The Long Run Effects of Uber on Public Transit, Congestion, Sprawl, and the Environment

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December 14, 2019

Abstract

Little is known about the long run effects of the widely adopted ride hailing transportation services such as Uber on our cities. This paper examines the long run general equilibrium effects of this new type of transportation service on public transit usage, traffic congestion, urban sprawl, and the environment using a spatial general equilibrium simulation model of a monocentric city with multiple transport modes. Households optimally choose a commuting mode to work: walking, taking public transit, driving, carpooling, taking Uber, or taking Uber to the nearby transit station to take public transit. The simulation results show that the adoption of Uber reduces traffic congestion, prevents urban sprawl, and lowers energy consumption and carbon emissions. Its effects on the public transit usage depend on the quality of the existing transit system. It complements public transit usage under a high quality transit system while serves as a substitute under a low quality system. In addition, public transit expansion has little effects on traffic congestion and the environment regardless of the entry of Uber. Finally, the regulation imposed on Uber reduces its usage and makes it less effective at complementing public transit and improving the environment.

JEL Codes: R11, R21, R28, R31, R41, C60

Keywords: ride hailing, public transit, traffic congestion, urban sprawl, housing price, energy consumption, carbon emissions

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1 Introduction

Transportation services offered through online platforms and apps have attained immense popularity across the world. It is predicted that the ride hailing services market will grow at a compound annual growth rate of almost 19% by 2023.[1] 36% of U.S. adults have used a ride-hailing service such as Uber or Lyft according to a survey conducted in 2018 by Pew Research center. The increased reliance on these services will likely have important consequences for urban development. How do ride hailing services affect traffic congestion, public transit, and carbon emissions? Should cities impose regulations on ride hailing industries? These are the relevant policy questions facing cities worldwide.

This paper estimates the long run general equilibrium effects of ride hailing services on public transit, traffic congestion, and the environment. There is mixed evidence in the literature on the effects of ride hailing services on public transit. Compared to public transit with fixed routes and fixed time schedules, ride hailing services provide more flexibility with regards to the commuting time and choice of route. Commuters use the ride booking apps to specify the pick up location and destination at any time and then the apps match the rider with an available nearby driver. The mobile applications are user-friendly and consumers are able to easily book rides using mobile devices. The door-to-door service offered through ride hailing industry could reduce public transit ridership by attracting commuters away from public transit. Clewlow and Mishra (2017) find ride hailing reduces bus usage by 6% and light rail transit usage by 3%. However, the flexibility and reliability of ride hailing services could help overcome the first/last mile problem for public transit users by taking commuters to the nearest transit station. Feigon and Murphy (2016) find ride hailing transportation services complement public transit and increase urban mobility. Hall et al. (2018) find Uber is a complement for public transit and increases public transit ridership by 5% after two years by exploring the variation in Uber penetration and the timing of Uber entry across different metro areas.

Similarly, there is little evidence in the literature on the effects of ride hailing services on traffic congestion. Compared to driving, ride hailing services save riders' the trouble of finding parking because customers will be dropped off at the destination. Potentially, the prevalence of ride hailing services could eliminate the need to own a car and to pay associated parking costs. Li et al. (2016) show that Uber reduces traffic congestion and Feigon and Murphy (2018) find that ride hailing services are associated with lower vehicle ownership

[1] See https://www.businesswire.com/news/home/20181212005667/en/Global-Ride-Hailing-Services-Market-2019-2023-19

and reduced solo driving. However, Henao and Marshall (2018) show that ride hailing leads to approximately an 83.5% increase in vehicle miles traveled (VMT) and increased traffic congestion.

The effects of ride-hailing services on energy consumption and carbon emissions are not yet well understood. Overall, our knowledge and understanding of the effects of ride hailing transportation services on cities is limited. This paper aims to broaden our understanding of the long run effects of ride hailing services on public transit, traffic congestions, and the environment. It is important to study the long run general equilibrium effects because it takes time for ride hailing industry to fully penetrate the market. In the long run, the change in the commuting cost caused by ride hailing services creates incentives for households to relocate within the city. In equilibrium, the change in households' mode choice and location leads to the change in housing price, structure density, and city size. The current empirical research with limited data from the ride hailing industry only provides a short term partial equilibrium estimates of the ride hailing services. Furthermore, this paper offers new insights regarding the long run effects of ride hailing service on urban sprawl, housing price, and structure density that have not been addressed in the literature before. The long run general equilibrium findings help to inform discussions about regulations on the ride hailing industry.

Due to the lack of data on ride hailing firms and the self-selection issues in survey data, it is difficult to explore the long run effects of ride hailing services empirically. Alternatively, this paper adopts the numerical simulation approach to investigate the long run general equilibrium effects of ride hailing services on cities. The model structure in this paper is an extension of the standard monocentric city model of Alonso (1964), Mills (1967), and Muth (1969). More specifically, the current model framework is based on Larson et al. (2012), which extends the monocentric city model to incorporate endogeneous traffic congestion, energy use, and carbon emissions. The monocentric city model has been generalized and used extensively to study different policies and new transportation technologies that affect transportation costs, land use, and energy use.[2] This model assumes that all employment is located at the Central Business District (CBD). Households with identical preference commute to the CBD via car for work. There is no public transit. Housing structure is not durable. The static nature of the model enables a long term interpretation of the results because it generates outcomes in the new equilibrium state after a policy change or a new technology innovation. Overall, it provides an ideal framework to model and predict the

[2]See Larson and Zhao (2019), Larson and Zhao (2017), Rappaport (2016), Borck and Brueckner (2018),Bertaud and Brueckner (2005), Wheaton (1998).

long run general equilibrium effects of ride hailing services.

To address the effects of ride hailing services on public transit, the current model extends the monocentric city model to include public transit and different travel modes. The simultaneous choice of residential location and travel modes has been explored by previous literature such as Arnott and MacKinnon (1977), Anas and Moses (1979), LeRoy and Sonstelie (1983), Sasaki (1989), and Sasaki (1990), and Xu et al. (2018). However, the previous models ignore the spatial variation with the distance to transit lines and focus on bi-modal transportation choice. The commuting cost for public transit or bus is solely based on the distance to the CBD without taking into account that a fraction of workers do not live within the walking distance to the public transit. The current model adds remarkably more realistic details. The public transit system comprises identical transit lines that are evenly spaced across the city. Before the entry of the ride hailing industry, households choose among different commuting modes to work: walking, taking public transit, driving, and carpooling. The entry of ride railing industry increases households' commuting options. It enables households to use ride hailing services directly to work or to the nearest transit station to take public transit. Households' locations are based on the distance to the CBD as well as the public transit. Commuting costs are determined by endogenous traffic congestion, mode choice, and the distance to the CBD and transit lines. These extensions attempt to lay out a more realistic spatial structure of the city with sufficient details by introducing multiple commuting modes and the spatial variation based on the distance to transit lines.

Given the complexity of the model, it is impossible to derive analytic solutions. Therefore, the model is first calibrated to Chicago before the entry of Uber. This paper uses Uber because it is the prototypical ride hailing service. It is assumed that the cost structure of ride hailing services follows Uber's fare structure. Parameters in the model are either borrowed from the literature or calibrated based on Chicago's characteristics. Then the model is solved numerically to achieve spatial equilibrium. Different parameters are altered to produce different counterfactual experiments. In the first counterfactual, the increase in commuting options due to the entry of Uber is simulated to study the long run general equilibrium effects of Uber. The second and third counterfactures are conducted to study the effects of Uber under different qualities of public transit systems. In the fourth counterfactual, the number of public transit lines is increased to study whether the public transit expansion is more beneficial with Uber. Lastly, the regulation imposed to restrict ride hailing market is simulated to study the consequences of regulations. This numerical simulation approach enables counter-factual experimentation and is able to generate rich insights that are difficult to test empirically.

The simulation results show that Uber is a complement to the public transit system under the simulated Chicago transit system. Although trips made by walking to work and walking to public transit stations are reduced after the introduction of Uber, public transit usage increases because 24.1% of workers start to take Uber to public transit. Uber increases public transit usage from 12.4% to 28.3%. This finding is consistent with Hall et al. (2018), who find that Uber increases ridership by 5% after two years. The magnitude of the complementary effect is larger in this paper because in the long run, the full penetration of Uber leads to a more significant effect on public transit. By attracting workers away from solo driving, Uber reduces highway traffic congestion. The reduction in traffic congestion creates incentives for households to live further away from the CBD. However, because Uber makes public transit more accessible and attractive, more households choose to live closer to the CBD and public transit, which leads to the contraction of the city. The net effect is Uber reduces urban sprawl and increases population density. This result is consistent with the findings in Sasaki (1989) and Sasaki (1990), where a city with multiple travel modes may experience contraction as a result of an improvement of the transportation system. This paper also finds that Uber reduces energy consumption and carbon emissions due to the increase in public transit usage and structure density.

However, under a low quality transit system, Uber serves as a substitute to the public transit system and increases energy consumption and carbon emissions. Although it improves public transit's accessibility, a low quality transit system remains too costly to attract more riders. Uber becomes a more appealing alternative commuting option and 10% of the population start to take it directly to work. In addition, the public transit expansion by adding another new transit line has little effect on traffic congestion and the environment both before and after the entry of Uber. The regulation limiting Uber's operation leads to higher fares, which reduces its usage. As a result, Uber becomes less effective at increasing public transit usage and reducing energy consumption and carbon emissions.

The remainder of the paper is organized as follows. Section 2 describes the theoretical framework and solution method in detail. Section 3 discusses the parameter calibration and the simulation of the baseline model. Section 4 presents the simulation results of several counterfactual scenarios. Section 5 concludes the paper.

2 Model Structure

The baseline model produces solutions that represent a present-day city before ride railing services are introduced. The model sets an exogenous wage rate and a fixed population size. Utility is endogenous and allowed to vary under different policy scenarios. This is referred to as a closed city model in the literature because no migration occurs between cities. The validity of the closed city assumption is based on the fact that Uber has been popular nationwide and its introduction everywhere should not provide a stimulus for intercity migration.

2.1 Theoretical Framework

The city is monocentric and lies on a featureless plane without geological constraints and housing regulations. It is assumed that the land is owned by absentee landlords. Firms are located in the CBD and pay the same wage rate to identical workers. Workers, who commute to the CBD to work every day, reside in the residential district between the CBD edge and city boundary. The city boundary is determined by the reservation agricultural land rent. Households' location is characterized by the distance to the CBD and the nearby transit stations. Land and housing prices vary across locations so that in equilibrium, households are indifferent across all locations within the city. Housing producers use land and structure inputs to maximize profit and receive zero economic profit at every location inside the city.

2.1.1 The Central Business District

All employment are concentrated in the CBD. Because this is a closed city model, total employment in the CBD is unchanged and hence the size and extent of this area is constant across simulations. For simplicity, this paper does not model the land market at the CBD and the potential effects of ride hailing transportation services on parking and the formation of employment sub centers. These simplified assumptions are necessary to facilitate simulation analysis.

