around and find places to dine. In city B, on the other hand, due to more dispersion, residents may only be aware of small pockets of dining establishments. Assuming that Yelp provides a bigger information change in dispersed cities, we would expect more restaurant net creation in dispersed cities after UberX's entry, all else equal. To test this hypothesis, I edit the main specification, running it for each city of the 34 cities separately, including year and zipcode fixed effects, as well as zipcode trends.

Figure F3 shows a scatter plot of the city-specific UberX impacts on inaccessible area restaurant flow versus a measure of restaurant concentration. Restaurant concentration is calculated as the share of land area required to cover 50% of the city's restaurants in the 5 mile radius. A highly concentrated city has a low concentration measure, and a dispersed city has a higher one. The results suggest a positive relationship between dispersion and UberX's impact (the overall point estimate for the stacked DID is 0.25). On average, a city with 50% of it's restaurants in 20% of its area would see 0.16 fewer additional outlying restaurants added than a city with 50% of its restaurants in 30% of its area, though the trend line in figure F3 is not statistically different from 0. These results suggest that while information may play an important story, it cannot account for the restaurant dispersion in the age of UberX.

Other platforms contributing to restaurant expansion include UberEats, Seamless (later merged with Grubhub), Grubhub. These services bring food to residential locations, allowing kitchens to locate in cheap areas and primarily make money from delivery orders. None of these were launched concurrently with UberX. UberEats launched in March, 2016, while Seamless and Grubhub launched in the mid-2000's, so none can explain the kinked event study estimated around UberX entry.

B Travel Appendix

With UberX changing within-city accessibility, restaurants disperse. Still unknown is how large this change in travel is that drives dispersion. To measure the change in travel, the ideal data set would have national representation, utilize the staggered UberX entry, and track individual trips to restaurants over time. In reality, travel data is much more limited. Instead, we can look to a few sources of data that cover all of the desired characteristics. Emissions data from the Environmental Protection Agency tracks emissions associated with onroad vehicles (ORVs) daily for the entire sample of cities, though it lacks individual trip accounts. The Taxi and Limousine Commission from New York City provides trip origin and destination information for all taxi rides from 2009-2018, with ridesharing data added in 2015. Finally, the confidential data for the National Household Travel Survey provides trip diaries for survey participants in 2017.

The travel results should not be taken as *sufficient* evidence that people travel differently using Uber. Without Uber data on trip counts between locations, we cannot test this hypothesis; however, it is *necessary* to show that travel patterns have changed in the post period as the distribution of activity has changed.

On-Road Vehicle Emissions

Changes in emissions give us an idea of how large the impact of UberX is on travel patterns; after UberX enters, the restaurant results suggest that people switch from public transit to driving. It is also possible that the wealth effect can induce more restaurant trips, as traveling to restaurants has become cheaper, and hence more driving even in non-transit cities.

Citywide Emissions Changes

To investigate the relationship between vehicle emissions and UberX's entry, I estimate the change in various emissions after UberX enters my suite of 34 cities, outlined in Equation 30.

$$Y_{icd} = \alpha + \beta Post_{cd} + \Gamma City_c + Year_d + Season_d + Trend_c + \varepsilon_{ict} \tag{30}$$

Y_{icd} is monitor level emissions for monitor i, in city c, on date d. $Post_{cd}$ is the city-specific UberX entry date, set to 1 after entry and 0 in the pre-period. The design includes city fixed effects to control for time-invariant city characteristics, $City_c$, year fixed effects to account for national policy changes, $Year_d$, and city-by-year trends to control for city level developments in pollution policy, $Trend_c$.

This equation exploits the staggered entry of UberX across the 34 cities and 4 time periods to construct a stacked difference-in-difference. The assumption of parallel trends requires that cities' emissions output move similarly in their respective pre-periods. Since cities differ in their emissions policies, I include city fixed effects and time trends; however, all results are robust to dropping the city trends. Exogeneity of UberX entry requires that UberX did not enter as it saw emissions changing.

I study carbon monoxide (CO) emissions as on road vehicles (ORV's) contribute 48% of all emissions, as shown in Table E9. As a placebo, I study the change in fine particulate matter (FRM/FEM PM2.5), as ORVs contribute less than 2% of the total output.[26] I use data from the EPA's Daily Outdoor Air Quality Data at the monitor level from 2009-2018. Each monitor is identified by it's latitude and longitude, which I reverse geocode to find the associated zipcode. I then map these zipcodes to the appropriate cities in my sample. All analyses is limited to non-exceptional event observations to remove observations during wildfires or dust storms, for example.

Before implementing the regression in Equation 30, two important characteristics of the data should be noted. Figure F4 panels (a) and (b) show that both pollutants are falling over the treatment period, so controls for years and city-specific trends are necessary. Second, panels (c) and (d) show there is a high degree of seasonality masking this overall negative trends in emissions. All regressions must control for the season of each date. Since these seasons are tied to weather, they differ from the traditional definitions of annual quarters,

[26] These two pollutants represent the largest differences in source share excepting S02: 48.41 vs. 4.5 and 1.79 vs. 17.34 for ORV vs. Industry/Electricity. While the source share difference for S02 is larger than for PM2.5, it contributes to PM2.5 formation and PM2.5 has been studied more often in the economic literature.

offset by one month.

An additional background note on emissions in the USA over 2009-2018, fracking has changed the way utilities choose their inputs. As shown in figure F5, the median state used coal for around 80% of its energy generation in 2009m1. After fracking reduced the relative cost of natural gas, utilities substituted gas for coal. By 2018m, the median state used coal for closer to 50% of its energy generation. Natural gas is notably cleaner than coal to burn, and should result in large declines in particulate matter. At the same time, since it is cheaper, it may lead to consumers using more energy as their utility bills fall. In either case, controlling for the ratio of inputs as well as the level of energy generation is important, especially as utilities contribute much of the total volume of PM 2.5 in the atmosphere.

Table E10 show the results of regressing various CO measures on a city-specific post period indicator. The analysis includes year fixed effects to control for national changes in CO policy, city trends to control for differing trajectories induced by local policies, city fixed effects to control for time-invariant city characteristics correlated with emissions production, and season fixed effects to control for emissions' sensitivity to weather patterns. The CO measurements are limited to the 8-hour daily averages. Column (1) shows that the average CO measure increases by 11.5% after UberX enters. Columns (2)-(3) add the state-by-month controls, ratio and level of inputs used, to capture the advent of the fracking boom. Because automobiles have not changed their fuel usage due to fracking, and utilities do not contribute much to CO levels, there is no statistical relationship between the fracking measures and CO output, as expected. Finally, we can control for monitor level fixed effects, to control for highly localized characteristics, such as airports or heavy industry, that might be correlated with the way people travel within cities. The results remain robust, varying between 9 and 11.8% rise in CO emissions after UberX entry.

Table E11 show the results of regressing $ln(PM2.5)$ on a city-specific post period indicator. The analysis includes year fixed effects to control for national changes in CO policy, city trends to control for differing trajectories induced by local policies, city fixed effects to control for time-invariant city characteristics correlated with emissions production, and season fixed effects to control for emissions' sensitivity to weather patterns. The PM 2.5 measurements are limited to the 24-hour daily averages. Column (1) shows that the average

PM 2.5 measure increases by 0.9% after UberX enters, though this is insignificant. Columns (2)-(3) add the state-by-month controls, ratio and level of energy inputs used, to capture the advent of the fracking boom. As suggested in the fracking discussion, these variables predict Pm 2.5 emissions well, especially the ratio of coal used in inputs. Finally, we can add monitor level fixed effects, to control for highly localized characteristics, such as airports or heavy industry, that might be correlated with the way people travel within cities. The results remain robust, varying between 0.3 and 1% rise in CO emissions after UberX entry, statistically not differentiated from zero.

Figure F6 plots the quarterly event studies. Since UberX enters the cities on 34 different dates, entry quarter is normalized to 0, allowing cities before entry to control for themselves post entry, as well as other cities in which UberX has entered. Panel (a) shows that CO emissions increase in the post period, while panel (b) show that the placebo emission, PM 2.5, sees little change driven by UberX entry and in fact continues to fall in line with the raw time series plots.

