# Taxing Uber

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**Abstract**

Transportation network companies (TNCs) such as Uber and Lyft create new challenges for local governments that finance public transit, but they also create new opportunities for cities to generate tax revenue. To shed light on the effect of taxing Uber, we adapt the monocentric city model to include multiple endogenously chosen transportation modes, including ride-hailing applications. We show that most tax and spending programs that cities have currently adopted only mildly increase transit usage. However, our model predicts significant increases in public transit ridership when TNCs are subsidized as a "last-mile" service. If designed correctly, these targeted subsidies more than half as effective at increasing road speed as the optimal congestion toll. Our model indicates that Uber and public transit are currently substitutes, but with sufficiently targeted subsidy policies, Uber and public transit can become complementary services. If cities seek to increase transit ridership, taxes on TNCs — even if earmarked for transit improvements — are not the optimal policy.

JEL: C60, H25, H71, L88, L98, R41, R51

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# 1 Introduction

Ride-hailing applications (aps) or transportation network companies (TNCs), including Uber, Lyft and Via, have revolutionized transportation in cities around the world. While the effect of these platforms on the labor market, public transportation, and pricing strategies are well-studied,[1] the effect of TNCs on government finances as well as expenditures on related public services such as public transportation remain completely unknown. Taxing Uber or changing expenditures on related services such as public infrastructure and transit, will affect the transit choices of individuals, possibly altering the business models of these platforms, and in the long-run, will affect urban form.[2] Given many policymakers have argued that ride-hailing aps lead to added congestion within city limits,[3] government regulations and policies are critical tools to alter the urban transit choice landscape. In this paper, we study various policy options discussed in cities around the world related to the taxation of ride-hailing aps, as well as changes in government spending on possibly complementary or substitute modes of transit such as buses or subways.[4]

Given the recent surge in the popularity of TNCs,[5] they pose many challenges for policymakers including how to update antiquated regulatory regimes and tax systems to deal with platform marketplaces. Furthermore, many cities are concerned about how to deal with pollution emissions from additional "idle" driving to pick up riders. Despite these challenges, many policymakers view TNCs as an attractive source of revenue, even though, absent policy reforms, they often escape sales taxation due to outdated sales tax laws not taxing new digital products and services. However, many states and cities have very recently reformed their tax laws to raise revenue from the services provided by ride-hailing aps. The motives for these new taxes vary from expanding the sales tax base as consumption shifts from retail sales to more intangible products and services,[6] seeking a way to raise revenue that can be

[1]See Chen et al. (2019), Angrist et al. (2017), Cramer and Krueger (2016), Hall et al. (2019), Hall and Krueger (2018), Berger et al. (2018) and Cohen et al. (2016). For a literature on alternative work arrangements, see Katz and Krueger (2019b,a), Jackson et al. (2017), and Garin et al. (2020).

[2]A recent Forum in the *National Tax Journal* highlights the role of autonomous vehicles on governments (Fox 2020; Fisher 2020; Clark 2020).

[3]Erhardt et al. (2019) find that Uber significantly contributed to congestion and delays in San Francisco.

[4]Hall et al. (2018) show that Uber is a complement to public transit.

[5]About a third of Americans have used aps like Uber and Lyft for rides. Even in 2016, TNCs were 15% of all intra-San Francisco vehicle trips. In 2018 alone, more than 100 million rides originated or ended in Chicago for a total of over 600 million miles. Moreover, data from the American Community Survey shows a rise of the "taxi, motorcycle, or other" category of commuting to work, which has increased over 15% in the United States from 2010 to 2018. Much of this increase is attributed to ride-hailing aps that became very popular in 2015. In many large cities, Uber Commute allows commuters to regularly share rides with neighbors or colleagues.

[6]This fits in a broader debate of how tax systems should evolve in the presence of technological change. For example Thuemmel (2018) considers the income tax treatment of robots in the labor market.

earmarked to fund public infrastructure or public transit, or, often due to political economy reasons, to help level the playing field for traditionally higher-cost taxis. Although objecting to many taxes currently in place, Uber has advocated for taxes, such as congestion taxes, that treat all modes of driving equally from a tax purpose. At the same time that some cities are taxing TNCs, other cities are subsidizing them as a means of improving the mobility and employment opportunities of low-income houses or, in less dense cities, as a way to provide "last-mile" services for individuals to get from their house to the closest public transit station. Little is known about the effect of taxes and subsidies on TNCs; we fill this void.

In the long run, TNCs and autonomous vehicles may improve quality of life by lowering costs of transportation. These lower costs affect the resources available, result in changes in the dominant mode of transit, and may shape the urban form of America's cities. The continued expansion of TNCs may threaten publicly provided transportation networks but may also complement them in a public-private partnership. Despite the critical need to know the cross-price elasticity of various models of transit, little is known about the cross-price elasticity between Uber and public transit. We shed light on each of these channels by showing how counterfactual subnational tax and spending policies on TNCs and related services influence modal choice and the long run development of cities.