2.1.2 Land Use

Urban land use is divided among highways, residential streets, residential housing, and other uses (public transit, park, school, etc.). It is assumed that a constant fraction θ_R of land area is allocated to highway, θ_s of land area is allocated to residential streets, a fixed fraction θ of land allocated for housing, and the remaining share $(1 - \theta_R - \theta_s - \theta)$ of land area devoted to other uses. The road system consists of radial highways and residential streets arced along the circumference at each radius. The radial highway lines are identical and evenly spaced. The length of residential streets is determined by each radius. The city will expand until the residential sector is unable to outbid the agriculture sector. At the city boundary $\bar{k}$, residential land price $p_L(\bar{k})$ is equal to agricultural land price p_L^a. These exogenous assumptions on land use do not take into account the potential effects of ride hailing industry on land use allocation, although in the long run, ride hailing services could potentially reduce parking usage in the CBD and residential areas.

2.1.3 Housing Production

Housing $H(k, j)$ at distance k from the CBD and distance j from the public transit, is produced using structure S and land L as inputs under a constant returns to scale technology. The production function takes a constant elasticity of substitution (CES) function form with an elasticity of substitution equal to $1/(1-\rho)$.

$$H(k, j) = A \left[\alpha_1 S(k, j)^\rho + \alpha_2 L(k, j)^\rho\right]^{1/\rho}, \tag{1}$$

where H is housing production, S is structure inputs that are perfectly elastically supplied, and L is land inputs.

Housing developers choose optimal structure and land inputs given structure price p_s and residential land price $p_L(k, j)$. Structure price is assumed exogenous and residential land price is determined endogenously in equilibrium.

2.1.4 Households

Homogeneous households consume housing and a composite commodity to maximize the CES utility function:

$$U = \left[\beta_1 y^\eta + \beta_2 h^\eta\right]^{1/\eta}, \tag{2}$$

where h is housing consumption, y represents numeraire good consumption, β_1 and β_2 are consumption share parameters, and $1/(1-\eta)$ represents the constant elasticity of substitution between housing and the numeraire good.

For households living at distance k from the CBD and distance j from the public transit, income, W, is spent on the numeraire good, $y(k, j)$, housing, $h(k, j)$, and transportation,

$T(k, j)$. Housing expenditure depends on housing rental price $r(k, j)$ and housing size $h(k, j)$.

$$W = y(k, j) + r(k, j)h(k, j) + T(k, j). \tag{3}$$

Households' utility is identical at each distance, k, from the the CBD edge, and j from the public transit.

The caveat of the homogeneous assumption imposed on households is that it fails to capture the heterogeneous effects of ride hailing transportation services across different income groups. The survey results from Clewlow and Mishra (2017) show that affluent American are more likely to adopt ride hailing services than lower income population.

2.1.5 Transportation Technology

Workers choose from different transportation modes to commute to work including walking, public transit, driving, and carpooling. These four means of transportation are the main commuting modes. According to the American Community Survey in 2010, 93.8% of U.S. population commute through these four modes. Workers optimally choose one mode to minimize transportation cost.

For households living at distance k from the CBD and distance j from the public transit station, the transportation cost for walking is

$$T_{walk}(k, j) = \tau_w \cdot W \cdot (k/V_{walk}), \tag{4}$$

where the time cost of walking is a fraction τ_w of the wage rate, W. The speed of walking is set at a constant pace V_{walk}.

For workers who commute to the CBD via automobile, the annual transportation cost only depends on the distance to the CBD. It includes the following: fixed costs of owning and operating an automobile m_0 (e.g. insurance, licensing), parking fee at the CBD $parking_{CBD}$, costs proportional to distance traveled (e.g. vehicle depreciation, maintenance) m_1, gasoline costs, and time cost of commuting. The gasoline cost is determined by the fuel efficiency of the car G and the price per gallon p_g. The gasoline consumption per mile G^{-1} depends on vehicle velocity, V. The velocity at each distance k is determined jointly by the number of commuters and road capacity. The time-cost of commuting depends on the value of time as a fraction, τ , of the wage rate, W and the travel time $\int_{k_{CBD}}^{k} \frac{1}{V(\kappa)} d\kappa$, where k_{CBD} represents the edge of the CBD. The highway network is assumed to be dense and next to households' location. This eliminates the need to model households' commuting from home to the highway. In addition, to simplify, the model assumes parking is next to the office and thus does not take into account the commuting from parking to the office. Taken together, the total commuting cost is given by:

$$T_{drive}(k,j) = m_0 + parking_{CBD} + \left[m_1 k + p_g \int_{k_{CBD}}^{k} \frac{1}{G(V(\kappa))} d\kappa + \tau W \int_{k_{CBD}}^{k} \frac{1}{V(\kappa)} d\kappa \right]. \quad (5)$$

Both fuel and commuting time are related to the velocity of the automobile at various locations in the city. The velocity is a function of the ratio of traffic volume to roads. Following Bureau of Public Roads specification, the function of velocity is

$$V(k) = \frac{1}{a + bM(k)^c} \quad (6)$$

where $M(k) = \overrightarrow{N(k)}/R(k)$. $\overrightarrow{N(k)}$ represents the traffic volume passing through distance k, which is a function of commuters living within distance k, $N(k)$. $R(k)$ represents the road capacity. At each radius k, road capacity is a fixed fraction θ_R of the land area. a, b, and c are congestion parameters.

If households choose to take public transit, they have to walk to the nearest public transit station and then take the public transit. The rail lines are evenly distributed. Each rail line offers a radial route that links the CBD with residential locations. It stops at each radius to transport workers to the CBD. The model does not take into account the commuting from the transit stops at the CBD to the office assuming the stops are next to the office. Therefore, for households walking to the public transit, the transportation cost is

$$T_{walkpub}(k,j) = \tau_w \cdot W \cdot (j/V_{walk}) + awt \cdot \tau_{pub} \cdot W + publicfare + \tau_{pub} \cdot W \cdot (k/V_{metro}), \quad (7)$$

where the first term represents the time cost of walking to the nearby transit station. awt is the average waiting time which depends on the frequency of the rail lines. The time cost of waiting is measured as a fraction, τ_{pub}, of the wage rate, W. $publicfare$ is the ticket cost. V_{metro} is the average speed of each transit line. Thus the average time riding the train from distance k to the CBD is k/V_{metro}. The last term represents the time cost of taking public transit.

The bus system as a part of the public transit system is omitted from the modeling. Although the bus system could be viewed as a slower version of the rail system and a faster version of walking, this simplification fails to capture that buses take commuters to transit stations and complement the use of public transit.

Households living further away from the CBD as well as the public transit have more incentives to carpool because parking fee, variable costs, and gasoline costs could shared among riders to save long distance commuting cost. If workers choose to carpool, each carpool has n riders. The shared parking cost is $parking_{CBD}/n$, the variable costs related to distance traveled become m_1/n per rider, and the shared gasoline price per gallon is p_g/n. It is assumed carpool does not affect or eliminate car ownership because people who carpool still need automobiles for other purposes such as shopping or errands. Carpool incurs an extra time cost for each rider because riders have to coordinate schedules and drivers have to pick up and drop off each rider. This extra carpooling time is assumed to be fixed at $t_{carpool}$. Thus the time cost of carpooling is $\tau_{carpool} \cdot W \cdot t_{carpool}$, where $\tau_{carpool}$ is the time cost of carpooling as a fraction of wage rate. Therefore, the total commuting cost for workers who carpool is

$$T_{carpool}(k,j) = m_0 + \tau_{carpool} \cdot W \cdot t_{carpool} + parking_{CBD}/n + (m_1/n)k + (p_g/n)\int_{k_{CBD}}^{k} \frac{1}{G(V(\kappa))} d\kappa + \tau W \int_{k_{CBD}}^{k} \frac{1}{V(\kappa)} d\kappa. \quad (8)$$

Each household chooses travel mode optimally to minimize commuting cost. As a result, the transportation cost for households living at radius k and distance j from public transit is the following:

$$T(k,j) = \min\Big\{T_{walk}(k,j), T_{drive}(k,j), T_{walkpub}(k,j), T_{carpool}(k,j)\Big\}. \quad (9)$$

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After the ride hailing service is introduced, workers have the option to take it either directly to work or to the nearby public transit stations. Pooled rides are omitted from modeling because the majority of all ride hailing trips are non-pooled. Gehrke et al. (2018) show that 80% of these trips are single customer services rather than a pooled option such as UberPool. Given that trips via taxicab account for less than 1% of total commuting according to ACS(2010), the model does not consider taxi services. Thus the competition between taxi services and ride hailing services is omitted in this paper.

The current model focuses on commuting trips and does not take into account the non-commuting trips using ride hailing services such as shopping trips or going to restaurants.

It also ignores the empty trips made by ride hailing drivers getting to different destinations without any passengers. Thus this paper does not capture the congestion created by non-commuting trips.

Households benefit from ride hailing transportation services by avoiding parking fees, lowering the time cost of commuting, and eliminating car ownership. Because Uber is the major player in the ride hailing industry, this paper uses Uber to represent the ride hailing transportation service. The cost structure of using ride hailing services follows the fare structure of Uber, which consists of a fixed base fare, a cost varies with distance, and a cost varies with time. The current model ignores the surge pricing scheme that Uber has adopted during rush hours to match the supply with the demand of rides. The omission of the surge pricing is based on the speculation that in the long run, after Uber has fully penetrated the market, the supply of Uber drivers would fully meet the demand from consumers at the rush hour. It is possible that in the long run, the Uber fare could decrease as the supply of Uber drivers increase or the self driving technology matures. For simplicity, the model assumes the fare structure is constant over time.

The cost of taking Uber to work includes the payment to Uber and the time cost of traveling, given by:

$$T_{uber}(k,j) = f_0 + f_1 \cdot k + f_2 \int_{k_{CBD}}^{k} \frac{1}{V(\kappa)} d\kappa + awt_{uber} \cdot \tau_{uber} \cdot W + \tau_{uber} \cdot W \cdot \int_{k_{CBD}}^{k} \frac{1}{V(\kappa)} d\kappa, \quad (10)$$

where f_0 represents the base fare, f_1 represents cost per mile, f_2 represents cost per hour, and awt_{uber} is the average waiting time for Uber drivers to arrive. To simplify, the fare structure of taking Uber is set exogenously without modeling the supply and demand of the services. The time cost of commuting is a fraction, τ_{uber}, of wage rate W. τ_{uber} is lower than the time cost of driving τ, because workers do not need to drive and can spend time working or other productive use. It ignores the commuting to the office after workers are dropped off by drivers assuming drivers drop off workers next to their workplaces.