Within City Emissions Changes

We can also look within cities to check whether localized emissions have changed. Due to data availability, analysis is limited to 12/34 cities. Additionally, because pollutants move around in the air, it is harder to distinguish inaccessible air from accessible air, introducing noise into the within-city analysis. If more trips are taken to inaccessible locations, we should see an increase in localized emissions in the zipcodes defined to be inaccessible. Equation 31 shows the estimation strategy, analogous to the main specification in Equation 10, but with more seasonal controls.

$$\begin{aligned} Y_{icd} =& \delta Inaccess_{ic}^{N} + \alpha Post_{cd} + \Gamma City_c + \beta Inaccess_{ic}^{N} \times Post_{cd} + \\ & \Lambda City_c \times Year_{cd} + \Psi Inaccess_{ic}^{N} \times City_c + Season_d + \varepsilon_{ict} \end{aligned} \tag{31}$$

β measures the percent change in emissions in the post period in inaccessible zipcodes above their peer accessible zipcodes. Due to local dispersion of emissions, this measure may be muddied and mis-measured across zipcodes, introducing noise to the highly local measures, biasing β downwards and also measuring it less precisely. Additionally, most cities do not have monitors in both types of locations, limiting my sample to only 12 of the original 34 cities.

Table E12 shows the differential growth in emissions for inaccessible zipcodes. As shown in the second row, the impact of being in the post period remains at 10-11% increase in citywide emissions, in line with the citywide results. The first row of the table implies that inaccessible zipcodes saw an additional 8-9% increase in emissions, though this is noisily estimated due to the drop in sample coverage.

We can do some back-of-the-envelope calculations to estimate the magnitude of this change in emissions. The Clean Air Act (CAA) legislation originally passed congress in 1963, and was updated in 1970 and 1977 greatly expanding the federal government's role in controlling air pollution. In 1990, the EPA adopted a set of major amendments (CAAA) which provide the current legal authority for federal programs relating to air pollution today. In 2011, the EPA produced a report analyzing air pollution emissions under the CAA relative to their projected emissions had the 1990 CAA amendments not been introduced. In this report, the EPA projected that without the CAAA carbon monoxide emissions would have been 80.5 million tons in 2010. With CAAA, actual emissions were 42 million tons, a reduction of 48%. If this were to be distributed uniformly across the US, so that each city realized a 48% drop in projected CO emissions, the increase in driving in the post period undoes a significant fraction of the CAAA reduction: the estimates in table E10 show the rise in CO is between $1/4^{th}$ and $1/5^{th}$ the magnitude of the CAAA decline. Since 48% of CO emissions come from on-road vehicles, it is likely that changes in travel patterns, for example switching from public transit to shared cars, is driving the increase in emissions.

Changing Taxi Trips in New York City

The second piece of evidence supporting travel pattern changes uses data from the NYC Taxi and Limousine Commission. If UberX, and later UberPOOL, has changed the distribution of amenities in cities, we might also expect the types of trips taken by a close substitute to Uber, yellow cabs, to also have changed as people travel to new and different destinations. 94% of trips in the data originate in Manhattan, which has always had a thick supply of travel options; other boroughs have historically had trouble attracting personalized transit in the form of yellow cabs. This means that yellow cabs are good substitutes for Ubers in Manhattan. If UberX has opened up new destinations to travelers in NYC, we expect yellow cabs to make trips to less accessible locations more often as Manhattanites travel farther than before, knowing they can get back to Manhattan with an Uber. More generally, taxis co-locate with economic activity; if the distribution of economic activity has changed, taxis should follow suit.

For data from 2009-2016, TLC provided pick-up and drop-off location latitude and longitude for all yellow cab trips. They introduced for-hire-vehicle trip details in 2016, but did not include pick-up and drop-off latitude and longitude, only pick-up and drop-off zones, which are not conformable with my zipcode treatment sample definition. As such, I limit study to yellow cab trips. I collect data for the month of January each year from 2009 to 2016, and reverse geocode the pick-up and drop-off locations of every trip by looking for the correct zipcode polygon encompassing each location. Not all latitudes and longitudes can be matched to a zipcode, but this yields a sample of 109,600,392 trips across 56,571 zipcode pairs from 934 pick-up zipcodes and 938 drop-off zipcodes. I then collapse the number of trips by zipcode pair, and merge in my zipcode treatment definitions for both pick-up and drop-off zipcodes. Because my treatment variable only assigns treated or untreated to zipcodes within 5 miles of a city center, many of my zipcode pairs are dropped from the sample. This leaves me with 68,322,472 trips across 2,787 zipcode pick-up drop-off pairs over 7 years.

I estimate the change in number of trips being picked up in an inaccessible location, dropped off in an inaccessible location, or being both picked-up and dropped off in inaccessible locations by yellow cabs over time, as in Equation 32.

$$\begin{aligned} ln(trips_{ijt}) = {} & Year_t + Inaccess_i + Inaccess_j + Inaccess_i \times Inaccess_j + \\ & \beta_1(t) Inaccess_i \times Year_t + \beta_2(t) Inaccess_j \times Year_t + \\ & \beta_3(t) Inaccess_i \times Inaccess_j \times Year_t + link_{ij} + \eta_{ijt}. \end{aligned} \tag{32}$$

Every observation is characterized by a pick-up location, i, a drop-off location, j, and a year in the sample, t. $\beta_1(t)$ measures the additional percentage of trips originating in inaccessible locations for each year t relative to those originating in accessible locations. $\beta_2(t)$ measures the additional percentage of trips ending in inaccessible locations for each year t, relative to trips ending in accessible locations. $\beta_3(t)$ measures the additional percentage of trips originating *and* ending in inaccessible locations for each year t. $link_{ij}$ is a route fixed effect, effectively controlling for the distance between any two routes. Positive coefficients on each of the three β's imply that yellow cabs travel more to, from, or between inaccessible locations after UberX entry than to, from, or between accessible locations; in short, they measure travel dispersion in the post period using a service substitutable for an Uber. Figure F8 plots the coefficients over time, with 2012 as the base year, the year UberX entered NYC. Vertical lines are dropped at 2012.75, when UberX entered NYC, and 2015, when UberPool entered. We see that, after UberX entry, pick-ups in inaccessible locations increased by approximately 14% on average in the post period, with no discernible pre-trend. Panel (b) shows that drop-offs in inaccessible locations also increased, by about 9.5% in the post-period. Finally, trips between farflung areas are the last to respond, only increasing once UberPOOL enters.

The results suggest that because yellow cabs historically have primarily been available in Manhattan, riders found it hard to venture into outer boroughs far from public transit lines. After UberX's entryWith UberX's introduction, riders are free to travel to locations underserved by taxis and public transit, knowing they can hail an Uber home.

Both the EPA daily emissions data and the NYC TLC data support the hypothesis that city residents travel differently after UberX enters cities. The emissions data show that emissions rise, consistent with taking longer trips by car or by taking more trip by car (the wealth effect), or by switching from public transit to cars (substitution effect). On top of the EPA findings, the NYC TLC data show that people are more likely to travel to and from transit inaccessible locations in the post period, suggesting movement away from using the subway or bus lines and towards personalized public transit. As people change their travel patterns, firms are more willing to locate in these far flung locations, perpetuating more trips to these locations over time. Putting the restaurant results together with the NYC TLC and EPA results implies that a 9-14% increase in travel to inaccessible areas is needed for a 6% (0.25/4.48) increase in restaurant stock, relative to their accessible peers.

C Consumer Theory Appendix

We need to know the spatial distribution of utilities in order to find the maximum trip ij utility for a given residence, i.

Given than z_{ij} is Frechet distributed, V will also be Frechet distributed as it is a monotone combination of the consumption index, $\left(\frac{h_i}{\beta}\right)^\beta \left(\frac{c_i}{\alpha}\right)^\alpha \left(\frac{n_i}{1-\alpha-\beta}\right)^{1-\alpha-\beta} \frac{1}{e^{\tau m_{ij}}}$, with the Frechet component, z_{ij}.