While the literature on consumption taxes, taxes on externality producing goods and services, and commodity taxes is well-developed, the taxation of TNCs poses challenges not traditionally found in standard (pre-digital economy) products. First, TNCs and thus taxation of TNCs will affect modes of transportation, land use, and public infrastructure investment (Larson and Zhao 2020). As a result, these taxes will have important general equilibrium effects and standard partial equilibrium models or reduced form empirical analysis within public finance are not sufficient to determine the long-run effect of taxing TNCs. Second, TNCs are a platform. The business model of platforms, like Uber, Facebook and Google, Amazon (market-place) is based on connecting two interdependent groups. For the case of Uber, a drivers' valuation of Uber increases the more passengers are active on the platform because their earnings opportunities increases. Likewise passengers' valuation of Uber increases the more drivers are active because their waiting time decreases. Taxes in this network setting can have important and non-standard effects. Despite the growth of platforms, their taxation remains understudied (Kind et al. 2008; Koethenbuerger 2020).[7]

Against this backdrop, we ask (and answer) several questions. First, how does taxing

[7]See D'Annunzio et al. (2020) for an example of taxation in industries that levy mutli-part tariffs, such as internet service providers, energy suppliers, and platforms. A large literature on platforms exists in industrial organization – see Aoyagi and Yoo 2020 – but this literature does not usually focus on taxation.

platforms like Uber affect welfare? Second, what effect does taxing TNCs have on the network of driver labor supply, ridership, and the mode of choice to get to work? Third, what is the "optimal" way for cities to tax TNCs? Finally, as taxes are used to finance public services, does the answer to each of these questions depend on whether the tax revenue is used finance transportation services or not?

To consider the normative question of the optimal policy with respect to TNCs, we consider several different policies debated by cities: flat unit taxes per ride, ad valorem sales tax rates applied to rides, subsidies on rides to and from a public transport stations,[8] and congestion pricing policies. For each tax policy we consider, we allow the government to use the revenue raised to finance various services: lump-sum rebates to residents, reductions in the fares for public transportation, and improving the quality of public transportation. Given many of these policies were implemented only months ago and data are not yet readily available, we simulate a model of an urban area. The simulation approach comes with the advantage of being able to shed light on the long term effects of these policies. Given the proliferation of these policies, these initial general equilibrium results are essential to helping cities find appropriate policies for the future.

Given difficulties in empirical estimation, in order to study the general equilibrium effects of tax policy, we extend the standard monocentric city model to allow for various transportation modes. Focusing on commuting allows us to use the structure of the monocentric city model. The monocentric city model was initially developed by Alonso (1964), Mills (1967), and Muth (1969). Thus far, it has been generalized and used extensively to study different policies and new transportation technologies that affect transportation costs, land use, energy use, and interstate commuting (Larson et al. (2012), Larson and Zhao 2020, Rappaport 2016, Wheaton 1998, Wildasin 1985, Agrawal and Hoyt 2018). Borck and Brueckner (2018) apply the monocentric city model to study the effects of optimal energy taxation. Bertaud and Brueckner (2005) analyze the impact of building height restrictions using the monocentric city model.

Although some models of the monocentric city include transit choice (e.g., Arnott and MacKinnon (1977); Anas and Moses (1979); Sasaki (1989); Sasaki (1990)), these models are limited in their applicability. In particular, these models only have two transport mode choices and ignore heterogeneity in distance to transit lines. We extend the monocentric city model to have multiple transport choices and consumer heterogeneity in the proximity of transit states, making the model realistic for our setting but also tractable for other

[8]For the literature on transit subsidies, see Parry and Small (2009) and Basso and Silva (2014). Other studies that have analyzed the effect of cars or car policies, include Kopecky and Suen (2010), Gutiérrez-i-Puigarnau and van Ommeren (2011), and Xiao et al. (2017).

researchers.

In our model, TNCs can be used for two choices: as a means of transportation directly to work – enabling the individual to avoid high parking fees in the central business district – or as a means of transportation to the nearest public transit station. The model allows for endogenous transit choices in addition to household locations and thus distances to work. We modify the model to feature a labor market for Uber drivers. The model necessarily makes several assumptions to focus on key aspects of policy. One critical assumption is that we focus on Uber as a means of transportation to work rather than for every-day "random" trips. This simplification is made for several reasons. First, Uber specifically targets becoming a reliable source for commuters as one of its long run goals as a ride-hailing service. Second, the policy debate has focused on Uber as a substitute for public transit, for which travel to work is an extremely important component. Indeed, in cities that have proposed Uber subsidies, many explicitly justify Uber as a "last-mile" service for people to get to and from work by public transportation. Third, the spatial structure of the monocentric city is likely to be most important for commuting rather than for ad hoc travel to shops or other small tasks; for these latter trips, agglomeration and city centers are less important, which implies the spatial path of these trips is likely to be more random and thus harder to quantify. Nonetheless, if these other non-random trips occur to points of agglomeration, like retail shopping centers or nightlife districts, we can view these points as analogous to our CBD and would expect qualitatively similar results.

The model must be solved numerically. Therefore, we calibrate this model to a large U.S. city – Chicago. Large cities such as Chicago are the most likely to pass specific taxes on TNCs and are most likely to face a tradeoff between TNCs are public transit modes. We first study the equilibrium without any taxes on Uber and then subsequently introduce various tax policies with tax revenue being used to finance various city services. Given we conduct our simulations for a model of the Chicago urban area, in this way, the results may generalize to large urban areas, but more study is necessary to determine the impacts in smaller areas where the "last-mile" from public transport may be even more critical than we already find it to be even in a large city like Chicago. Rather than focusing on many different city sizes, we have elected to focus on many different policies, such that the largest urban areas will have the most comprehensive information available to them.