If workers choose to take Uber to the nearby transit station, the transportation cost is:

$$\begin{aligned} T_{uberpub}(k,j) = f_0 + f_1 k + f_2 \cdot j/V_{res} + awt_{uber} \cdot \tau_{uber} \cdot W + \tau_{uber} W \cdot j/V_{res} \\ + awt \cdot \tau_{pub} W + publicfare + \tau_{pub} W \cdot k/V_{metro}, \quad (11) \end{aligned}$$

where the first five terms represent the cost of talking Uber to the nearby transit station and the last three terms represent the cost of taking public transit. V_{res} represents the driving speed through residential streets. Given the driving distance to transit stations is short, it is assumed Uber drivers drive through residential streets to take riders to transit stations without getting on the highway. Before Uber is introduced, workers do not need to commute through residential streets and there is no traffic congestion. Residential streets are used for other purposes such as shopping or errands besides commuting. However, after Uber is adopted, trips made by Uber to nearby transit stations may lead to traffic congestion on residential streets.

Traffic congestion on residential streets follows the same equation for highway traffic congestion, where the commuting speed is based on the traffic volume and road capacity.

$$V_{res} = \frac{1}{a_r + b_r M_{uber}^{c_r}}, \tag{12}$$

where M_{uber} is the ratio of number of people taking Uber to the residential street capacity, and a_r, b_r, c_r are congestion parameters.

With the introduction of ride hailing service, the transportation cost for households is

$$T(k,j) = \min\Big\{T_{walk}(k,j), T_{drive}(k,j), T_{carpool}(k,j), T_{walkpub}(k,j), T_{uber}(k,j), T_{uberpub}(k,j)\Big\}. \tag{13}$$

2.2 Model Solution

To solve the model, the city is discretized into grids of uniform squares along each radius. Each grid point corresponds to a distance k from the CBD and distance j from the public transit station. Because all transit lines are evenly distributed within the city and households choose to go to the nearest transit stop, each transit line has an equal market area. Due to the city is radial uniform and symmetric with respect to identical rail lines, it is sufficient to examine the half of the market area for one rail line as depicted in Figure 1. After the solution for the half of the market area is obtained, it is aggregated cross all market areas to generate the solution for the whole city.

Given the initial values for the housing price and the traffic volume at the CBD edge, commuting cost for each mode, optimal mode choice, and population density at each location are solved recursively. With the solutions for commuting cost and population density, housing price, housing demand, land price, and structure density are derived.

In order to achieve spatial equilibrium, the following conditions must be met. First, all households achieve the same utility level and all housing producers earn zero economic profit.

Second, the land price at the edge of the city must be equal to the agricultural land rent $p_L(\bar{k}) = p_L^a$. This condition is used to determine the city boundary $\bar{k}$ in equilibrium. The city expands until the residential land price falls to the agricultural land rent.

Third, the total population must be housed within the city. Given the exogenous number of households in the city N, the following population constraint condition must be met.

$$N = \int_{k_{CBD}}^{\bar{k}} \int_{0}^{J(k)} \theta \cdot D(k,j) dj dk, \tag{14}$$

where $D(k,j)$ is the endogenous households density at distance k from the CBD edge and distance j from the public transit, which is derived from $\frac{H(k,j)/L(k,j)}{h(k,j)}$, θ is the fixed fraction of land devoted to housing, $\bar{k}$ is the city boundary which is determined endogenously in the equilibrium, and $J(k)$ is the maximum distance to the public transit at each radius k.

Fourth, at the carpooling boundary, commuting costs for solo drivers and carpools are equal. This condition determines the endogenous fraction of population who choose to carpool.

Lastly, the total number of cars on the highway determined by the population who choose to drive or carpool is equal to the total traffic volume passing through the CBD edge. This determines the endogenous traffic volume on highways.

If any one of these equilibrium conditions is not met, the simulation is re-initialized and simulated until subsequent iterations achieve an equilibrium solution.

2.3 Energy Consumption and Carbon Emissions

Following Larson et al. (2012), the energy consumption is calculated based on the equilibrium solutions. Total energy consumption at distance (k,j), $E(k,j)$, is derived from the gasoline consumption for driving, $E^C(k,j)$, electricity in public transit usage, $E^P(k,j)$, electricity in dwellings, $E^D(k,j)$, and numeraire goods, which embodies all other forms of consumption, $E^N(k,j)$.

$$E(k,j) = E^C(k,j) + E^P(k,j) + E^D(k,j) + E^N(k,j). \tag{15}$$

Energy used in driving to the CBD by a household living at distance (k,j) is given by

$$E^C(k,j) = E_g \int_{k_{CBD}}^{k} \frac{1}{G(V(k))} dk \tag{16}$$

where E_g is the energy embodied in a gallon of gasoline in British thermal units (BTUs), which includes the base energy content of a gallon of 100% petroleum-based gasoline and the additional energy needed during the process of production and distribution. Given the base energy of a gallon of gasoline is 125,000 BTUs and the additional energy for production is 25,602 BTUs, $E_g = 150,602$ BTUs.[3] $\int_{k_{CBD}}^{k} \frac{1}{G(V(k,j))} dk$ represents the total gasoline consumption, where $G(V(k)))$ represents gasoline consumption per mile as a function of the velocity $V(k)$ at each distance k.

The use of gasoline for driving depends on the velocity of traveling. The engineering relationship between gasoline consumption and velocity is based on the estimation from Larson et al. (2012).

$$G(V(k)) = .822 + 1.833V(k) - .0486V(k)^2 + .000651V(k)^3 - .00000372V(k)^4. \tag{17}$$

For public transit, the main energy source is electricity. According to transportation energy data book (2012), the energy used for the transit system in Chicago is $2,520$ BTU per passenger per mile. Therefore, energy used in commuting by public transit is given by

$$E^P(k,j) = e^p \int_{k_{CBD}}^{k} \int_{0}^{j} kN_{pub}(k,j) dj dk, \tag{18}$$

where e^p is energy consumption per passenger per mile, $N_{pub}(k,j)$ is the public transit riders at distance k from the CBD and distance j from the public transit stations, and $\int_0^k \int_0^j kN_{pub}(k,j) dj dk$ represents the total distance traveled by all passengers using public transit.

There are three major factors determining dwelling energy consumption: the income of the household, the square feet of interior space, and the structure type. Higher income, larger housing size, and lower structure density lead to higher dwelling energy consumption. Larson et al. (2012) find that the estimated elasticity of dwelling energy consumption with respect to income is 0.07 and the estimated elasticity of dwelling energy consumption with respect to interior space is 0.23. Buildings with higher structure density are more energy efficient. Single family attached dwelling units consume 7% less energy than single family detached units and multifamily units consume 31% less. The structure type, s, is determined by the floor area ratio, $q(k,j)$, which is the ratio of housing square footage over lot size. Given the threshold values q_1, q_2, and q_3, the structure type is single-family detached if $q \in [0, q_1]$, single-family attached if $q \in (q_1, q_2]$, 2-4 unit multifamily if $q \in (q_2, q_3]$, and 5+ unit multifamily

[3] The data comes from the Federal Register (2000) published by the Energy Information Administration.

when q is above q_3. In order to simplify the calculation, it is assumed all energy consumed in the dwelling is from electricity. Each kilowatt hour of electricity consists of 3,412 BTUs of energy. After taking into account the energy embodied in production and distribution of electricity, the electricity efficiency parameter E_e is 1/0.303. (Federal Register, 2000).

Therefore, the function for dwelling electricity demand is

$$E^D(k,j) = E_e \exp\left[\gamma_1 + \gamma_2 \ln I + \gamma_3 \ln p_e + \gamma_4 \ln h(k,j) + s(q(k,j))'\Gamma\right], \tag{19}$$

where I represents income, p_e is the price of electricity, $h(k,j)$ represents housing consumption, and $s(q(k,j))$ represents the vector of structure type as a function of floor area ratio $q(k,j)$.

Energy consumption embodied in the numeraire good is estimated using the following equation:

$$E^N(k,j) = E_N \left(w - p_g E^C(k,j)/E_g - p_e E^D(k,j)/E_e - P_e^p E^P(k,j)\right), \tag{20}$$

where E_N is the the energy embodied in \$1 of numeraire good consumption, which is set at 7,470 BTUs (Energy Information Administration, 2011). $p_g E^C(k,j)$ represents the gasoline expenditure from driving, Uber, or carpooling. $p_e E^D(k,j)$ represents residential electricity cost, P_e^p is the electricity price for public transit sector, and $P_e^p E^P(k,j)$ represents the electricity cost for taking public transit which is paid as part of the ticket price.

To calculate greenhouse gas emissions, each type of energy consumption is multiplied by a carbon dioxide (CO_2) emissions coefficient reported by the Energy Information Administration. This paper only considers CO_2 emissions because other types of greenhouse gases account for less than 5% of all greenhouse gas emissions from gasoline and electricity consumption. Based on the data from the Energy Information Administration in 2016, the combustion of gasoline results in 157 pounds of CO_2 per million BTUs and electricity consumption leads to 115 pounds of CO_2 per million BTUs on average. The CO_2 emissions coefficient for numeraire energy consumption is assumed to be the same as for dwelling energy consumption.

3 Baseline Calibration and Simulation

The calibration of the numerical urban simulation model is evaluated by comparing the simulation outputs to the characteristics of Chicago in year 2010 before the entry of Uber.

Uber entered Chicago in year 2011. The Chicago urbanized area is selected as calibration target due to its city size and substantial rail transit system. The population in Chicago urbanized area is over 8 millions and the number of occupied housing units is $3,012,005$ in year 2010. A large city is selected because of the popularity of public transit and Uber users. In 2010, according to American Community Survey (ACS), for Chicago urbanized area, 12.4% of commuters take public transit, 69.4% drive alone, 3.3% walk, 8.7% carpool, and 6.2% use other means. In addition, according to Gyourko et al. (2008), Chicago has relatively low regulatory barriers. This characteristic is used to match the assumption of zero zoning regulations in the theoretical model as closely as possible.

Figure 2a shows the rapid transit system in Chicago. The total route length is 102.8 miles with 8 rail lines. The route length for each line ranges from 5.1 miles to 26.9 miles. In the simulation, it is assumed there are 7 lines with equal route length of 15 miles. These 7 lines divide the city into 6 pieces equally. To facilitate analysis, it is assumed that transit stops are built at each radius along each radial transit line. The simulated city geometry and public transit system is shown in Figure 2b. The simulated city has a CBD, a residential district, and an agricultural hinterland, which occupies 60% of the circular area. It is consistent with the data from Saiz (2010) where only 60% of city area is available for development in Chicago due to the geographical constraint imposed by Lake Michigan

Parameter calibration is performed following the literature on numerical urban simulations. These parameter values are shown in Table 1. For housing production function, the elasticity of substitution between structure and land inputs is set at 0.75 following Larson et al. (2012) and others. The distribution parameter for structure input is normalized to one. The technology parameter and the distribution parameter for land input are calibrated to match the data on median unit size and median lot size. The median unit size, $2,000$ square feet, and the median lot size for 1 unit structure, 0.17 acre, are from the data of American housing survey in year 2009 for Chicago metro area due to the lack of data in year 2010 for Chicago urbanized area. The city radius is measured from the map of the Chicago urbanized area using the boundaries defined in year 2000 from the Census. The radius is about 33 miles, which generates a land are of $2,123$ square miles that are consistent with the data from the ACS (2010).