Taking

$$V = \frac{I_i z_{ij}}{e^{\tau m_{ij}} q_i^\beta p^\alpha}$$

solve for z_{ij}:

$$z_{ij} = \frac{V e^{\tau m_{ij}} q_i^\beta p^\alpha}{I_i} \tag{33}$$

Define the distribution of utilities for trips along ij as follows:

$$G_{ij}(v) = P(V \leq v) = F\left(\frac{v e^{\tau m_{ij}} q_i^\beta p^\alpha}{I_i}\right) = e^{-E_j (e^{\tau m_{ij}} q_i^\beta p^\alpha)^{-\varepsilon} I_i^\varepsilon v^{-\varepsilon}} = e^{-\Phi_{ij} v^{-\varepsilon}} \tag{34}$$

where

$$\Phi_{ij} = E_j (e^{\tau m_{ij}} q_i^\beta p^\alpha)^{-\varepsilon} I_i^\varepsilon \tag{35}$$

then the associated p.d.f. is

$$g_{ij}(v) = \Phi_{ij} \varepsilon v^{-\varepsilon - 1} e^{-\Phi_{ij} v^{-\varepsilon}} \tag{36}$$

With the distribution of local utilities in hand, we can calculate the probability that a resident chooses trip ij over all other trips $\{is, \forall s\}$. Since this is a binary choice between any two trips, $P(\text{choose } ij) = E(\text{choose } ij)$.

$$\rho_{ij}^N = P(\text{choose } ij) = E(\text{choose } ij) = \int_0^\infty g_{ij}(v) \prod_{s \neq j} G_{is}(v) dv \tag{37}$$

where the first term in the integral is the p.d.f. of the indirect utilities, while the second term is the probability that j is the best destination from i among the set of destinations, s.

$$\rho_{ij} = \int_0^\infty \Phi_{ij}\varepsilon v^{-\varepsilon-1} e^{-\Phi_{ij}v^{-\varepsilon}} \prod_{s\neq j} e^{-\Phi_{is}v^{-\varepsilon}} dv \tag{38}$$

$$= \int_0^\infty \Phi_{ij}\varepsilon v^{-\varepsilon-1} \prod_{s} e^{-\Phi_{is}v^{-\varepsilon}} dv \tag{39}$$

$$= \int_0^\infty \Phi_{ij}\varepsilon v^{-\varepsilon-1} e^{-v^{-\varepsilon}\sum_s \Phi_{is}} dv \tag{40}$$

$$= \int_0^\infty \Phi_{ij}\varepsilon v^{-\varepsilon-1} e^{-v^{-\varepsilon}\Phi_i} dv \tag{41}$$

Note that $\frac{d}{dv}\left[-\frac{1}{\Phi_i}e^{-\Phi_i v^{-\varepsilon}}\right] = \varepsilon v^{-\varepsilon-1}e^{-\Phi_i v^{-\varepsilon}}$, then

$$\rho_{ij}^N = \int_0^\infty \Phi_{ij}\frac{d}{dv}\left[-\frac{1}{\Phi_i}e^{-\Phi_i v^{-\varepsilon}}\right]dv \tag{42}$$

$$= \Phi_{ij}\left[-\frac{1}{\Phi_i}e^{-\Phi_i v^{-\varepsilon}}\right]_{v=0}^{v=\infty} \tag{43}$$

$$= \Phi_{ij}\left[\lim_{v\to\infty} -\frac{1}{\Phi_i}e^{-\Phi_i v^{-\varepsilon}} + \lim_{v\to 0} -\frac{1}{\Phi_i}e^{-\Phi_i v^{-\varepsilon}}\right] \tag{44}$$

$$= \Phi_{ij}\left[0 + \frac{1}{\Phi_i}\right] \tag{45}$$

$$\rho_{ij}^N = \frac{\Phi_{ij}}{\Phi_i} \tag{46}$$

$$= \frac{E_j(e^{\tau m_{ij}}q_i^\beta p^\alpha)^{-\varepsilon}I_i^\varepsilon}{\sum_s E_s(e^{\tau m_{is}}q_i^\beta p^\alpha)^{-\varepsilon}I_i^\varepsilon} \tag{47}$$

$$= \frac{E_j(e^{\tau m_{ij}})^{-\varepsilon}}{\sum_s E_s(e^{\tau m_{is}})^{-\varepsilon}} \tag{48}$$

$$\tag{49}$$

Now we have the probability of taking trip ij coming from location i.

D NHTS Appendix

The model does not embed a layer of travel mode choice. Instead, we can construct $m_{ij} = \eta m_{ij}^{drive} + (1-\eta) m_{ij}^{transit}$, where η is the share of trips taken via driving. These trips include personal vehicles, taxis, and ridesharing. Transit trips include those by any form of public transportation.

In order to calculate the share of trips driven, we can look to the National Household Travel Survey (NHTS). The NHTS is conducted every 8 years, the most recent two years being 2009 and 2017, which bookend the pre- and post-ridesharing era. Using data from the two surverys separately yields an η^{pre} and an η^{post}. Furthermore, the survey identifies the CBSA in which the trip takes place, providing city-level variation in the shares, η_c^{pre} and η_c^{post}.

To calculate the relevant η_c^{pre} and η_c^{post}, I use data for all home based social and recreation trips in 31/34 of the cities in my main sample.[27] I classify trips taken via car, suv, van, pickup truck, motorcycle, or rental car as driving trips; trips via public bus, commuter rail, subway, elevated rail, light rail or street car as transit trips; and trips via taxi, Uber or Lyft as ridesharing/taxi trips. Driving share, η_c^t, is the sum of driving and taxi/ridesharing trips over all trips. Table 1 shows the breakdown of all trips in the sample by travel mode and year. Over the two periods, driving in personal cars declined, while taxi/ridesharing use and public transit increased. Regardless of period, nationally, we are a nation of personal cars.

The table shows the *equilibrium* η^t; we need the shares due to ridesharing's entry, exogenous to any other changes in travel patterns. To get closer to exogenous driving shares, $\hat{\eta}_c^t$, we can run the simple difference of city-level shares on a post dummy and use the predicted values. This long-difference specification assumes no other changes to the transportation landscape than the introduction of ridesharing. This yields $m_{ijt} = \hat{\eta}_c^t m_{ij}^{drive} + (1-\hat{\eta}_c^t) m_{ij}^{transit}$

[27] Colorado Springs, CO, Santa Barbara, CA and Tucson, AZ are missing in the NHTS survey. I use Denver, CO data for Colorado Springs, Los Angeles data for Santa Barbara, and Phoenix data for Tucson.

E Appendix Tables

Table E1: List of Subway and Light Rail Systems by City

City	name	Subway	Lightrail	OnlyBus
Atlanta	MARTA	X	X	
Baltimore	Maryland Transit Administration	X	X	
Boston	MBTA	X	X	
Charlotte	CATS: Blue and Gold Lines		X	
Chicago	Chicago "L"	X		
Cincinnati	Bell Connector		X	
Colorado Springs				X
Dallas	DART		X	
Denver	Denver RTD		X	
Detroit	Q-Line, People Mover	X	X	
Houston	METRORail		X	
Kansas City	KC Streetcar		X	
Las Vegas	Monorail		X	
Los Angeles	Metro Rail	X	X	
Miami	Metrorail	X		
Minneapolis	METRO Light Rail		X	
New York	MTA	X		
Orlando				X
Philadelphia	SEPTA	X	X	
Phoenix	Valley Metro Rail		X	
Pittsburgh	The T		X	
Portland	MAX Light Rail		X	
Raleigh				X
Riverside	RTA			X
Sacramento	Sacramento RT Light Rail		X	
San Antonio				X
San Diego	San Diego Trolley		X	
San Francisco	BART	X	X	
Santa Barbara				X
Seattle	Central Link		X	
St. Louis	MetroLink		X	
Tampa	TECO Streetcars		X	
Tucson	Sun Link		X	
Washington DC	Metro	X	X	

Table E2: 2010 ACS Public Transit Commuting Shares

CIty	Fraction Transit
New York	0.305
San Francisco	0.146
Washington DC	0.139
Boston	0.119
Chicago	0.114
Philadelphia	0.0932
Seattle	0.0820
Baltimore	0.0627
Portland	0.0617
Los Angeles	0.0609
Pittsburgh	0.0578
Denver	0.0463
Minneapolis	0.0463
Santa Barbara	0.0378
Miami	0.0368
Las Vegas	0.0364
Atlanta	0.0336
San Diego	0.0330
Sacramento	0.0268
St. Louis	0.0258
Houston	0.0257
Tucson	0.0251
Cincinnati	0.0244
San Antonio	0.0224
Phoenix	0.0221
Charlotte	0.0201
Orlando	0.0171
Riverside	0.0159
Dallas	0.0156
Detroit	0.0150
Tampa	0.0138
Kansas City	0.0127
Colorado Springs	0.0124
Raleigh	0.00905

Notes: This table shows the share of surveyed commuters in each city that commute via public transit, defined as $hc04\_est\_vc01/hc01\_est\_vc01$ from the 2010 ACS 5-year estimates, from table S0802.