We have several findings that are applicable for large cities. The first set of results concern taxes on Uber as they are implemented in most cities – unit taxes or sales taxes. First, taxes on all Uber rides regardless of their destination have the expected effect of decreasing Uber usage. Although cities have argued that these taxes reduce congestion on the roadways and encourage public transit usage, our model suggests that most of the substitution away from

Uber is toward solo driving. Increases in public transit usage are mild and reductions of congestion externalities are almost non-existent. Taxing Uber also prevents it from being a reasonable source of a "last-mile" service for individuals that need to get from their home to public transit. Second, at the margin, what the tax revenue is used for matters for what mode of transit individuals substitute toward after being taxed. If the goal of cities is to increase transit usage, taxes on Uber that fund fare reductions are more successful than increasing spending on transit frequency improvements. Intuitively, transit improvements are extremely expensive and the revenue raised from these taxes cannot sufficiently change transit quality. However, even with targeted spending on public transit, most of the substitution away from using Uber is toward solo driving and reductions of congestion externalities are minimal.

The second set of results focuses on transit proposals adopted in a limited number of cities that aim at forming a public-private partnership between TNCs and public transportation. First, we show that subsidies on Uber rides (to transit stations only) are an effective way of increasing public transit usage. Indeed, a three dollar subsidy for all rides to and from public transit, increases the usage of public transportation by 50%. Even though these subsidies reduce the number of people that take Uber directly to work, total ridership on Uber increases because households use it as a "last-mile" service. The implication of this is that if cities enact the appropriate policies to make last mile service by Uber viable, then, Uber is a complement to public transportation. If cities enact policies, such as flat taxes on Uber that are then spent on subsidizing transit, then Uber and public transit are substitutes: Uber remains too costly to act as a last mile provider. Overall, we estimate the cross-price elasticity of taking public transit to work with respect to the price of taking Uber to work as 0.30 when cities tax Uber and the cross-price elasticity of total Uber ridership with respect to transit prices as -0.21 when cities enact policies that facilitate the link between transit and Uber.

Lastly, we consider the use of optimal congestion tolls (Hall 2018, 2020; van den Berg and Verhoef 2011). Many cities see this as a viable policy because TNCs are likely to be more supportive of a policy that treats all drivers (solo, carpool, TNCs, taxis, etc.) in the same manner. While the optimal congestion toll does not increase transit usage as much as Uber subsidies, using the optimal congestion toll to fund fare reductions is effective at encouraging transit usage and reducing congestion externalities. However, we show that suboptimal tolls – implemented to raise the same amount of revenue as the flat tax on Uber rides in the city of Chicago – results in smaller increases in transit usage and driving speeds than taxing Uber directly. This suggests that if cities are worried about Uber causing too much congestion on roadways, taxing Uber may be a better way to reduce congestion externalities.

We conclude that taxes specifically on Uber are sub-optimal for a variety of welfare criterion. Subsidies for targeted Uber rides to public transit and congestion tolls are extremely effective at increasing transit use and thus reducing negative externalities. Moreover, in the case of taxes and tolls, how cities use the revenue is critical. TNCs create many challenges and opportunities for cities; our paper provides some of the first policy guidance for how cities must adapt to the increasingly important use of TNCs.

# 2 Institutional Details

In this paper, we focus on a large metropolitan area: Chicago. In January 2018, the city of Chicago passed a \$0.67 per trip tax on ride-hailing services in the city of Chicago. In January 2020, these surcharges increased to \$1.25 per ride, with slightly lower unit taxes for shared rides. The city has pledged to use (part of) the revenue generated from the taxes to improve the public transportation system in the city. These unit taxes represent some of the highest ride-hailing fees in the country. While Chicago uses a flat fee for most rides, and many other cities also follow this model, other options have been considered by Chicago and other states and cities. Here, we review these alternative policy options.

Chicago is not alone in its unit tax per trip, though the amount of the tax differs substantially across cities. For example, Seattle featured a \$0.24 per trip tax on rides originating in the city, while New York City has taxes of \$2.75 on each ride, with reductions to \$0.75 for pooled rides. The state of Connecticut and Massachusetts also have taxes set on a per ride basis. The amount devoted to improving public transportation varies by city with New York City earmarking 100% of the revenue to the Metropolitan Transportation Authority, but with the state of Connecticut depositing all revenue into the General Fund.

Other cities and states have elected to levy state and local sales taxes on the total fare of an Uber ride. In New York City, in addition to the flat unit tax, the state and local sales tax (8.875%) is also assessed, but unlike the fee, most of the revenue goes to the general fund. Other states and localities do not levy the sales tax rate, but rather have a specific ad valorem tax that applies to ride-hailing apps. These rates range from 1.4% in Philadelphia to much higher amounts. In the case of many of these taxes, cities and states differ in their implementation, including whether they apply uniformly to both ride-hailing aps and taxis.

Finally, other cities have taken the opposite approach of taxing TNCs and are instead providing subsidies for riders. This approach is most common in smaller cities that have lower density. The rational for the subsidy is as follows: TNCs act as the "last-mile" provider for individuals wishing to take public transportation. Especially in low density areas, it is not cost effective for cities to have a high density transportation network. Instead, these cities often have infrequent and low density transportation services. Cities view companies like

Uber as a way for low income households to get from their home to city bus lines in order to take the bus to work. However, Uber is prohibitively costly for many low-income households. These subsidies are now becoming more common in large urban areas as well. One urban area that has extensively used subsidies is the Pinellas Suncoast Transit Authority (PSTA), which services 15 million riders per year using a fleet of 210 vehicles. The PSTA partnered with Uber to create designated stops and allows subsidies on rides within a fifteen square mile area of those stops. Then, for rides starting in the zone and starting or ending at a designated stop during daytime hours, the PSTA subsidizes the ride by 50% up to a maximum of $3. The PTSA also provides free TNC rides (up to 23 rides per month) for low income qualifying riders between 9 pm and 6 am. For a larger city with a public-private partnership, San Diego has partnered with Uber to provide $5 off UberPool trips during conferences or large sporting events. In Philadelphia, the Southeastern Pennsylvania Transportation Authority discounts rides by 40% and up to $10 per ride for rides to and from suburban rail stations.