For utility function, the elasticity of substitution between housing and consumption goods is 0.75 which has been commonly used in the literature. The share parameter for composite goods is normalized to one. From the consumer expenditure survey conducted by Bureau of Labor Statistics in year 2010, the income share of housing expenditure is 27% and transportation expenditure accounts for 11% of income. According to ACS (2010), the median income in Chicago is \$56,069. Using these data, the share parameter for housing consumption is calculated using the following equation derived from the consumer optimization problem.

$$\beta_2 = r\left[\frac{h}{1-T-rh}\right]^{1-\eta} \tag{21}$$

This approach is consistent with Muth (1975), Altmann and DeSalvo (1981), and Larson et al. (2012).

Given the lack of data in land use for Chicago urbanized area in year 2010, various data sources are combined to approximate the land use allocation in Chicago. According to Overman et al. (2008), there are 980 square miles of land area used for residential purpose in Chicago area in year 1992. It implies 46% of land is for residential use based on Chicago's urban area 2,221 square mile. Chicago has 34,800 miles of local streets and 19,800 miles of highways in 1990s according to the documentation from Encyclopedia of Chicago.[4]. Therefore, local streets account for 64% and highways account for 36% of the land area used for roads. Based on the report from American Society of planning officials using 1940 census, about 20% of land area is allocated to roads. Thus, approximately, 15% of the land is used for residential streets and 10% is devoted to highways. These values for land share are close to those used in Muth (1975) and Altmann and DeSalvo (1981).

The average farmland value with an average quality at Illinois is 4,624 in year 2010 based on the report from the Illinois Society of Professional Farm Managers and Rural Appraisers (2018). This yields an agricultural rental price per acre per year of \$231.7 assuming a 5% discount rate.

The commonly used value for the time cost of driving is between 30% and 50% of wage rate. In this paper, the value of driving time is set at 30% of the wage rate. The time cost of other commuting modes is calibrated to match the fraction of population using different transportation means to commute. The time cost of taking public transit, τ_{pub}, is 50% of the wage rate. For walking, the time cost τ_w is 1.1 times of the wage rate. The time cost of coordinating carpool is 76.7% of the wage rate. The fixed and marginal commuting costs for driving and congestion parameter c are borrowed from Larson et al. (2012). The congestion parameters b and c are calculated based on equation 6. The maximum speed on the highway, v_{high}, is set at 45 mph when there is no traffic. Therefore, $v_{high} = 1/b$, which implies that $b = 1/v_{high}$.The minimum speed assumed as 5 mph occurs at the CBD edge

[4]http://www.encyclopedia.chicagohistory.org/pages/1209.html

with heaviest traffic when all workers drive to the CBD. Based on equation 6, it implies that $v_{low} = \frac{1}{a+b(N/R(CBD))^c}$, which is used to back out b given population N and road capacity at the CBD, $R(CBD)$. For the parking fee at the CBD, it is set at 8 dollar per day based on the Google search for Chicago downtown.

To avoid high dimensionality problem in the simulation, the traffic through residential streets at each distance from the transit stations is not calculated. Instead, the commuting speed is based on the average traveling speed on local streets which is determined endogenously. The average traveling speed is determined by total traffic volume on residential streets which is solved in equilibrium and local road capacity. It is derived from equation 12. The congestion parameter c_r takes the same value as c. The calibration for a_r and b_r follows the same approach used for calibrating a and b based on the assumption that the maximum speed on residential streets is 30 mph and the minimum is 1 mph.

The critical value of q for each structure type is calibrated to match the average fraction of housing units for each structure type in Chicago. The structure type is single-family detached if $q \in [0, 0.53]$, single-family attached if $q \in [0.53, 0.61]$, 2-4 unit multifamily if $q \in [0.61, 0.79]$, and 5+ unit multifamily when q is above 0.79.

Results from simulating the calibrated model are shown in the final column of Table 2. Overall, the simulated baseline city matches the average characteristics of Chicago quite well. The simulated average commute time to work is 24.19 minutes, which is lower than the 30.7 minutes reported in the American Housing Survey (2010). This discrepancy is due to this model does not take into account the commuting from parking or public transit to workplace or from home to highways.

The solid lines in Figure 3 show that median housing price, median land price, and median structure to land ratio which is the floor area ratio decrease with the distance from the CBD, while median housing demand increases with the distance from the CBD. The solid lines in Figure 4 show the change in median housing price, housing demand, land price, and structure to land ratio by the distance from the nearby public transit stations. Median housing price, land price, and structure density decrease with the distance from the nearest public transit station, while housing consumption increases with the distance from the public transit. These results are consistent with that in the literature.

4 Counterfactual Scenarios and Simulation Results

To simulate the long run effects of Uber, in the first counterfactual design, workers have the option to take Uber to work or take Uber to a nearby public transit station. The simulation results from this counterfactual city are compared to the baseline.

Whether Uber is a complement or substitute to the public transit depends on the quality of transit systems. Although Uber could help transport workers from their home to transit stops, a low quality transit system remains costly and fails to attract more transit users with the entry of Uber. In contrast, with a high quality transit system, Uber makes public transit more accessible and attracts more transit users. To investigate the long run effects of Uber under different public transit systems with different qualities, parameters on public transit speed and average waiting time are altered to simulate both high quality and low quality transit systems.

Furthermore, the impact of public transportation investment on traffic congestion and the environment is a major debate in the literature. Anderson (2014) finds evidence that public transit relives traffic congestion while Winston and Maheshri (2007) show that urban rail transit system is not socially desirable. Will it be more beneficial to expand public transit with the entry of Uber? Will public transit expansion augment Uber's complementary effects on public transit? To simulate the interplay between Uber and public transit expansion, the number of transit lines is increased to represent the expansion.

Chicago has attempted to regulate ride hailing industry. In 2018, the city has been urged to impose a cap on Uber and Lyft cars.[5] This regulation is similar to those enacted in New York City in 2018. To predict the consequences of imposing regulations on Uber, the last experiment is conducted where the city imposes a regulation that limits the number of Uber drivers.

4.1 The Long Run General Equilibrium Effects of Uber

In this counterfactual, Uber enters into the Chicago transportation system. Workers have the option to use the app to book rides to work or a nearby public transit station. After a short period of waiting, which is assumed as 5 minutes in the simulation, Uber drivers arrive and pick up the workers. It is assumed Uber drivers drive through residential streets to the nearby public transit stations. If workers book rides to the CBD, Uber drivers have to drive

[5]https://www.chicagotribune.com/business/ct-biz-chicago-taxi-ride-share-drivers-limit-20181030-story.html

through the highway, which potentially adds highway traffic congestion. The commuting cost for Uber is based on the current Uber fare structure with a base fare of \$3.64 per trip, a cost per mile of \$0.81, and a cost per minute of \$0.28. Because workers could relax and work during Uber rides, the time cost of taking Uber is assumed to be 20% lower than driving solo.

Locations that are further away from transit stations and unaccessible through walking now become accessible by taking Uber to transit stations. As a result, Uber improves the accessibility of public transit. Table 3 shows that it increases public transit usage from 12.42% to 28.32%[6]. While the fraction of population walking to public transit is reduced by 31%, 24.1% of the population start to take Uber to transit stations. The improved accessibility of the public transit creates incentives for households to move closer to the transit stations and the CBD, which increases the housing price and land price near the transit stations and the CBD. Figure 3 shows that the introduction of Uber steepens the housing price and land price gradients. Figure 4 shows that the adoption of Uber increases housing price and land price for areas closer to the public transit stations. As a result, the structure densities near the CBD and the transit stations increase. Table 3 shows that Uber increases median housing price by 0.9%, median land price by 6.26%, and median structure land ratio by 3.96%.

Furthermore, it reduces solo driving by 26.57% and carpooling by 13.41%. 6.39% of the population start to take Uber directly to work. The net effect is that it reduces traffic volume on the highway and increases the commuting speed by 4.66%[7]. Figure 5 shows that Uber effectively reduces highway traffic congestion at each distance from the CBD.

The reduction in highway traffic congestion creates incentives for households to live further away from the CBD, which tends to lead to urban sprawl. However, the improved public transit accessibility attracts workers to live closer to the CBD and transit stations, which tends to lead to city contraction. The net effect is city contraction as shown in Table 3, where the city radius is reduced by 2.79%.

In addition, the commuting energy consumption is decreased by 9.95% and the dwelling energy consumption is reduced by 1.09%. The total energy consumption per household decreases by 0.73%. While the carbon emissions from public transit are more than doubled due to the increased number of passengers, the carbon emissions from driving are reduced

[6] Because this paper does not consider the complementary effect of bus on public transit and the congestion created by non-commuting trips, the estimates could be viewed as a upper bound.

[7] This estimate could be interpreted as a upper bound because the model does not take into account the congestion created by non-commuting Uber trips.

by 14.64%. Overall, the carbon emissions from commuting are reduced by 11.66% and the total carbon emissions per household are decreased by 1.19%.

The aggregate welfare analysis follows Sullivan (1985) and Borck and Brueckner (2016). The entry of Uber leads to a 0.61% increase in each household's utility. The welfare gain experienced by households as a result of the adoption of Uber is calculated based on the compensation variation (CV) associated with the entry of Uber. It is measured by the fall in income required to achieve the same utility level as before Uber is introduced. The model is re-simulated to compute the compensation variation holding households' utility level constant. After Uber is adopted, the compensation variation per household is $55,756, which is $312 less than original wage rate $56,069. Landowners also experience welfare gain due to the adoption of Uber. The welfare gain experienced by landowners is measured by the increase in aggregate land rent. By holding aggregate land area used for the city and agriculture constant with 40 miles radius, aggregated land rent is increased by 6.58%. In addition, externalities generated from carbon emissions is measured by the social cost of carbon emissions. According to Environmental Protection Agency (EPA) in 2015, under a 3% discount rate, the social cost of carbon emissions is $36 per ton. The adoption of Uber reduces externalities by 1.19%. In aggregate, Uber generates a net welfare gain of $1,016 million.

4.2 Low Quality Public Transit Services and Uber

With infrequent trains, delays, and breakdowns, a low quality transit system does not provide reliable services. It is simulated with infrequent services and a slower speed. The average waiting time is increased from the baseline value of 7.5 minutes to 20 minutes and the train speed is decreased from 20 mph to 15 mph.

Compared to the unreliable transit services, Uber has the advantage of being more predictable and flexible to meet consumers' demand. The first three columns in Table 4 show that Uber serves as a substitute to the low quality public transit system. The public transit usage is reduced by 40%. Although Uber could help transport commuters to nearby transit stations, the low quality system remains too costly to attract any workers to take Uber to transit stations. However, taking Uber to work becomes a more appealing commuting option. 9.99% of the population start to use it to work. For traffic congestion, Uber has a negligible effect. The average commuting speed is increased by only 0.61%. Overall, Uber makes public transit less attractive and does not provide any incentives for households to live close to the transit stations or the CBD. It leads to urban sprawl and the city radius is increased by 2.15%.