Table E3: Restaurant Net Creation: Transit vs. Driving Inaccessible Locations

	(1)	(2)	(3)
$\text{Post}_t \times \text{Inaccess}_j^{N,trans} \times \text{Inaccess}_j^{N,drive}$	-0.179	-0.290	-0.325
	(0.415)	(0.494)	(0.498)
$\text{Post}_t \times \text{Inaccess}_j^{N,drive}$	0.238	0.318	0.332
	(0.443)	(0.502)	(0.443)
$\text{Post}_t \times Inaccess_j^{N,trans}$	0.822***	0.859***	0.900***
	(0.230)	(0.245)	(0.284)
$\text{Inaccess}_j^{N,trans} \times \text{Inaccess}_j^{N,drive}$			0.109
			(0.435)
$\text{Inaccess}_j^{N,trans}$			0.682
			(0.411)
$\text{Inaccess}_j^{N,drive}$			0.308
			(0.608)
Post_t	-0.124	0.191	-0.0620
	(0.420)	(0.432)	(0.359)
R-Squared	0.253	0.270	0.173
Observations	3336	3026	3341
Year FE	X	X	X
Zip FE	X	X	
Inc, Edu, Pop	X		
CBSA FE			X
CBSA X Inaccess.			X
CBSA X Post			X

Notes: This table shows the estimates from $Y_{jt} = \beta Inaccess_j^{N_trans} \times Inaccess_j^{N_drive} \times Post_t + \gamma Inaccess_j^{N_trans} \times Post_t + \delta Inaccess_j^{N_drive} \times Post_t + year_t + zip_j + \varepsilon_{jt}$. All columns contain the same specification as in column (1) of Table 6. Standard errors clustered by $City_c \times Post_{ct}$ in parentheses.

Significance: *** p<0.01, ** p<0.05, * p<0.1.

Table E4: Restaurant Net Creation Results: Disaggregated Panel by Size Category

	(1)	(2)	(3)	(4)
Post$_t \times$ Inaccess$_j^N$	0.246***	0.248***	0.205*	0.243***
	(0.0698)	(0.0696)	(0.117)	(0.0764)
Inaccess$_j^N$	0.241*			
	(0.142)			
Post$_t$	0.0935	0.00237	-1.025***	0.121
	(0.130)	(0.0985)	(0.244)	(0.107)
R-Squared	0.0407	0.0567	0.0814	0.0607
Observations	10023	10023	10023	9084
Year FE	X	X	X	X
Zip FE		X	X	X
Zip Trend			X	
Inc$_{jt}$, Edu_{jt}, Pop_{jt}				X

Notes: This table uses a zipcode by year by employment class size panel, instead of a zipcode by year panel as in the main results. This table shows the estimates from $Y_{ict} = \delta Inaccess_{ic} + \alpha Post_{ct} + \Gamma City_c + \beta Inaccess_{ic} \times Post_{ct} + \Lambda City_c \times Post_{ct} + \Psi Inaccess_{ic} \times City_c + \varepsilon_{ict}$, in column (2). Additional columns control for zipcode fixed effects, ζ_{ic}, zipcode trends, $\zeta_{ic} \times \tau$, and year fixed effects, τ_t from Equation 10 in the text. As a final check, column (4) uses demographic characteristics instead of zipcode level trends to control for changing residential composition patterns. Standard errors clustered by $City_c \times Post_{ct}$ in parentheses.
Significance: *** p<0.01, ** p<0.05, * p<0.1.

Table E5: Restaurant Net Creation Results: Different City Radii

	(1)	(2)	(3)	(4)	(5)	(6)
	5 mi.	6 mi.	7 mi.	8 mi.	9 mi.	10 mi.
Post$_t \times Inaccess_j^N$	0.744***	0.397**	0.364**	0.290**	0.211*	0.144
	(0.223)	(0.196)	(0.169)	(0.139)	(0.124)	(0.0996)
Post$_t$	0.00710	0.455**	0.472**	0.386**	0.426***	0.357***
	(0.316)	(0.220)	(0.183)	(0.164)	(0.145)	(0.134)
R-Squared	0.253	0.244	0.240	0.238	0.231	0.225
Observations	3336	4313	5228	6200	7280	8417
Year FE	X	X	X	X	X	X
Zip FE	X	X	X	X	X	X

Notes: This table shows the estimates from $Y_{jt} = \beta Inaccess_j^N \times Post_t + year_t + zip_j + \varepsilon_{jt}$, with the sample covering zipcodes in increasingly wider city radii. Results from specification as in column (1) of Table 6, and use the public transit inaccessibility metric. Standard errors clustered by $City_c \times Post_{ct}$ in parentheses.
Significance: *** p<0.01, ** p<0.05, * p<0.1.

Table E6: Restaurant Net Creation Results: Dose Response Design

	(1)	(2)	(3)
$\text{Post}_t \times \text{m}_j^N$	0.0161	0.0137	-0.00417
	(0.0101)	(0.0111)	(0.0127)
Post_t	-0.198	0.279	1.367*
	(0.480)	(0.547)	(0.686)
m_j^N			-0.0305***
			(0.0115)
R-Squared	0.251	0.268	0.168
Observations	3375	3052	3341
Year FE	X	X	X
Zip FE	X	X	
Inc, Edu, Pop	X		
CBSA FE			X
CBSA X Inaccess.			X
CBSA X Post			X

Notes: This table shows the estimates from $Y_{jt} = \beta m_j^N \times Post_t + year_t + zip_j + \varepsilon_{jt}$, where m_j^N is the average public transit time to destination j for the average city resident. Results from specification as in column (1) of Table 6. Standard errors clustered by $City_c \times Post_{ct}$ in parentheses.
Significance: *** p<0.01, ** p<0.05, * p<0.1.

Table E7: Restaurant Net Creation Results: Binned Dose Response Design

	(1)	(2)	(3)
$\text{Post}_t \times$ 2.Inaccess_j^N	-0.0442	-0.412	-0.0743
	(0.301)	(0.392)	(0.273)
$\text{Post}_t \times$ 3.Inaccess_j^N	1.517***	1.174***	1.486***
	(0.263)	(0.324)	(0.245)
$\text{Post}_t \times$ 4.Inaccess_j^N	1.322***	1.105***	1.292***
	(0.331)	(0.403)	(0.306)
$\text{Post}_t \times$ 5.Inaccess_j^N	0.891**	0.622	0.874**
	(0.357)	(0.423)	(0.334)
Post_t	-0.327	0.283	-0.186
	(0.359)	(0.424)	(0.326)
2.Inaccess_j^N			1.051
			(1.056)
3.Inaccess_j^N			1.021
			(0.695)
4.Inaccess_j^N			0.674***
			(0.238)
5.Inaccess_j^N			0.527**
			(0.249)
R-Squared	0.258	0.274	0.202
Observations	3336	3026	3341
Year FE	X	X	X
Zip FE	X	X	
Inc, Edu, Pop	X		
CBSA FE			X
CBSA X Inaccess.			X
CBSA X Post			X

Notes: This table shows the estimates from $Y_{jt} = \sum_{k=2}^{5} \beta_k Inaccess_j^N(k) \times Post_t + year_t + zip_j + \varepsilon_{jt}$, where $Inaccess_j^N(k)$ is the quintile of restaurant inaccessibility. Results from specification as in column (1) of Table 6. Standard errors clustered by $City_c \times Post_{ct}$ in parentheses.
Significance: *** p<0.01, ** p<0.05, * p<0.1.