The debate between taxes or subsidies for TNCs is influenced by whether TNCs are a complement or substitute for public transportation. Hall et al. (2018) finds that Uber is a complement. Those cities that view Uber as a complement are likely to implement policies that encourage its use, especially if these policies can be targeted to transit ridership. Under the view that these two modes of transportation are substitutes, then the optimal policy can never be a subsidy and cities have taxed Uber to discourage negative externalities from congestion, including from idle driving, and environmental externalties. However, externalities cannot likely be the sole motive. To see this, assume that the only externalties were congestion externalities. Then, the optimal toll is unlikely to be a fixed fee or a fixed percentage, but rather it should vary by time of day or the duration of the trip. Against this backdrop, Uber has also lobbied for policies that treat taxis, TNCs and other modes of diving equally – one example could be an optimal congestion toll. Despite Uber advocating for uniform policies, many Uber related taxes have been driven by political economy concerns, resulting from, for example, a desire to keep a level playing field between TNCs and taxis.

# 3 Model Structure

In order to model the general equilibrium effects of tax policy, we construct a baseline model which produces solutions that represent a present-day city before ride hailing services are introduced. 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. While many models of the monocentric city can be solved analytically, the complexity of extending the baseline model to include public transportation, ride-hailing, and tax policy requires the model be solved numerically. We assume a closed city model 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 due to city-wide tax policies. The goal of the numerical simulation models of the monocentric city model is to calibrate it to a real-world city and then change the model's parameters to produce general equilibrium comparative statics. We first describe the general setup of the model and then subsequently explain how we calibrating it to a given present-day city.

## 3.1 Theoretical Framework

The model sets an exogenous wage rate (or income) and a fixed population size. Utility is endogenous and allowed to vary under different policy scenarios. 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 a residential district between the CBD edge and city boundary. The city boundary is determined endogenously by the reservation rent of agricultural land. A households' location decision is characterized by a multi-dimensional vector given by the distance to the CBD and the distance to the nearest transit stations. Land and housing prices vary across locations so that in equilibrium, households are indifferent across all locations within the city.

### 3.1.1 The Central Business District

All employment is concentrated in the CBD, which is a point at the center of the monocentric circle. Because this is a closed city model, total employment in the CBD is unchanged and hence the size 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.

### 3.1.2 Land Use

Urban land use is divided among highways, residential streets, residential housing, and other uses (public transit, parks, schools, etc.). It is assumed that a constant fraction, $\theta_R$, of land area is allocated to highway, $\theta_s$, of land area is allocated to residential streets, a fixed proportion, $\theta$, of land is 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 that follow along the circumference of each radius. The radial highway lines are identical and cover the entire city such that each house is next to a given highway. The length of residential streets is determined at each radius. Residential roads are used to get to the transit lines. The rail lines are evenly distributed, i.e. the distance between transit lines is equal at a given annulus $k$. Each rail line offers a radial route that links the CBD with residential locations. Stops are located at each radius to transport workers to the CBD. It is assumed that the stops are next to the office.

The city expands until the residential sector is unable to outbid the agriculture sector. At the city boundary $\overline{k}$, the residential land price $p_\ell(\overline{k})$ is equal to agricultural land price $p_\ell^a$. The ride hailing industry has no effect on the exogenously given fixed proportions of land use although, in practice, in the long run, ride hailing services could potentially reduce parking usage in the CBD and residential areas. The fixed proportions assumption is reasonable if land use regulations or zoning allocates development in fixed proportions.

### 3.1.3 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 $\ell$ 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 $1/(1-\rho)$.

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

where $H$ is housing production, $S$ is structure inputs that are perfectly elastically supplied, and $L$ is land inputs. Housing producers maximize profits by using land and structure inputs to assemble housing. In equilibrium, given the production function is constant returns to scale, these producers receive zero economic profit at every location inside the city.

Housing developers choose optimal structure and land inputs given a structure input price $p_s$ and residential land prices $p_\ell(k,j)$. The structure input price is assumed exogenous and residential land price is determined endogenously in equilibrium.

### 3.1.4 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 numéraire good consumption, $\beta_1$ and $\beta_2$ are consumption share parameters, and $1/(1-\eta)$ represents the constant elasticity of substitution between housing and the numéraire good.

For households living at distance $k$ from the CBD and distance $j$ from the public transit, a given level of annual income, $W$, is spent on the numéraire 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 $h(k,j)$ such that the budget constraint is given by

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

In equilibrium, households' utility is identical at each distance, $k$, from the the CBD edge, and $j$ from the public transit.

The assumption of homogeneous income imposed on households 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.

#### 3.1.5 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. After the ride hailing service is introduced, workers have the option to either take it directly to work or to the nearest 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. Workers optimally choose the one mode that minimizes 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 $\tau_w$ of the annual income, $W$. 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 depends only on the distance to the CBD. It includes the following: fixed costs of owning and operating an automobile $m_0$ (e.g. insurance, licensing), a 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, $\tau$ , 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 and $\kappa$ represents each distance from 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, the model assumes parking is next to the office and thus does not take into account the time needed to walk from parking to the employment location. 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 $\theta_R$ of the land area. $a$, $b$, and $c$ are congestion parameters.