The reduction in public transit usage and the rise in Uber usage to work increase commuting energy consumption and carbon emissions. Energy consumption increases by 0.61% and carbon emissions rise by 0.15%. Under a low quality transit system, Uber has a small impact on social welfare. The aggregate welfare is only \$80.49 millions.

4.3 High Quality Public Transit Services and Uber

High quality public transit services are reliable, frequent, and fast. European and Asian countries such as China have public transit systems with high speed trains and greater schedule frequency. What if the US were to improve the quality of public transit system? To address the effects of Uber under a high quality public transit system, the average waiting time is decreased from 7.5 minutes to 2 minutes and train speed is increased from 20 mph to 30 mph.

The last three columns in table 4 show that Uber functions as a complement to the public transit. The public transit usage is doubled and increases from 23.68% to 46.18%. 40.5% of the population start to take Uber to nearby transit stations. Only 5.67% of the population take Uber directly to work. The fraction of the population who drive solo decreases from 66.39% to 40.86%. This effectively relieves the traffic congestion on the highway by 6.24%.

In addition, under a higher quality transit system, Uber becomes more effective at preventing urban sprawl and increasing density. The city radius is reduced by 1.26% and the average residential density is increased by 2.57%. Furthermore, it has larger impacts on the environment and carbon emissions. It reduces energy consumption by 1.18% and lowers carbon emissions by 1.9%. The city experiences a significant welfare gain with $\$1,711$ millions.

These results have implications for the heterogeneous effects of Uber on transit usage during weekdays and weekends. When public transit is more frequent during weekdays, Uber helps to attract transit users, while during weekends, when transit service is less reliable and less frequent, Uber attracts commuters away from the public transit.

Overall, under a low quality transit system, Uber reduces public transit trips, while under a high quality transit system, Uber increases public transit riderships. In order to avoid losing transit riders after Uber is adopted, the government needs to improve the quality of the public transit system.

4.4 Public Transit Expansion and Uber

Public transit has been advocated as a way to reduce traffic congestion, although the evidence for the effects of public transit on congestion is mixed in the literature. Public transit investment has been used to improve transit services and attract transit users. Chicago transit authority has proposed several projects to expand public transit services.[8] In this scenario, the public transit investment is used to increase the number of transit lines from 7 to 8.

Table 5 shows that before the entry of Uber, the public transit expansion has little effect on traffic congestion and the environment, although the public transit usage is increased from 12.42% to 14.27%. The average speed on highways is increased by only 0.55%. Total energy consumption is reduced by only 0.09% and carbon emissions is lowered by 0.15% on average. The negligible effect of public transit expansion on traffic congestion is consistent with the findings in Winston and Maheshri (2007), Rubin et al. (1999), Stopher (2004), and Small (2005).

The last three columns in Table 5 show that with the entry of Uber, the effects of increasing transit lines on traffic congestion and environment remain small. The traffic speed is increased by 0.36%, energy consumption is reduced by 0.06%, and carbon emissions is decreased by 0.1%.

Although the expansion does improve the accessibility of public transit, the increase in public transit usage is not significant, which is less than 2%. Overall, the effects of public transit expansion on traffic congestion and the environment is negligible regardless of the presence of Uber. In addition, the expansion does not significantly improve welfare and the welfare gain is smaller with the entry of Uber.

4.5 Imposing Regulation on Uber

Given that several cities such as Chicago have been attempting to regulate Uber, the revelant police questions are: should Uber be regulated? What will be the long run consequences after Uber is regulated? In this counterfactual, the regulation imposes a cap on the number of drivers who can drive for Uber. This is a supply shock to the market of ride hailing transportation services. The reduction in the supply of Uber service eventually leads to an increase in Uber fare. In the simulation, the base fare, cost per minute, and cost per mile increase by 50%.

[8] https://www.transitchicago.com/planning/

Table 6 demonstrates that after the regulation is imposed, due to the increased Uber fare, less people take it to transit stations or workplaces. The public transit usage increases by 105.8% with regulation, compared to 128% increase without any regulation.

Uber becomes less effective at relieving traffic congestion, reducing energy consumption, and lowering carbon emissions. With regulation, traffic congestion decreases by 3.61%, energy consumption is reduced by 0.5%, and carbon emissions is lowered by 0.84%. In comparison, without any regulation, Uber reduces commuting speed by 4.66%, energy consumption by 0.73%, and carbon emissions by 1.19%.

In addition, the aggregate welfare gain, $726 millions, is lower under the regulation than that without any regulation.

5 Conclusion

This paper offers new insights on the long run general equilibrium effects of Uber on our cities by incorporating the new transportation service provided by ride hailing companies, i.e. Uber, and multiple commuting modes into the monocentric city model. Different counterfactual experiments are designed to answer the following policy relevant research questions: how do ride hailing transportation services affect public transit usage and traffic congestion? Will they lead to urban sprawl? How do they affect energy use and carbon emissions? Should cities impose regulations?

The simulation results show that the effects of this new transportation service on the public transit usage depend on the quality of the existing public transit system. Uber increases public transit usage under a high quality transit system while lowers transit ridership under a low quality transit system. It has the potential to reduce urban sprawl, make the city denser, decrease energy consumption and carbon emissions, and enhance welfare. Public transit expansion has little effects on traffic congestion and energy consumption regardless of the entry of Uber. The regulation restricting the supply of ride hailing services increases the commuting cost using Uber, reduces its usage, and limits its beneficial effects.

In addition to offer new insights on the effects of Uber, this paper provides theoretical contributions to the literature. This is the first paper to model households' location based on the distance to the CBD as well as the public transit. It incorporates six different commuting modes with the entry of Uber. The modeling adds remarkable realistic details to describe transportation network and households' commuting choice.

However, several simplification assumptions fail to take into account the effects of ride hailing services on parking usage, the potential endogenous change in the cost structure of taking Uber and surge pricing scheme, the heterogeneous effects of Uber across income groups, and the effects of non-commuting Uber trips on traffic congestion and carbon emissions. All of these assumptions could be relaxed to address different policy questions in the future research.

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Figure 1: The Market Area for Each Transit Line

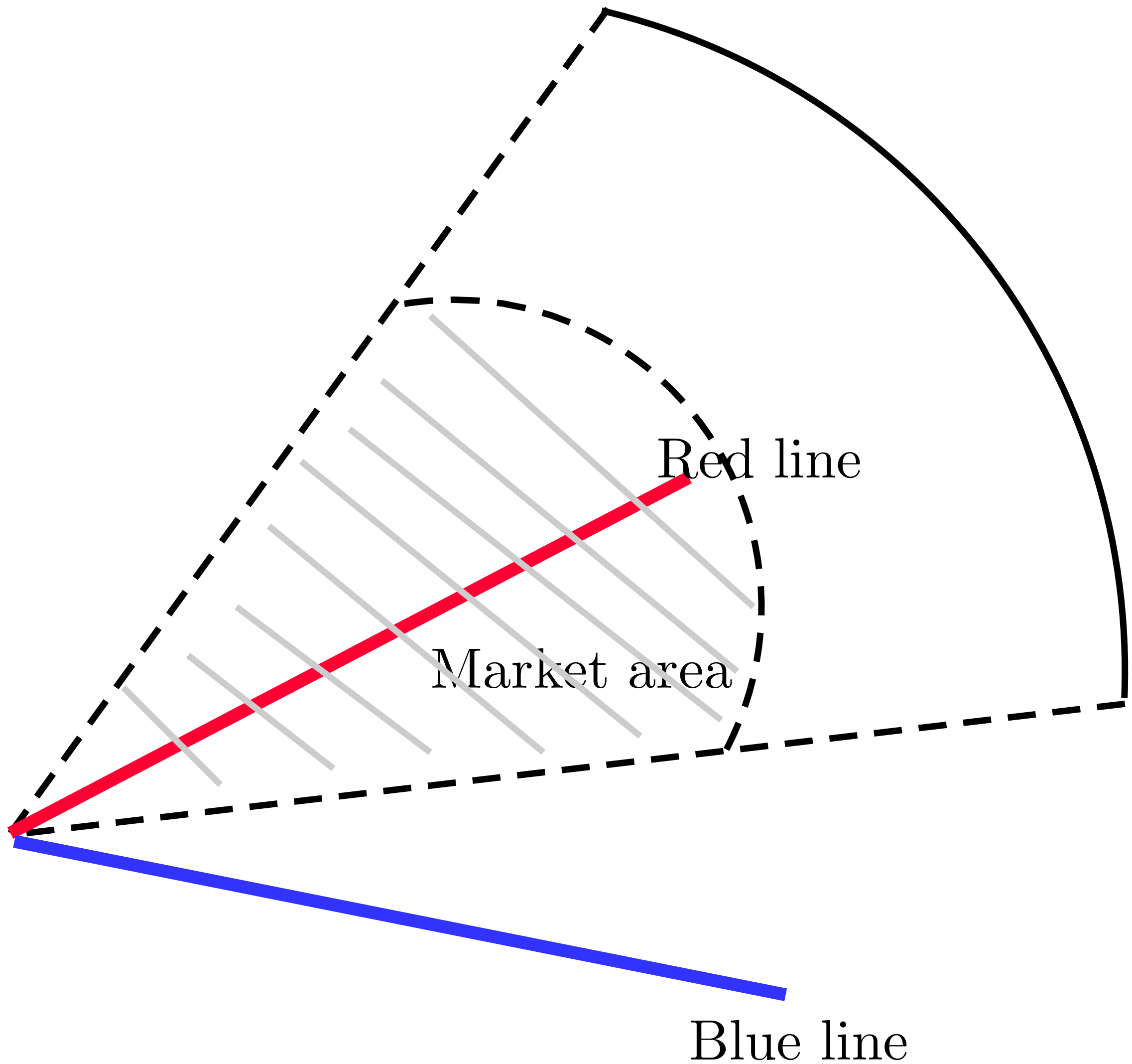
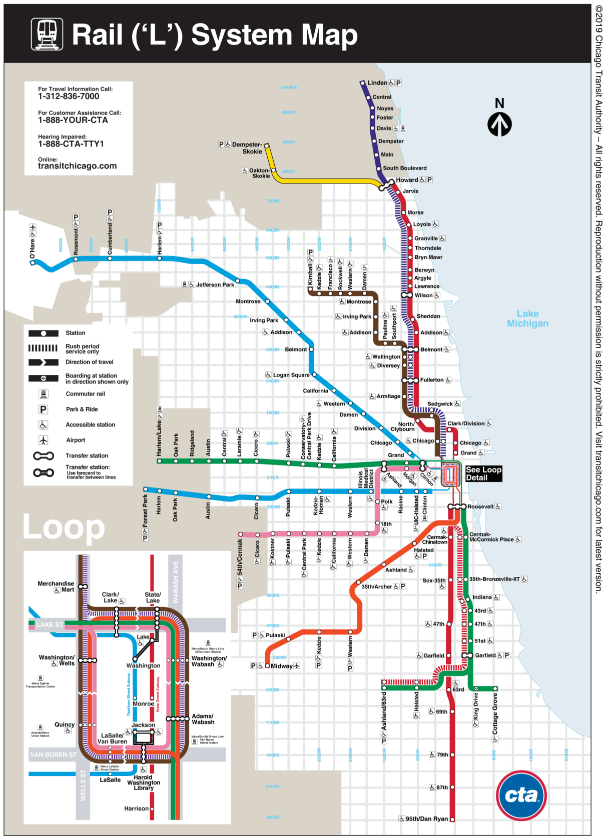