Table E8: Restaurant Net Creation Results: Not limited to public transit heavy cities

	(1)
$\text{Post}_t \times \text{Inaccess}_j^N$	0.637**
	(0.245)
$\text{Post}_t \times \text{Top5}_j$	0.198
	(0.482)
$\text{Post}_t \times \text{Inaccess}_j^N \times \text{Top5}_j$	0.328
	(0.692)
Post_t	0.0756
	(0.332)
R-Squared	0.253
Observations	3336
Year FE	X
Zip FE	X

Notes: This table shows the estimates from $Y_{jt} = \beta Inaccess_j^N \times Post_t + \gamma Top5_j \times Post_t + \delta\beta Inaccess_j^N \times Top5_j \times Post_t year_t + zip_j + \varepsilon_{jt}$, where $Top5_j$ identifies the top 5 cities for public transit usage, as defined in Table E2. Results from specification as in column (1) of Table 6. Standard errors clustered by $City_c \times Post_{ct}$ in parentheses.
Significance: *** p<0.01, ** p<0.05, * p<0.1.

Table E9: EPA Air Quality Pollutants in 2010: Pollution Sources

Pollution Source	VOC	NOx	CO	SO2	PM10	PM2.5	NH3
	% of total output						
On-Road Vehicles	18.04	31.87	48.41	0.29	0.74	1.79	7.92
Industry/Electricity	10.27	30.91	4.5	81.4	5.99	17.34	4.14

Notes: This table shows the output of carbon monoxide (CO) due to different pollution sources, and the share of total output in 2010. Author's calculations use data from exhibit 1-7, "Summary of National (48 state) Emission Estimates by Scenario Year" in the report "Emissions Projections for the Clean Air Act Second Section 812 Prospective Analysis," February, 2011. Prepared for the Office of Air and Radiation at the U.S. EPA. Prepared by Industrial Economics, Inc. and E.H. Pechan & Associates, Inc. under EPA contract no. EP-D-04-006.

Table E10: Citywide UberX Impact on Carbon Monoxide Emissions

	(1) ln(Mean CO)	(2) ln(Mean CO)	(3) ln(Mean CO)	(4) ln(Mean CO)
$Post_{cd}$	0.114***	0.114***	0.117***	0.0920***
	(0.0339)	(0.0323)	(0.0329)	(0.0280)
$FractionCoal_{sm}$		-0.250	-0.253	0.194
		(0.247)	(0.246)	(0.152)
$GasGen_{sm}$			-0.00774	-0.00419
			(0.00834)	(0.00810)
R-Squared	0.179	0.184	0.184	0.348
Observations	442354	423724	423724	423724
	Stacked DiD Controls			
CBSA FE	X	X	X	
CBSA Trend	X	X	X	X
Year FE	X	X	X	X
	Additional Controls			
Season	X	X	X	X
Monitor			X	X

Notes: This table shows the estimates from $Y_{icd} = \beta Post_{cd} + City_c + Year_d + Trend_c + Season_d + \varepsilon_{icd}$. Standard errors clustered by city and post-period.
Significance: *** p<0.01, ** p<0.05, * p<0.1.

Table E11: Citywide UberX Impact on PM 2.5 Emissions

	(1) ln(Mean PM 2.5)	(2) ln(Mean PM 2.5)	(3) ln(Mean PM 2.5)	(4) ln(Mean PM 2.5)
$Post_{cd}$	0.00539	0.00605	0.00419	-0.000782
	(0.0156)	(0.0156)	(0.0164)	(0.0175)
$FractionCoal_{sm}$		0.0457	0.0220	0.316***
		(0.0774)	(0.0668)	(0.0907)
$GasGen_{sm}$			0.0273***	0.0353***
			(0.00343)	(0.00432)
R-Squared	0.116	0.116	0.120	0.156
Observations	302066	300290	300290	300289
	Stacked DiD Controls			
CBSA FE	X	X	X	
CBSA Trend	X	X	X	X
Year FE	X	X	X	X
	Additional Controls			
Season	X	X	X	X
Monitor			X	X

Notes: This table shows the estimates from $Y_{icd} = \beta Post_{cd} + City_c + Year_d + Trend_c + Season_d + \varepsilon_{icd}$. Standard errors clustered by city and post-period.
Significance: *** p<0.01, ** p<0.05, * p<0.1.

Table E12: Within-City Results for CO

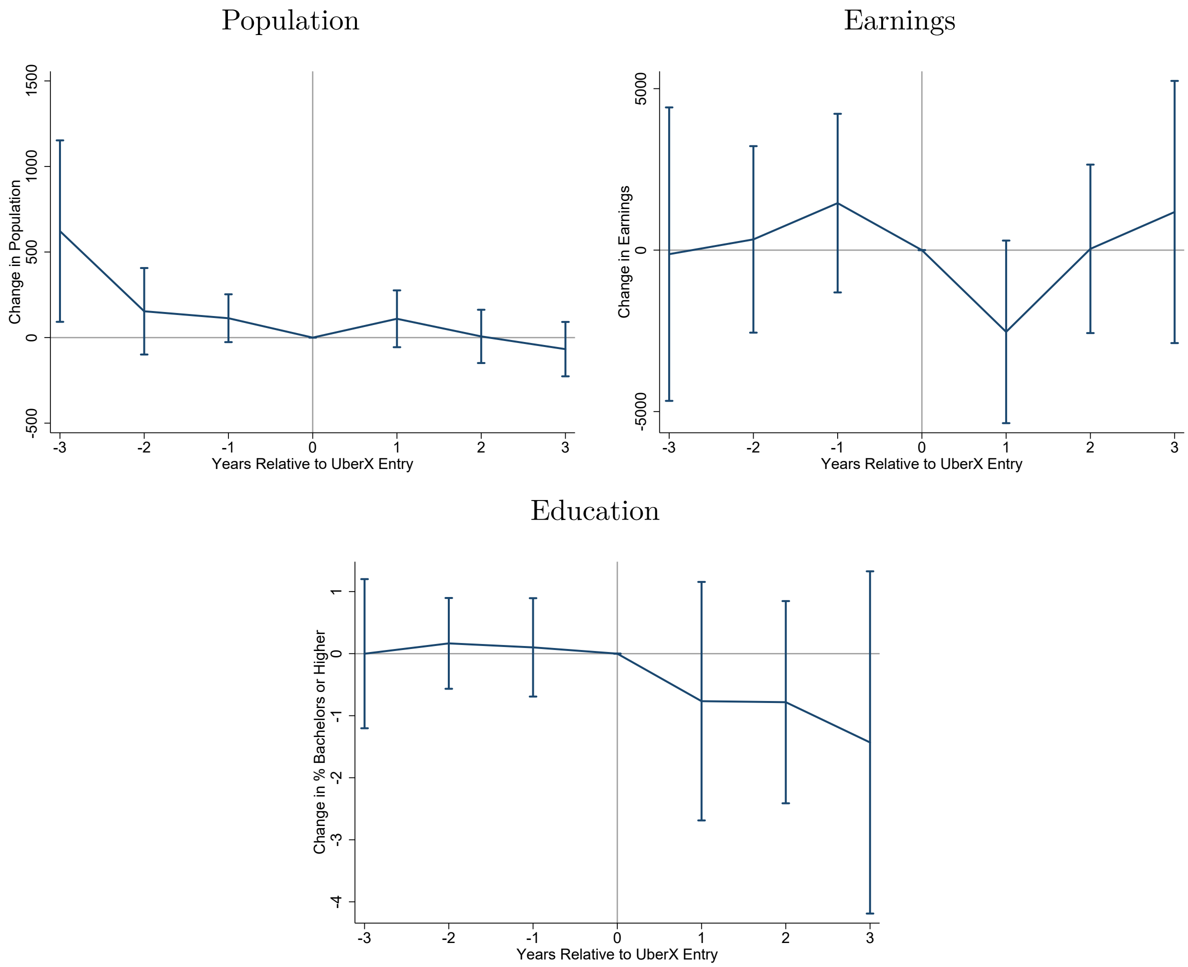
	(1) ln(Mean CO)	(2) ln(Mean CO)	(3) ln(Mean CO)	(4) ln(Mean CO)
post=1 × Innaccessible=1	0.0917	0.0906	0.0915	0.0873
	(0.100)	(0.0793)	(0.0795)	(0.0776)
post=1	0.116	0.112	0.105	0.108
	(0.0873)	(0.0823)	(0.0807)	(0.0795)
R-Squared	0.360	0.354	0.355	0.376
Observations	71112	70230	70230	70230
		Stacked DiD Controls		
CBSA FE	X	X	X	
CBSA X Year	X	X	X	X
CBSA X Access	X	X	X	X
		Additional Controls		
Year FE	X	X	X	X
Season FE	X	X	X	X
Zip FE	X	X	X	
Zip Trend	X	X	X	X
Monitor FE				X
		Fracking Controls		
Fraction Coal		X	X	X
Gas Gen.			X	X