If households choose to take public transit, in the absence of ride-hailing aps, 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. Stops are located at each radius to transport workers to the CBD. Just as time needed to walk from parking to employment, the commuting time from the transit stops at the CBD to the office is set to zero 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.The time cost of waiting is measured as a fraction, $\tau_{pub}$, of the wage rate, $W$ and $publicfare$ 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.

Some metro lines may already be at or near capacity, implying that any large policy change that dramatically increases demand may substantially increase wait times. To account for this, we model public transit crowding following the engineering literature. Assuming passengers arrive randomly at transit stations and if passengers can be served by the first arriving vehicle, the average waiting time is estimated as the half of the headway. Therefore, $awt = \frac{1}{2}\Gamma$, where $\Gamma$ is the service headway or the frequency of the train. This approach has been widely used in transit studies (Osuna and Newell (1972); Ansari Esfeh et al. (2020)).

However, if overcrowding is an issue, passengers who are not able to board the fist-arriving train have to wait another time period of $\Gamma$ for the next train. For passengers who are left behind, their waiting time is $\Gamma/2 + \Gamma$. Assuming the load capacity of all of the trains in one time period of $\Gamma$ is $\overline{Z}$, it implies that the trains could fit population of $\overline{Z}$ just comfortably. If the number of passengers using public transit, $Z$, is greater than $\overline{Z}$, the public transit is overcrowded. There are $(Z - \overline{Z})$ passengers left behind by the first arriving train and have to wait for the next train. Therefore, following Liu et al. (2013), if there is overcrowding, the average waiting time for all passengers is

$$awt = \frac{\overline{Z}}{Z} \cdot \frac{\Gamma}{2} + \frac{Z - \overline{Z}}{Z} \cdot (\Gamma/2 + \Gamma) \tag{8}$$

If $Z < \overline{Z}$, there is no overcrowding issue and the average waiting time is $\Gamma/2$.[9]

Households living further away from the CBD as well as public transit have greater 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 carpooling does not reduce car ownership because people who carpool still need automobiles for other purposes such as shopping or errands. Carpools incur 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 $z_{carpool}$. Thus

[9]The bus system as a part of the public transit system is omitted from the model. Although the bus system could be viewed as a combination of 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. As a result, our model may overestimate the usage of Uber as means of transportation to transit stations.

the time cost of carpooling is $\tau_{carpool} \cdot W \cdot z_{carpool}$, 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

$$T_{carpool}(k,j) = m_0 + \tau_{carpool} \cdot W \cdot z_{carpool} + parking_{CBD}/n + (m_1/n)k + (p_g/n) \int_{k_{CBD}}^{k} \frac{1}{G(V(\kappa))} d\kappa + \tau W \int_{k_{CBD}}^{k} \frac{1}{V(\kappa)} d\kappa. \quad (9)$$

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. However, in this way, our model captures a long run perspective of the use of TNCs where they are predominantly used as transport to work. According to survey data in Young and Farber (2019), 17.7% of ride-hailing trips are to work, but this number is larger for younger workers and for workers traveling at irregular hours.

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. 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, $\tau_{uber}$, of wage rate $W$. $\tau_{uber}$ is lower than the time cost of driving $\tau$, because workers do not need to drive and can spend time working or other productive use. As with driving and taking transit, this formulation assumes drivers drop off workers next to their workplaces. "Dead trips" where the driver needs to find the next passenger also do not cause added congestion given that in our model, they must always be in the opposite direction on the highway as rush hour traffic.

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

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

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 always drive through residential streets to take riders to transit stations without getting on the highway. Before Uber is introduced, given all drives are radial, 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. To simplify, traffic congestion on residential streets is assumed to be constant at 30 mph. Given our model will initially yield a corner solution where Uber is not used to get to transit stations, the presence of "dead trips" where Uber causes congestion by looking for the next pickup, is a limited issue. Even in scenarios where Uber is used as means to getting to public transit, any dead trip must be in the opposite direction of a trip to the transit line, and so the effects of such congestion would be limited in our setting.

Each household chooses a 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:

$$T(k,j) = \min\Big\{T_{walk}(k,j), T_{drive}(k,j), T_{walkpub}(k,j), T_{carpool}(k,j), T_{uber}(k,j), T_{uberpub}(k,j)\Big\}. \quad (12)$$

Much of the intuition of the model can then be seen using the transportation cost curves. Unlike prior models, our model features distance to the CBD and distance to transit lines, so that the transportation cost curves vary across both dimensions. To gain intuition Figure 2 show the transport cost curves with respect to distance to the CBD, conditional on various proximities to transit lines. The online appendix extensively discusses the fixed and marginal cost of each mode of transit and explicitly demonstrates how the optimal transit modes result from the construction of several cutoff rules.

Focus initially on Panel 2a. The vertical intercept shows the fixed cost conditional on a given distance from the transit station. The fixed cost of walking is the lowest. The fixed costs of taking Uber directly to work is lower than taking it to a transit station due to the added transit cost. The fixed cost of carpooling is higher than the fixed cost of driving because the added cost of carpooling is larger than the savings from sharing parking costs, but the fixed cost of taking Uber is lower than both other driving options. Whether the fixed cost of taking Uber to a transit station is lower than the cost of walking to transit depends on the distance from the transit station.