Figure 2: Chicago public transit system, Actual and Simulated

(a) Public Transit Map



(b) Simulated

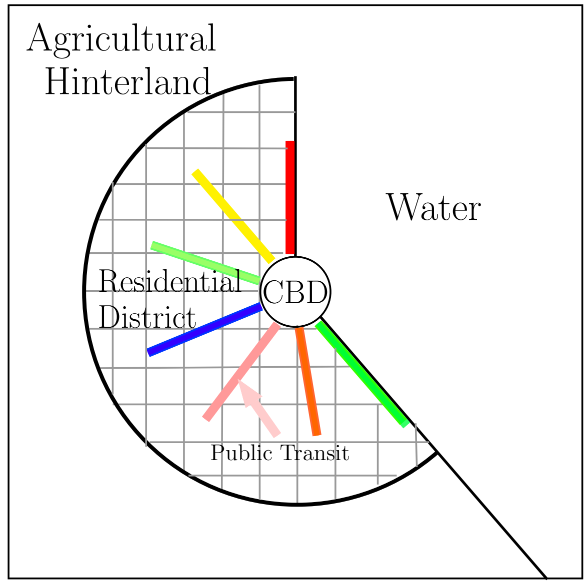


Figure 3: Baseline and Uber Adoption-Urban Form (by Distance from the CBD)

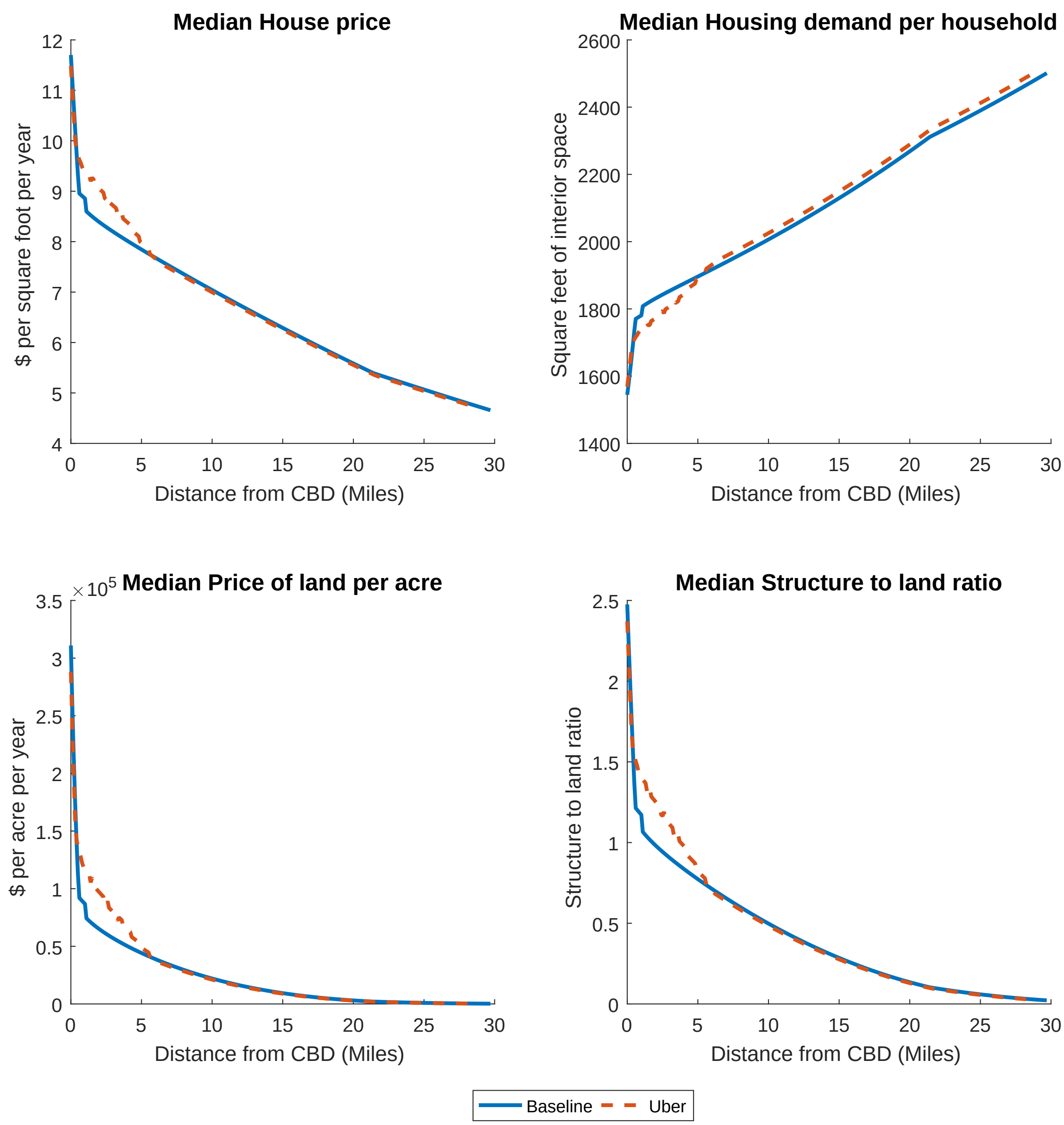


Figure 4: Baseline and Uber Adoption - Urban Form (by Distance from the Public Transit)