Table E13: Within-City Results for PM25

	(1) ln(Mean PM 2.5)	(2) ln(Mean PM 2.5)	(3) ln(Mean PM 2.5)	(4) ln(Mean PM 2.5)
post=1 × Innaccessible=1	-0.0150	-0.0143	-0.0169	-0.0168
	(0.0210)	(0.0243)	(0.0247)	(0.0245)
post=1	0.0275	0.0290	0.0415	0.0415
	(0.0532)	(0.0566)	(0.0559)	(0.0558)
R-Squared	0.129	0.130	0.139	0.140
Observations	43416	42453	42453	42453
		Stacked DiD Controls		
CBSA FE	X	X	X	
CBSA X Year	X	X	X	X
CBSA X Access	X	X	X	X
		Additional Controls		
Year FE	X	X	X	X
Season FE	X	X	X	X
Zip FE	X	X	X	
Zip Trend	X	X	X	X
Monitor FE				X
		Fracking Controls		
Fraction Coal		X	X	X
Gas Gen.			X	X

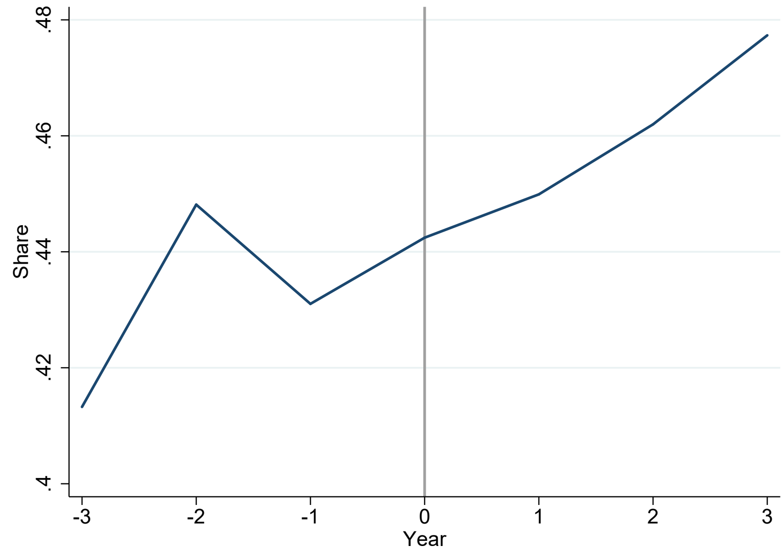
F Appendix Figures

Figure F1: No Evidence of Neighborhood Sorting in $Inaccess_j^N$ Zipcodes



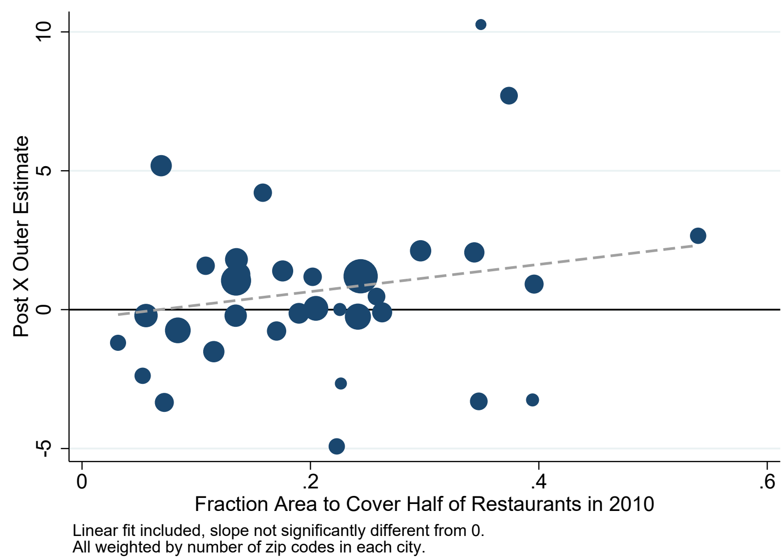
Notes: The figure plots $Y_{jt} = \beta Inaccess_j^N \times Post_t + year_t + zip_j + \varepsilon_{jt}$. Y_{jt} is population change, change in fraction of population with at least a bachelor's degree, or change median income in a zipcode.
95% confidence intervals shown.

Figure F2: Share of Yelp Reviews in Inaccessible Areas



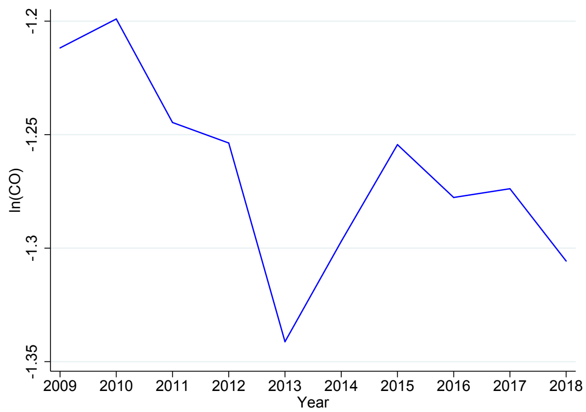
Notes: This figure shows the raw share of all Yelp reviews in restaurant inaccessible zip-codes in Pittsburgh, Phoenix and Charlotte around the 3 years of UberX's entry into each city.

Figure F3: City Level UberX Impact by Restaurant Concentration

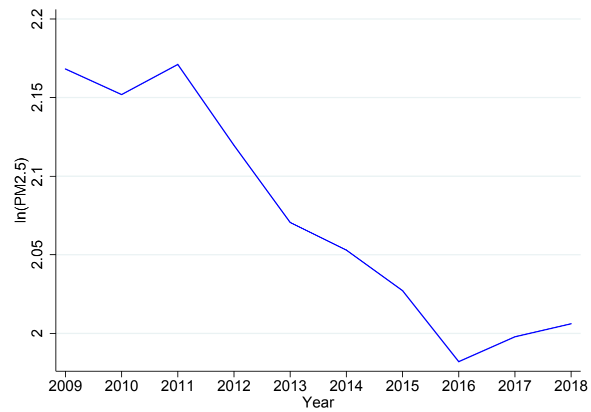


Notes: This figure shows the β_{ct} estimated from city level regressions of specification 10, including year and zipcode fixed effects, scattered against a measure of restaurant concentration. Restaurant concentration is defined as the share of a city's geographic area within 5 miles of the center required to cover half of the city's restaurants. The trend lines regresses the β_{ct}'s on restaurant concentration, and cannot be differentiated from 0.

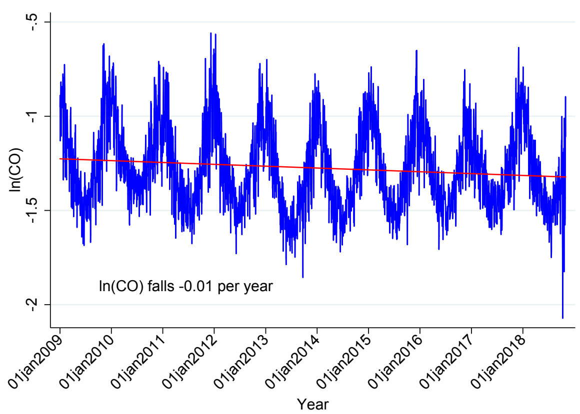
Figure F4: Time Series of Pollutants



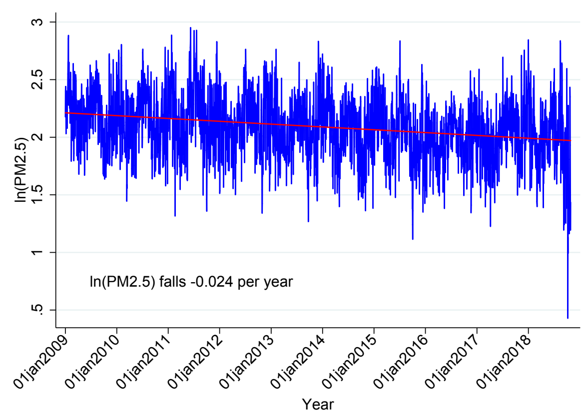
(a) Annual Average, ln(CO)