With respect to marginal costs, the marginal cost of walking is the highest. Uber's marginal cost is the next highest because it charges a higher fare per mile and minute than would be realized by using one's own car. With a low fixed cost and high marginal cost, Uber will mainly be used for shorter trips. Finally, the marginal cost of carpooling is lower than solo-driving because maintenance and gas costs are split. With respect to transit stations, conditional on a given distance from transit, the marginal cost of walking or taking Uber to transit are the same. Both curves have a kink after fifteen miles, where the transit line reaches its endpoint.

Putting all this together, the aggregate city-wide transport cost curve is the lower envelope of all of the individual curves. The intersections of each individual curve along this lower envelope partition the city into various modal choices along each transportation array. Then, moving across panels, as distance to a transit station increases, the cost of walking to public transit and the cost of taking Uber to public transit each shift upward. However, the walking curve shifts up faster as the cost of walking an additional mile is much higher. Thus, after approximately 0.5 miles from a transit station, the Uber curve is lower than the walking curve, but given it is always above another curve, taking Uber to transit is never viable unless subsidized. Thus, the four panel of graphs show that modal choice differs based on distance to the CBD and distance to transit stations, with the aggregate lower envelope of these curves being different at different distances from transit lines.

Going forward, public policies will directly and indirectly shift some of these curves, providing the intuition underlying our model.

### 3.1.6 Tax Policy

There have been several tax policies proposed in the past years. Currently, Chicago adopts a policy that imposes a constant tax rate per Uber trip regardless of the distance or cost. The constant tax rate per Uber trip, $t_{triptax}$,is \$0.67 per trip in Chicago. Given aggregate Uber trips $Trips_{uber}$, the aggregate tax revenue is $t_{triptax} \cdot Trips_{uber}$. The number of aggregate Uber trips is determined endogenously by the population who choose to take Uber to transit station or work. Given the tax rate per Uber trip, the transportation cost for taking Uber to work becomes

$$T_{uber}(k,j) = t_{triptax} + f_0 + f_1 \cdot k + f_2 \int_{k_{CBD}}^{k} \frac{1}{V(\kappa)} d\kappa + awt_{uber} \cdot \tau_{uber} \cdot W + \tau_{uber} \cdot W \cdot \int_{k_{CBD}}^{k} \frac{1}{V(\kappa)} d\kappa, \quad (13)$$

The cost of taking Uber to transit stations is

$$T_{uberpub}(k,j) = t_{triptax} + f_0 + f_1 j + f_2 \cdot j/V_{res} + awt_{uber} \cdot \tau_{uber} \cdot W + \tau_{uber} W \cdot j/V_{res} + awt \cdot \tau_{pub} W + publicfare + \tau_{pub} W \cdot k/V_{metro}, \quad (14)$$

Another tax policy that has been implemented in other places such as New York City is sales tax, which is proportional to the cost of each Uber trip. This is a potential alternative tax policy for Chicago to adopt. If sales tax policy is adopted, given the sales tax rate, $t_{salestax}$, the cost of taking Uber to work is

$$T_{uber}(k,j) = (1 + t_{salestax}) \cdot (f_0 + f_1 \cdot k + f_2 \int_{k_{CBD}}^{k} \frac{1}{V(\kappa)} d\kappa) + awt_{uber} \cdot \tau_{uber} \cdot W + \tau_{uber} \cdot W \cdot \int_{k_{CBD}}^{k} \frac{1}{V(\kappa)} d\kappa, \quad (15)$$

The cost of taking Uber to a nearby transit station is

$$T_{uberpub}(k,j) = (1 + t_{salestax}) \cdot (f_0 + f_1 j + f_2 \cdot j/V_{res}) + awt_{uber} \cdot \tau_{uber} \cdot W + \tau_{uber} W \cdot j/V_{res} + awt \cdot \tau_{pub} W + publicfare + \tau_{pub} W \cdot k/V_{metro}, \quad (16)$$

Tax on mileage is another policy that has been proposed to regulate Uber. It is a tax rate that is imposed on the driving distance by Uber. Given the tax rate per mile, $t_{miletax}$, the cost of taking Uber to work becomes

$$T_{uber}(k,j) = f_0 + f_1 \cdot k \cdot (1 + t_{miletax}) + f_2 \int_{k_{CBD}}^{k} \frac{1}{V(\kappa)} d\kappa + awt_{uber} \cdot \tau_{uber} \cdot W + \tau_{uber} \cdot W \cdot \int_{k_{CBD}}^{k} \frac{1}{V(\kappa)} d\kappa, \quad (17)$$

The cost of taking Uber to a nearby transit station becomes

$$T_{uberpub}(k,j) = f_0 + f_1 \cdot j \cdot (1 + t_{miletax}) + f_2 \cdot j/V_{res} + awt_{uber} \cdot \tau_{uber} \cdot W + \tau_{uber} W \cdot j/V_{res} \\ + awt \cdot \tau_{pub} W + publicfare + \tau_{pub} W \cdot k/V_{metro}, \quad (18)$$

### 3.1.7 Tax Return Scheme

Several tax return schemes have been considered by the city government to spend the tax revenue effectively. The first one is to invest the total tax revenue to improve public transit system by increasing train frequency which reduces average waiting time at each metro station. It is assumed that the average waiting time is a function of total budget devoted to public transit system. The elasticity of average waiting time with respect to public transit budget is assumed to be a constant, $\epsilon_{metro}$. Under the constant tax rate $t_{tax}$ per trip and aggregate Uber trips, the aggregate tax revenue is $t_{tax} \cdot Trips_{uber}$, therefore

$$awt = C_{metro}(basebudget + t_{tax} \cdot Trips_{uber})^{\epsilon_{metro}}, \quad (19)$$

where $C_{metro}$ is a constant. This tax return scheme has the potential to increase public transit usage. Under the sales tax policy, the aggregate tax revenue is $t_{salestax} \cdot Revenue_{salestax}$, where $t_{salestax}$ is the sales tax rate and $Revenue_{salestax}$ is the aggregate sale revenue from all Uber trips. As a result,

$$awt = C_{metro}(basebudget + t_{salestax} \cdot Revenue_{salestax})^{\epsilon_{metro}}, \quad (20)$$