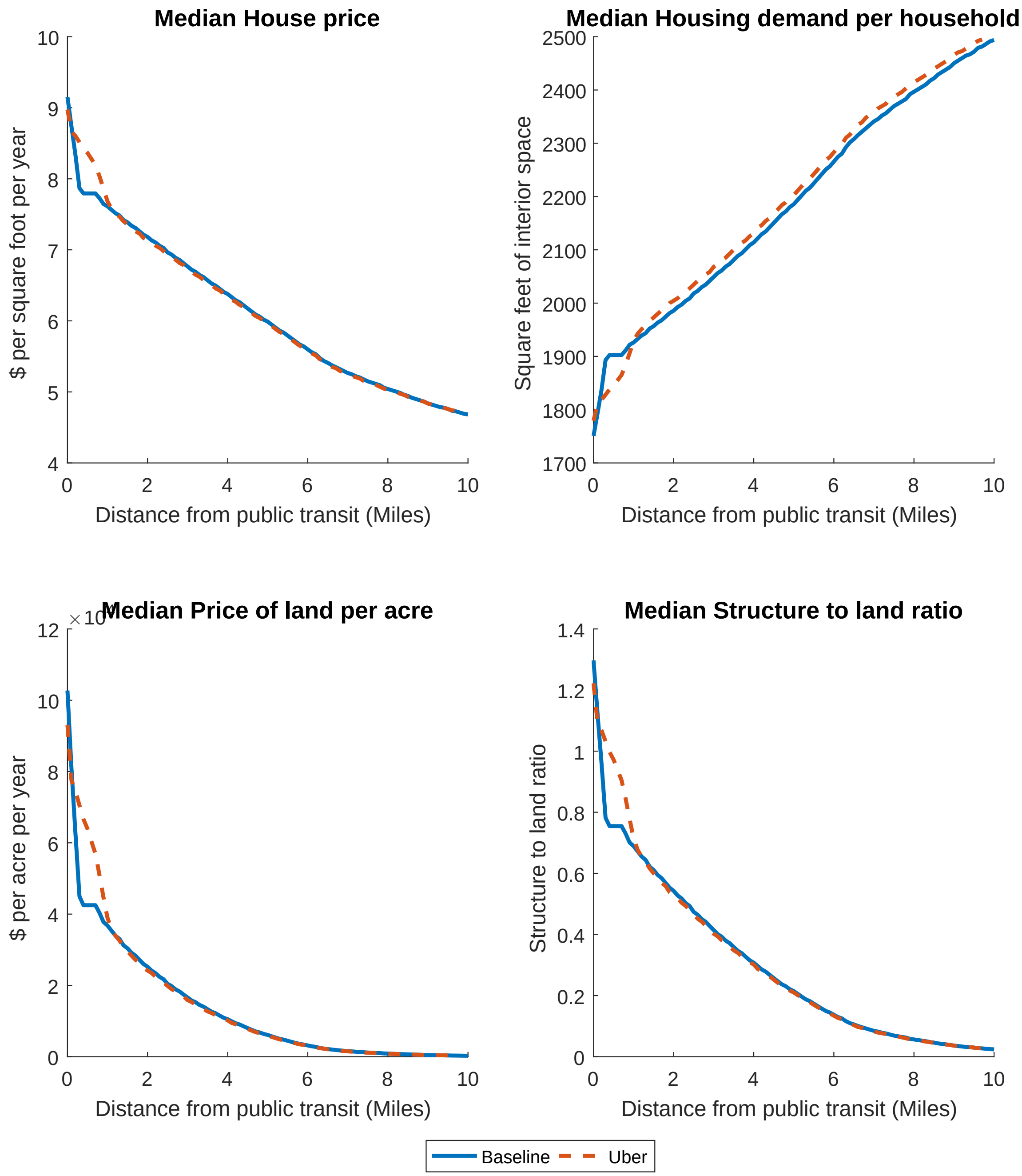


Figure 5: Baseline and Uber Adoption - Traffic Congestion

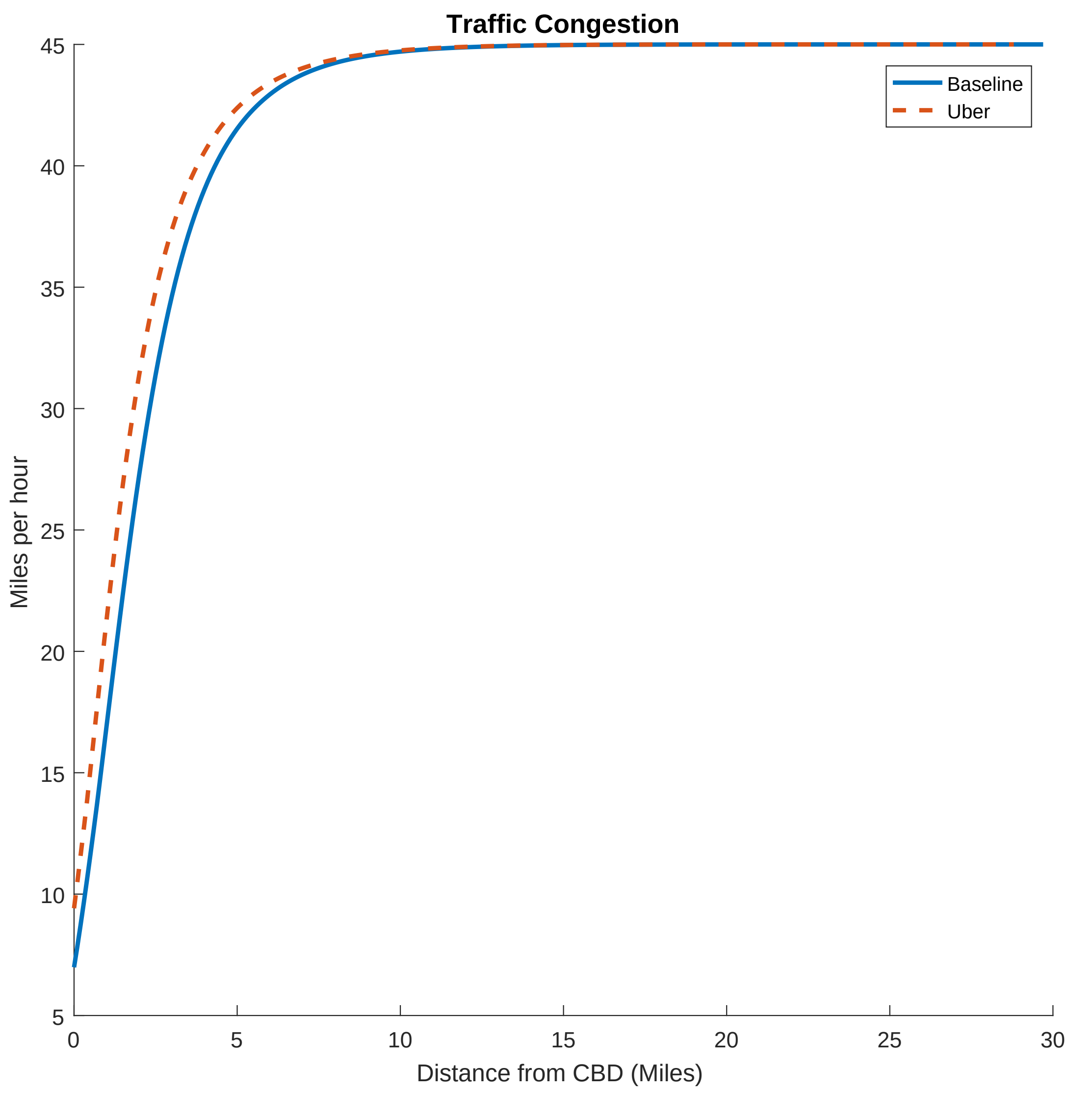


Table 1: Simulation Parameters

Parameter	Baseline Value	Description	Source
City Income and Size			
W	56,069	Annual earnings	American Community Survey(2010)
N	3,012,005	Households	American Community Survey(2010)
Housing Production			
$1/(1-\rho)$	0.75	Elasticity of substitution	Altmann and DeSalvo (1981)
α_1	1	Structure share	Muth (1975); Altmann and DeSalvo (1981)
α_2	0.117	Land share	Calibrated
A	0.265	Technology parameter	Calibrated
Household Utility			
$1/(1-\eta)$	0.75	Elasticity of substitution	Larson et al. (2012)
β_1	1	Numeraire share	Numeraire
β_2	0.168	Housing share	Bureau of Labor Statistics (2010), Calculated
Land Use			
θ	0.46	Fraction of land used for housing	Overman et al. (2008)
k_{CBD}	2.5	Radius of the CBD	Boundaries for the CBD from the City of Chicago Dataset
p_L^a	231.7	Reservation agricultural land rent per acre	2018 Illinois Land Values and Lease Trends
Transportation			
v_{low}	5	Minimum commuting speed	Larson et al. (2012)
v_{high}	45	Maximum commuting speed	Larson et al. (2012)
c	1.75	Parameter in speed function	Larson et al. (2012)
$CBD_{parking}$	8	Daily parking fee in dollar	Web search
τ	0.3	Commuting time cost of driving	Muth (1975)
p_g	2.5	Gasoline price (USD) per gallon	Energy Information Administration
m_0	2,654	Fixed cost of commuting	American Automobile Association
m_1	0.222	USD per mile of depreciation	American Automobile Association
V_c	0.822	Miles per gallon constant term in polynomial	American Automobile Association, Larson et al. (2012)
$publicfare$	2.5	Metro ticket per trip	Chicago Transit Authority
V_{metro}	20	Average metro speed per hour	Chicago Transit Authority
V_{walk}	2.5	Average walking speed	Assumed
awt	7.5	Average waiting time in minutes at the transit station	Chicago Transit Authority
V_{res}^{max}	30	Driving speed limit on residential streets	Statutory speed limit in Chicago
V_{res}^{min}	1	Minimum average speed on residential streets	Assumed
f_0	3.64	Uber basefare	Uber
f_1	0.81	Uber cost per mile	Uber
f_2	0.28	Uber cost per minute	Uber
τ_{uber}	0.24	Time cost of commuting using Uber	Calibrated
τ_w	1.11	Time cost of walking	Calibrated
τ_{pub}	0.5	Time cost of taking public transit	Calibrated
$\tau_{carpool}$	0.767	Time cost of coordinating carpool	Calibrated
$t_{carpool}$	15	Time cost of coordinating carpool in minutes	Calibrated
Energy consumption			
p_e	11.9 cents	Residential electricity price per Kwh	Energy Information Administration (2010)
p_e^p	4.84 cents	Electricity price per passenger mile per Kwh for public transit	Energy Information Administration (2010)
e^p	2,520 Btu	Energy consumption of public transit per passenger mile	Transportation Energy data book (2012)

Table 2: Calibration Simulation

City characteristics	Chicago urbanized area	Simulated characteristics
Total Occupied Units[1]	3,012,005	3,012,589
Median Income[1]	56,069	56,069
Median Lot Size (Acres, 1 unit structure)[2]	0.17	0.15
Median Unit Size[2]	2,000	1997.25
City Radius (miles)[1]	33.56	32.30
Land area (square miles)[1]	2122.8	1954.4
Time to work (Residential Avgerage)[1]	30.7	24.19
Fraction housed in 1 unit structures[1]	58.8%	58.72%
Fraction housed in 2-4 unit structures[1]	14.6%	15.35%
Fraction housed in 5+ unit structures[1]	26.6%	25.93%
Means of transportation to work[1]		
Walked	3.30%	3.06%
Public transportation	12.40%	12.42%
Drove alone	69.40%	75.95%
Carpooled	8.70%	8.57%
Other (Bicycle, motorcycle, taxicab, other means, or worked at home)	6.2%	0.00%

[1] Source: American Community Survey 1 year estimates (2010)

[2] Source: American Housing Survey (2009)

Table 3: The Long Run General Equilibrium Effects of Uber

Scenario	**Baseline**	**Uber**	**%Δ**
Urban Form			
Total Occupied Units	3012589	3011645	
Median Lot Size (acre) – I unit structure	0.15	0.16	1.42%
Median Unit Size (square feet) – All Units	1997.25	1999.99	0.14%
City Area (sq. miles)	1954.40	1846.67	-5.51%
City Radius (assuming circle)	32.30	31.40	-2.79%
Meidan House Price per Sq. Ft.	7.10	7.17	0.90%
Meidan Land Price per Acre	23427.78	24895.13	6.26%
Median Residential Struct./Land ratio	0.52	0.54	3.96%
Residential Density (hh per sq. mile)	1541.14	1630.82	5.82%
Average Commuting Time to work	24.19	25.16	4.01%
Fraction housed in 1 unit structures	58.72%	56.21%	-4.28%
Fraction housed in 2-4 unit structures	15.35%	13.49%	-12.12%
Fraction housed in 5+ unit structures	25.93%	30.30%	16.88%
Fraction of population by Commuting Mode			
Walking	3.06%	2.11%	-31.09%
Public transit	12.42%	28.32%	128.00%
Walking to public transit	12.42%	4.21%	-66.07%
Taking Uber to public transit	0.00%	24.10%	
Solo driving	75.95%	55.76%	-26.57%
Carpooling	8.57%	7.42%	-13.41%
Taking Uber to work	0.00%	6.39%	
Traffic Congestion			
Average speed on highways	38.14	39.91	4.66%
Average speed on residential streets	30.00	12.97	-56.77%
Energy Consumption per Household (million BTUs)			
Total	573.91	569.74	-0.73%
Commuting	34.04	30.65	-9.95%
Dwelling	135.97	134.49	-1.09%
Numeraire	403.90	404.59	0.17%
Carbon Emissions per Household (tons)			
Total	29.28	28.93	-1.19%
Commuting	2.64	2.34	-11.66%
Driving	2.59	2.21	-14.64%
Public transit	0.05	0.12	139.15%
Residential	6.71	6.63	-1.09%
Numeraire	19.92	19.96	0.17%
Welfare			
Wage rate	56069.00	56069.00	0.00%
Utility	11351.77	11420.87	0.61%
Aggregate Welfare Analysis			
Aggregate residential land rent (millions)	313.95	325.26	3.60%
Agriculture land rent (millions)	262.35	288.98	10.15%
Aggregate land rent (millions)	576.31	614.24	6.58%
Compensation variation per household	56069.00	55756.67	-0.56%
Social cost of carbon emissions (millions)	3174.59	3136.95	-1.19%
Aggregate welfare gain (millions)		1016.32	