(b) Annual Average, ln(PM2.5)



(c) Daily Mean ln(CO)



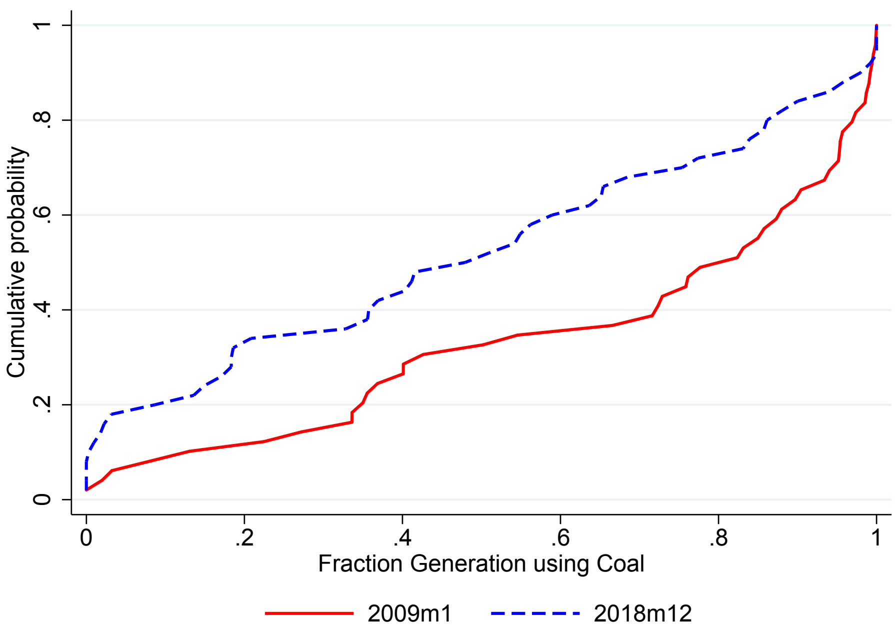
(d) Daily Mean ln(PM2.5)

Notes: Panel (a) plots monitor level daily CO 8-hour arithmetic means, averaged annually for the 34 cities in the sample. Panel (b) plots monitor level daily PM25 24-hour arithmetic means, averaged annually for the 34 cities in the sample. Panels (c) and (d) plot the annual point estimates from

$$Y_{icd} = \beta_y relative\_year_{cd} + City_c + Quarter_d + Season_d + Trend_c + \varepsilon_{ict}$$

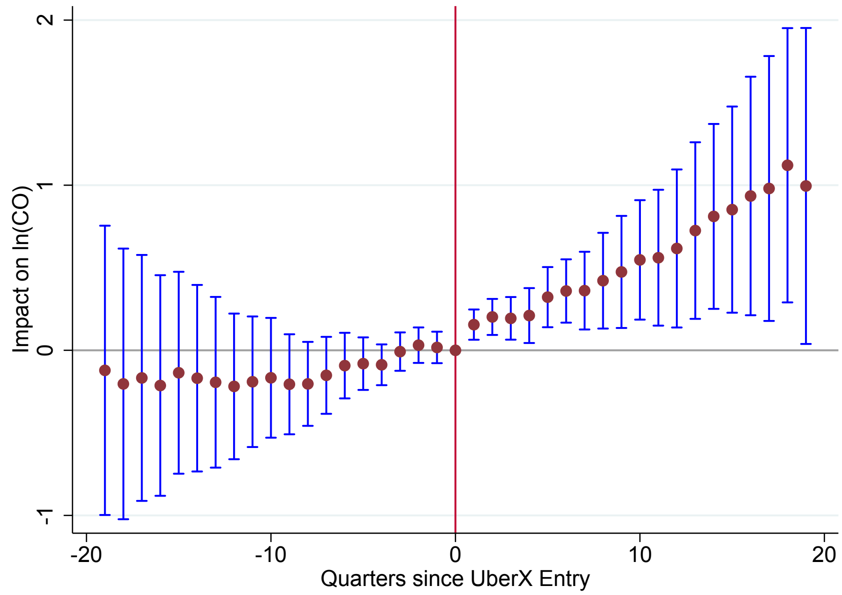
standard errors clustered by and post-period, 95% confidence intervals shown, panel (c) plots for ln(CO) and panel (d) plots for ln(PM2.5). Data from the EPA's daily AQI data.

Figure F5: Electricity Generation Inputs

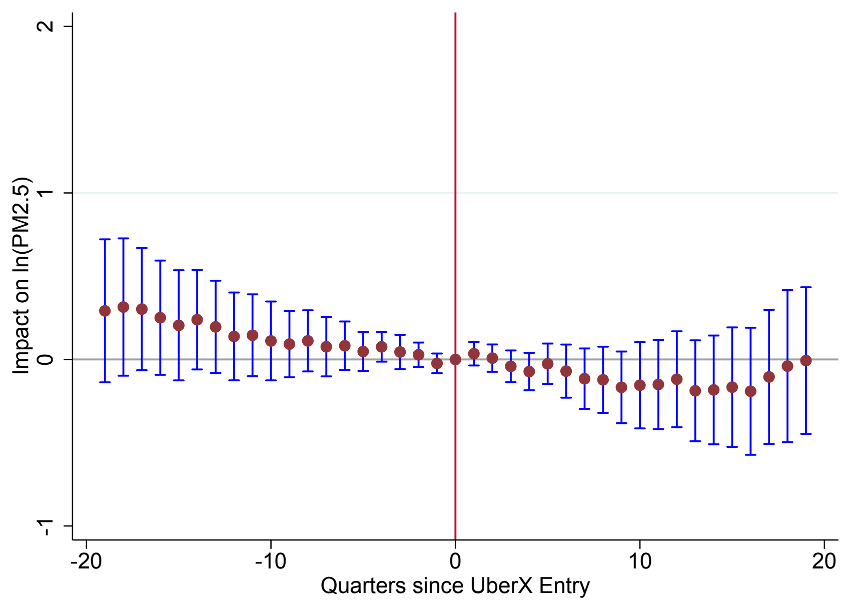


Notes: This figure shows the distribution of fraction coal used in electricity generation, $\frac{Coal_{sm}}{(Coal_{sm}+Gas_{sm})}$, over the 50 U.S. states. The figure compares the distributions for 2009m1 to 2018m12. State, s, by month, m, data on coal and gas generation obtained from the U.S. Energy Information Administration.

Figure F6: Citywide Event Study: ln(CO) and ln(PM2.5)