Under the mileage tax policy, the aggregate tax revenue is $t_{miletax} \cdot Distance_{miletax}$, where $t_{miletax}$ is the tax rate per mile and $Distancemiletax$ is the aggregate drivers' driving distance from all Uber trips. Therefore,

$$awt = C_{metro}(basebudget + t_{miletax} \cdot Distance_{miletax})^{\epsilon_{metro}}, \quad (21)$$

An alternative tax return scheme is to invest the total tax revenue in the public transit system by reducing the one way ticket cost of taking metros. As the cost of taking public transit decreases, it is expected that public transit usage increases. In equilibrium, the aggregate tax revenue should equal to the aggregate public transit fare reduction.

A third tax return scheme is to return the tax revenue as a lump sum to each household, which increase households' income.

### 3.1.8 Labor Market of Uber

An important part of Uber is connecting riders and drivers. Given this, we must model the driver labor market in order to determine the number of Uber trips. Aggregate labor supply, $L_S$, is measured by Uber drivers' total working hours. Aggregate working hours is assumed to be a function of aggregate income revenue from providing ride hailing services. For each Uber trip, the driver revenue depends on base fare, cost per mile, cost per minute, trip length, and the driving time. If it is a Uber trip to work, the revenue for trip $i$ that pick up a worker at location $(k(i), j(i))$, is

$$Revenue_{uber}(i) = f_0 + f_1 \cdot k(i) + f_2 \int_{k_{CBD}}^{k(i)} \frac{1}{V(\kappa)} d\kappa. \tag{22}$$

If it is a Uber trip to public transit, the revenue for trip $i$ is

$$Revenue_{uber}(i) = f_0 + f_1 j(i) + f_2 \cdot j(i)/V_{res}. \tag{23}$$

Given aggregate Uber trips $Trips_{uber}$, the aggregate income revenue for Uber drivers is

$$Revenue_{uber} = \sum_{i=1}^{Trips_{uber}} Revenue_{uber}(i). \tag{24}$$

However, the company of Uber takes a certain fraction, $\pi_{uber}$ of drivers' revenue as fees. On average, this is about 30% of drivers' revenue. Therefore, Uber drivers' net revenue is $(1 - \pi_{uber})Revenue_{uber}$.

The labor supply elasticity, $\epsilon_{labor}$ is assumed as a constant. The value for labor supply elasticity is set at 1.72 based on Chen et al. (2019). The aggregate labor supply function is:

$$L_S = C_{uber}((1 - \pi_{uber})Revenue_{uber})^{\epsilon_{labor}}, \tag{25}$$

where $C_{uber}$ is a constant.

A household who choose to take Uber to work demands driving service from a Uber driver. The demand is measured by the driving time from Uber trips. If it is a Uber trip to work, the demand for this trip $i$ is

$$demand_{uber}(i) = \int_{k_{CBD}}^{k(i)} \frac{1}{V(\kappa)} d\kappa. \tag{26}$$

If it is a trip to public transit, the demand for trip $i$ is

$$demand_{uber}(i) = j(i)/V_{res}. \tag{27}$$

Aggregate labor demand is

$$L_D = \sum_{i=1}^{Trips_{uber}} demand_{uber}(i). \tag{28}$$

In equilibrium, it must be the case that $L_S = L_D$. The aggregate Uber trips, $Trips_{uber}$, are determined endogenously by households who choose to take Uber given the tax rate and fare structure. Uber adjusts the fraction taken from drivers' revenue to achieve market equilibrium in response to different policies or regulations.

After tax is imposed, the price of taking Uber goes up, as a result, the demand for Uber trips goes down. As demand goes down, aggregate income revenue for Uber drivers goes down as well, which leads to a decrease in Uber supply. This disrupts market equilibrium. To ensure supply meets the demand, the company of Uber has to decrease the fraction taken from drivers' revenue to increase supply to restore market equilibrium.

## 3.2 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. Because the city is radial uniform and symmetric with respect to rail lines, it is sufficient to examine half of the market area for one rail line. After the solution for 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 again solved recursively.

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 $p_\ell(\overline{k}) = p_\ell^a$. This condition is used to determine the city boundary $\overline{k}$ 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.

$$N = \int_{k_{CBD}}^{\overline{k}} \int_{0}^{J(k)} \theta \cdot D(k,j) dj dk, \tag{29}$$

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 $\frac{H(k,j)/\ell(k,j)}{h(k,j)}$, $\theta$ is the fixed fraction of land devoted to housing, $\overline{k}$ 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.

Furthermore, 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.

In addition, to clear Uber labor market, labor supply is equal to labor demand in equilibrium. This conditions determines endogenous fraction of drivers' revenue that Uber company takes.

Lastly, the aggregate tax revenue is equal to the aggregate tax return or aggregate fare reduction. This condition determines the improvement in public transit, fare reduction, or the amount of lump sum return endogenously.

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

# 4 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 2010 before the entry of Uber. The Chicago urbanized area is selected as calibration target due to its city size and substantial rail transit system. In 2010, the population in Chicago urbanized area was over 8 millions and the number of occupied housing units was $3,012,005$ 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.