Table 4: Public Transit Systems with Different Qualities and Uber

Scenario	Baseline	Uber	%Δ	Baseline	Uber	%Δ
	Low Quality			**High Quality**		
Public transit: average waiting time (mins)	**20.00**	**20.00**		**2.00**	**2.00**	
Public transit: speed (mph)	**15.00**	**15.00**		**30.00**	**30.00**	
Urban Form						
Total Occupied Units	3011436	3011689		3012594	3012117	
Median Lot Size (acre) – I unit structure	0.15	0.15	0.32%	0.16	0.16	4.62%
Median Unit Size (square feet) – All Units	1994.23	1996.70	0.12%	1991.97	1978.24	-0.69%
City Area (sq. miles)	1978.75	2065.18	4.37%	1882.24	1834.89	-2.52%
City Radius (assuming circle)	32.50	33.20	2.15%	31.70	31.30	-1.26%
Meidan House Price per Sq. Ft.	7.06	7.06	-0.05%	7.22	7.46	3.32%
Meidan Land Price per Acre	22529	22457	-0.32%	26261	32488	23.71%
Median Residential Struct./Land ratio	0.50	0.50	-0.21%	0.56	0.64	14.47%
Residential Density (hh per sq. mile)	1521.54	1457.81	-4.19%	1600.41	1641.58	2.57%
Average Commuting Time to work	24.92	24.93	0.05%	21.83	22.84	4.66%
Fraction housed in 1 unit structures	60.93%	60.62%	-0.52%	54.53%	47.94%	-12.08%
Fraction housed in 2-4 unit structures	16.42%	16.20%	-1.36%	13.90%	12.56%	-9.64%
Fraction housed in 5+ unit structures	22.64%	23.18%	2.37%	31.57%	39.50%	25.11%
Fraction of population by Commuting Mode						
Walking	3.61%	2.38%	-33.90%	2.64%	1.75%	-33.79%
Public transit	1.60%	0.96%	-40.11%	23.68%	46.18%	95.00%
Walking to public transit	1.60%	0.96%	-40.11%	23.68%	5.64%	-76.20%
Taking Uber to public transit	0.00%	0.00%		0.00%	40.54%	
Solo driving	85.43%	77.29%	-9.53%	66.39%	40.86%	-38.45%
Carpooling	9.36%	9.38%	0.17%	7.28%	5.53%	-24.01%
Taking Uber to work	0.00%	9.99%		0.00%	5.67%	
Traffic Congestion						
Average speed on highways	36.96	37.19	0.61%	39.30	41.76	6.24%
Average speed on residential streets	30.00	30.00	0.00%	30.00	8.28	-72.40%
Energy Consumption per Household (million BTUs)						
Total	577.39	577.95	0.10%	569.16	562.44	-1.18%
Commuting	36.83	37.41	1.57%	30.83	26.01	-15.62%
Dwelling	137.12	136.93	-0.14%	133.84	130.95	-2.16%
Numeraire	403.44	403.62	0.04%	404.49	405.48	0.25%
Carbon Emissions per Household (tons)						
Total	29.56	29.60	0.15%	28.91	28.36	-1.90%
Commuting	2.89	2.94	1.58%	2.35	1.89	-19.40%
Driving	2.89	2.94	1.60%	2.23	1.64	-26.32%
Public transit	0.00	0.00	-20.23%	0.12	0.25	105.43%
Residential	6.76	6.75	-0.14%	6.60	6.46	-2.16%
Numeraire	19.90	19.91	0.04%	19.95	20.00	0.25%
Welfare						
Wage rate	56069	56069.00	0.00%	56069.00	56069.00	0.00%
Utility	11300.79	11311.99	0.10%	11422.62	11539.30	1.02%
Aggregate Welfare Analysis						
Aggregate residential land rent (millions)	305.20	308.32	1.02%	330.14	346.51	4.96%
Agriculture land rent (millions)	256.34	234.98	-8.33%	280.19	291.89	4.18%
Aggregate land rent (millions)	561.54	543.30	-3.25%	610.32	638.40	4.60%
Compensation variation per household	56069.00	56034.60	-0.06%	56069.00	55529.91	-0.96%
Social cost of carbon emissions (millions)	3205.17	3210.05	0.15%	3134.35	3074.76	-1.90%
Aggregate welfare gain (millions)		80.49			1711.40	

Table 5: Public Transit Expansion and Uber

Scenario	Baseline	Baseline	%Δ	Uber	Uber	%Δ
Number of Public transit lines	**7.00**	**8.00**		**7.00**	**8.00**	
Urban Form						
Total Occupied Units	3012589	3012585.72		3011645	3012161.20	
Median Lot Size (acre) – I unit structure	0.154	0.15	-0.68%	0.16	0.15	-0.84%
Median Unit Size (square feet) – All Units	1997.25	1997.59	0.02%	1999.99	1999.50	-0.02%
City Area (sq. miles)	1954.40	1954.40	0.00%	1846.67	1858.49	0.64%
City Radius (assuming circle)	32.30	32.30	0.00%	31.40	31.50	0.32%
Meidan House Price per Sq. Ft.	7.10	7.11	0.12%	7.17	7.18	0.14%
Meidan Land Price per Acre	23427.78	23616.21	0.80%	24895.13	25131.04	0.95%
Median Residential Struct./Land ratio	0.52	0.52	0.51%	0.54	0.54	0.60%
Residential Density (hh per sq. mile)	1541.14	1541.14	0.00%	1630.82	1620.69	-0.62%
Average Commuting Time to work	24.19	24.12	-0.30%	25.16	25.22	0.24%
Fraction housed in 1 unit structures	58.72%	58.67%	-0.09%	56.21%	56.29%	0.15%
Fraction housed in 2-4 unit structures	15.35%	15.13%	-1.42%	13.49%	13.24%	-1.86%
Fraction housed in 5+ unit structures	25.93%	26.20%	1.04%	30.30%	30.47%	0.55%
Fraction of population by Commuting Mode						
Walking	3.06%	3.04%	-0.73%	2.11%	2.15%	1.96%
Public transit	12.42%	14.27%	14.87%	28.32%	29.44%	3.98%
Walking to public transit	12.42%	14.27%	14.87%	4.21%	4.88%	15.91%
Taking Uber to public transit	0.00%	0.00%		24.10%	24.56%	1.89%
Solo driving	75.95%	74.22%	-2.28%	55.76%	54.87%	-1.60%
Carpooling	8.57%	8.47%	-1.13%	7.42%	7.41%	-0.20%
Taking Uber to work	0.00%	0.00%		6.39%	6.13%	-4.07%
Traffic Congestion						
Average speed on highways	38.14	38.35	0.55%	39.91	40.05	0.36%
Average speed on residential streets	30.00	30.00	0.00%	12.97	12.03	-7.23%
Energy Consumption per Household (million BTUs)						
Total	573.91	573.39	-0.09%	569.74	569.41	-0.06%
Commuting	34.04	33.57	-1.37%	30.65	30.36	-0.96%
Dwelling	135.97	135.85	-0.09%	134.49	134.43	-0.05%
Numeraire	403.90	403.97	0.02%	404.59	404.63	0.01%
Carbon Emissions per Household (tons)						
Total	29.28	29.23	-0.15%	28.93	28.90	-0.10%
Commuting	2.64	2.60	-1.56%	2.34	2.31	-1.12%
Driving	2.59	2.55	-1.87%	2.21	2.18	-1.41%
Public transit	0.05	0.06	14.50%	0.12	0.13	4.19%
Residential	6.71	6.70	-0.09%	6.63	6.63	-0.05%
Numeraire	19.92	19.93	0.02%	19.96	19.96	0.01%
Welfare						
Wage rate	56069.00	56069.00		56069.00	56069.00	
Utility	11351.77	11360.74	0.08%	11420.87	11426.41	0.05%
Aggregate Welfare Analysis						
Aggregate residential land rent (millions)	313.95	270.28	-13.91%	325.26	279.41	-14.10%
Agriculture land rent (millions)	262.35	262.35	0.00%	288.98	286.06	-1.01%
Aggregate land rent (millions)	576.31	532.64	-7.58%	614.24	565.46	-7.94%
Compensation variation per household	56069.00	56028.00	-0.07%	56069.00	56041.76	-0.05%
Social cost of carbon emissions (millions)	3174.59	3169.84	-0.15%	3136.95	3133.96	-0.10%
Aggregate welfare gain (millions)		84.58			36.27	

Table 6: The Long Run General Equilibrium Effects of Uber Regulations

Scenario	Baseline	Uber	%Δ	Uber	%Δ
		Unregulated		**Uber regulation: increases Uber fare**	
Uber fare: Base fare	3.64	3.64	3.64	5.46	5.46
Uber fare: cost per min	0.28	0.28	0.28	0.42	0.42
Uber fare: cost per mile	0.81	0.81	0.81	1.22	1.22
		Urban Form			
Total Occupied Units	3012589	3011645		3012130	
Median Lot Size (acre) – I unit structure	0.15	0.16	1.42%	0.16	1.09%
Median Unit Size (square feet) – All Units	1997.25	1999.99	0.14%	2000.23	0.15%
City Area (sq. miles)	1954.40	1846.67	-5.51%	1966.56	0.62%
City Radius (assuming circle)	32.30	31.40	-2.79%	32.40	0.31%
Meidan House Price per Sq. Ft.	7.10	7.17	0.90%	7.14	0.50%
Meidan Land Price per Acre	23427.78	24895.13	6.26%	24244.39	3.49%
Median Residential Struct./Land ratio	0.52	0.54	3.96%	0.53	2.22%
Residential Density (hh per sq. mile)	1541.14	1630.82	5.82%	1531.36	-0.64%
Average Commuting Time to work	24.19	25.16	4.01%	24.99	3.31%
Fraction housed in 1 unit structures	58.72%	56.21%	-4.28%	57.57%	-1.96%
Fraction housed in 2-4 unit structures	15.35%	13.49%	-12.12%	14.22%	-7.37%
Fraction housed in 5+ unit structures	25.93%	30.30%	16.88%	28.21%	8.81%
		Fraction of population by Commuting Mode			
Walking	3.06%	2.11%	-31.09%	2.58%	-15.85%
Public transit	12.42%	28.32%	128.00%	25.56%	105.81%
Walking to public transit	12.42%	4.21%	-66.07%	4.32%	-65.20%
Taking Uber to public transit	0.00%	24.10%		21.24%	
Solo driving	75.95%	55.76%	-26.57%	63.75%	-16.06%
Carpooling	8.57%	7.42%	-13.41%	8.11%	-5.37%
Taking Uber to work	0.00%	6.39%		0.00%	
		Traffic Congestion			
Average speed on highways	38.14	39.91	4.66%	39.52	3.61%
Average speed on residential streets	30.00	12.97	-56.77%	13.91	-53.65%
		Energy Consumption per Household (million BTUs)			
Total	573.91	569.74	-0.73%	571.02	-0.50%
Commuting	34.04	30.65	-9.95%	31.45	-7.61%
Dwelling	135.97	134.49	-1.09%	135.28	-0.51%
Numeraire	403.90	404.59	0.17%	404.29	0.10%
		Carbon Emissions per Household (tons)			
Total	29.28	28.93	-1.19%	29.03	-0.84%
Commuting	2.64	2.34	-11.66%	2.41	-8.78%
Driving	2.59	2.21	-14.64%	2.31	-10.82%
Public transit	0.05	0.12	139.15%	0.10	94.53%
Residential	6.71	6.63	-1.09%	6.67	-0.51%
Numeraire	19.92	19.96	0.17%	19.94	0.10%
		Welfare			
Wage rate	56069.00	56069.00	0.00%	56069.00	0.00%
Utility	11351.7744	11420.87	0.61%	11398.79	0.41%
		Aggregate Welfare Analysis			
Aggregate residential land rent (millions)	313.95	325.26	3.60%	319.20	1.67%
Agriculture land rent (millions)	262.35	288.98	10.15%	259.35	-1.15%
Aggregate land rent (millions)	576.31	614.24	6.58%	578.55	0.39%
Compensation variation per household	56069.00	55756.67	-0.56%	55837.57	-0.41%
Social cost of carbon emissions (millions)	3174.59	3136.95	-1.19%	3147.82	-0.84%
Aggregate welfare gain (millions)		1016.32		726.09	