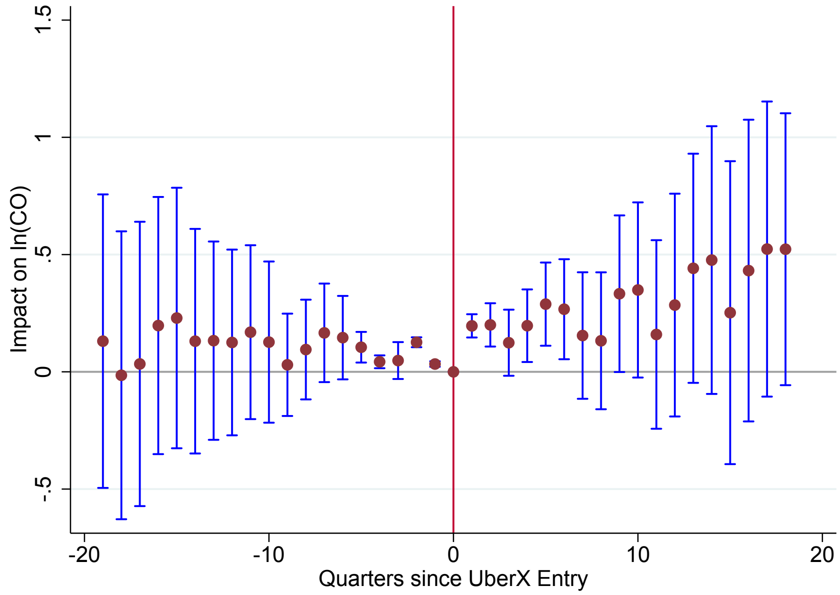
(a) β_q



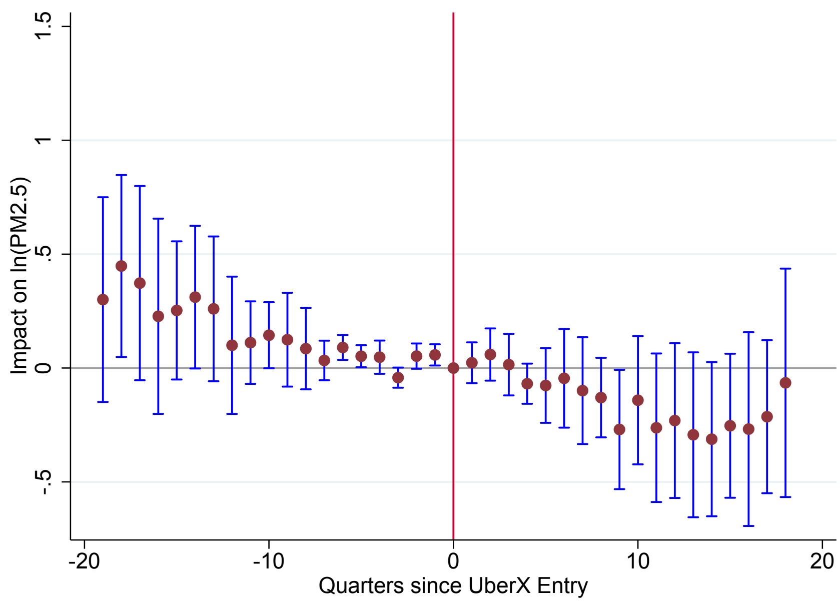
(b) β_q

Notes: Panel (a) Plots the monthly point estimates from $ln(CO)_{icd} = \beta_q relative\_quarter_{cd} + City_c + Month_d + Season_d + Trend_c + \varepsilon_{ict}$ standard errors clustered by and post-period, 95% confidence intervals shown. Panel (b) Plots the quarterly point estimates from $ln(PM2.5)_{icd} = \beta_q relative\_quarter_{cd} + City_c + Year_d + Season_d + Trend_c + GasGen_{icd} + FracCoal_{icd} + \varepsilon_{ict}$ standard errors clustered by and post-period, 95% confidence intervals shown. Panel (b) uses year fixed effects instead of month fixed effects, which are collinear with the β's.

Figure F7: Within-City Event Study: ln(CO) and ln(PM2.5)



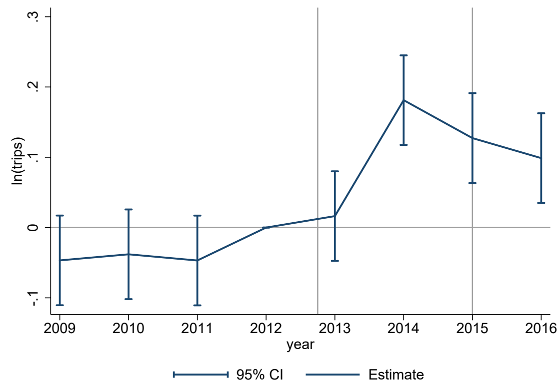
(a) β_q



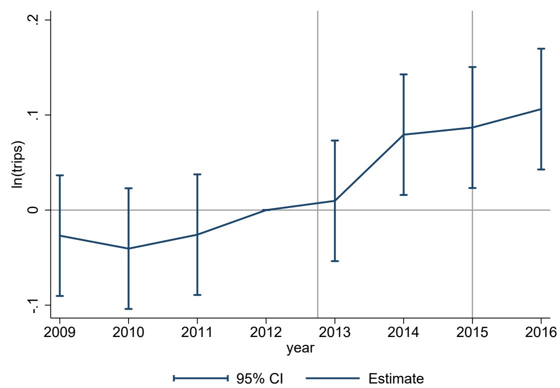
(b) β_q

Notes: Panel (a) Plots the monthly point estimates from $ln(CO)_{icd} = \beta_q relative\_quarter_{cd} + City_c + Month_d + Season_d + Trend_c + \varepsilon_{ict}$ standard errors clustered by and post-period, 95% confidence intervals shown. Panel (b) Plots the quarterly point estimates from $ln(PM2.5)_{icd} = \beta_q relative\_quarter_{cd} + City_c + Year_d + Season_d + Trend_c + GasGen_{icd} + FracCoal_{icd} + \varepsilon_{ict}$ standard errors clustered by and post-period, 95% confidence intervals shown. Panel (b) uses year fixed effects instead of month fixed effects, which are collinear with the β's.

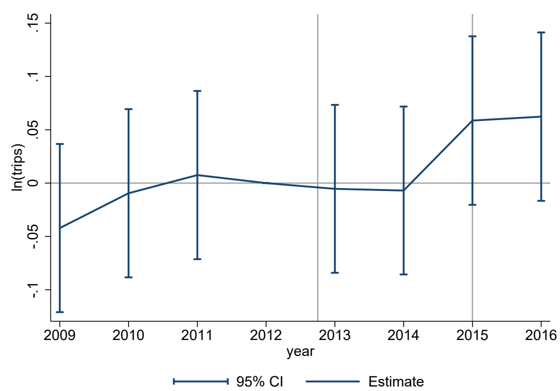
Figure F8: Changing Pick-up and Drop-Off Locations in the UberX Era in NYC



(a) Pick-ups in Inaccessible Locations, $\beta_1(t)$



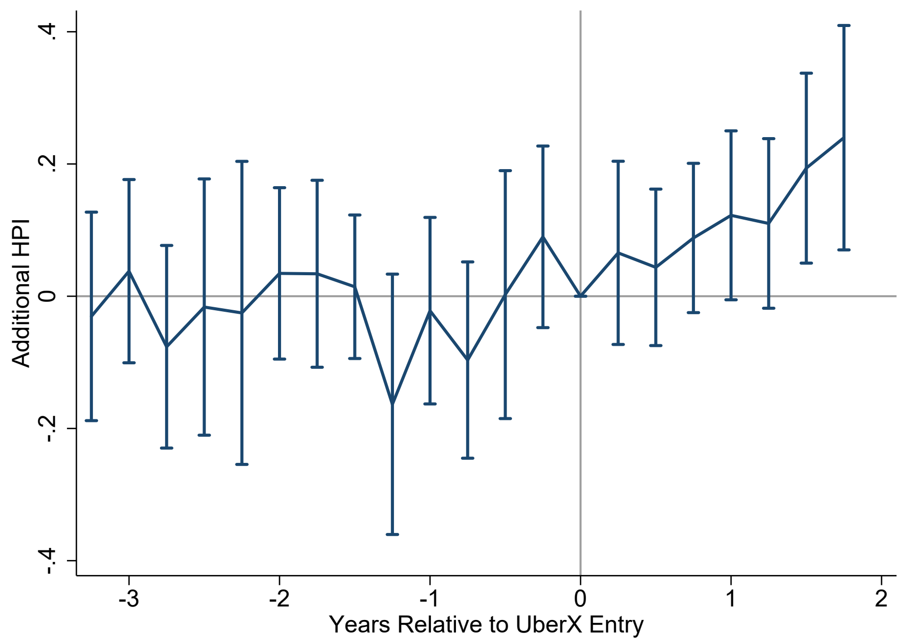
(b) Drop-offs in Inaccessible Locations, $\beta_2(t)$



(c) Both in Inaccessible Locations, $\beta_3(t)$

Notes: The panels plot the event study for $ln(trips_{ijt}) = Year_t + Inaccess_i + Inaccess_j + Inaccess_i \times Inaccess_j + \beta_1(t) Inaccess_i \times Year_t + \beta_2(t) Inaccess_j \times Year_t + \beta_3(t) Inaccess_i \times Inaccess_j \times Year_t + \eta_{ijt}$. Vertical lines are dropped at 2012 and 2015, when UberX and UberPool were introduced.

Figure F9: UberX Impact on mean HPI in Transit Inaccessible Areas



Notes: This table shows the β_t estimated from $HPI_{ict} = Year_t + \sum_{\tau=-4}^{\tau=3}\{\beta_\tau Inaccess_{ic} \times Year_\tau\} + City_c \times Year_t + \zeta_{ic} + \varepsilon_{ict}$. Standard errors clustered by $City_c \times Post_{ct}$. The shaded area denotes 95% confidence intervals.