For 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 has a CBD, a residential district, and an agricultural hinterland, which occupy 60% of the circular area. This is consistent with the data from Saiz (2010) who estimates that only 60% of city area is available for development in Chicago due to the geographical constraint imposed by Lake Michigan. The rapid transit system, the simulated city geometry, and simulated public transit system are shown in Figure 1.

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 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).

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 the 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.

$$\beta_2 = r \left[ \frac{h}{1 - T - rh} \right]^{1-\eta} \tag{30}$$

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

Given the lack of detailed data in land use for the 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 were 980 square miles of land area used for residential purpose in Chicago area in year 1992. This implies 46% of land is for residential use. Chicago had $34,800$ miles of local streets and $19,800$ miles of highways in 1990s according to the documentation from Encyclopedia of Chicago.[10] 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 the 1940 census, over 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). For a description of some land use in Chicago, see Jacob and McMillen (2015).

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, $\tau_{pub}$, is 50% of the wage rate. For walking, the time cost $\tau_w$ 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 with heaviest traffic when all workers drive to the CBD. Equation 6 implies that $v_{low} = \frac{1}{a+b(N/R(CBD))^c}$ to back out $b$ given population $N$ and road capacity at the CBD, $R(CBD)$. The parking fee at the CBD is set at 8 dollar per day based on the Google search for Chicago downtown.

As stated previously, to simplify, traffic congestion on residential streets is assumed to be constant at 30 mph.

The labor supply elasticity, $\epsilon_{labor}$ is assumed as a constant. The value for labor supply elasticity is set at 1.72 based on Chen et al. (2019). Uber claims that it only takes 25% of drivers' earnings. However, the effective commission ranges from 20% to 50%.[11] Therefore, in the simulation, the fraction that Uber takes from drivers' revenue is set at 30%.

For public transit improvement, assuming operating budget is proportional to the rider-

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

[11] see https://www.ridester.com/uber-fees/

ship, given rail ridership is twice as the bus ridership, we assume 2/3 of the budget goes to the rail system. In 2010, 0.84 billion dollar is allocated for rail system based the data from Chicago Transit Agency. Because at this budget, the average waiting time is 7.5 minutes, which is equivalent to 0.125 hour, normalizing $C_{metro}$ to unity, the elasticity, $\epsilon_{metro}$, could be calibrated using the following:

$$7.5 = (budget/1000000)^{\epsilon_{metro}}, \tag{31}$$

which yields $\epsilon_{metro} = -0.30882$.

It is assumed that on average, the current Chicago transit is near the load capacity per headway because some stations are overcrowded while others are not. Therefore, $\overline{Z}$ is assumed as 12.4% of the population.[12]

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 24.23 minutes, which is lower than the 30.7 minutes reported in the American Housing Survey (2010). The reason for this discrepancy is that our model does not take into account the commuting from parking or public transit to the workplace or from home to highways. The model fits the modal choices well, although ride-hailing ap usage is not reported in the ACS. In this way, we view our model as a long-run (future-oriented) model of commuting when ride-hailing is critical.

# 5 Simulation Results and Counterfactual Scenarios

In this section, we discuss various tax policies including unit taxes and ad valorem taxes. We emphasize how the counterfactual results depending critically and where revenue of these taxes is spent.[13] Our focus is mainly on mode the of transit and congestion metrics such as speed, but we also briefly discuss welfare implications.

[12] The assumption on $\overline{Z}$ may sound ad hoc, although consistent with rush hour patterns on many lines, therefore we conduct robustness analysis for different values of $\overline{Z}$.

[13] Fajgelbaum et al. (2019) show that how much people value government spending and how infrastructure affects production are key parameters.

## 5.1 No Tax Equilibrium

Before discussing our counterfactual exercises, we first consider the laissez-faire equilibrium where the city of Chicago does not tax Uber. The first column of table 3 presents this case.

Given the no tax case will be an important benchmark for all subsequent counterfactual simulations, we first discuss it extensively here. Focus on column (1) of table 3. With respect to transit choice, solo driving to work is the most common means of transportation. In addition, just under 9% of people take a TNC to work. The share of commuters taking Uber is slightly smaller than those that take public transportation to work. Among individuals taking public transportation, we allow two means to get from one's house to the L-train: walking to public transportation or by taking Uber to public transportation. Here, the model predicts a corner solution: no individuals will take Uber to public transportation. The reason for this is that Uber charges a base fare that is too high to make Uber a viable option. Even if the time and distance to the train station are small, the base fare of $3.64 is larger than the fare to use the L-train, which is $2.50. Given no Uber rides are used to get to public transit, the average Uber commute to work takes 7.66 minutes and is at a distance of 1.68 miles. Given the city radius is approximately 24 miles, households that use Uber to get to work are most likely to be drivers that live close to the city center. The reason for this is that the price per mile and per minute is relatively high, which implies that even in the presence of the fixed base fare, using Uber will only be a preferred choice for short commutes where Uber allows these drivers to save on costly parking fees. Additional rows of Table 3 show the aggregate income and hours driven by Uber. Given we do not model the number of trips taken per driver, and our model clears the labor market in the aggregate.

## 5.2 A Brief Descriptions of Counterfactual Exercises

We next proceed by considering various tax and spending policies. In the remainder of Table 3, we consider Chicago's historical policy on Uber: a fixed tax of $0.67 on each trip. Recently, Chicago raised this tax on ride-hailing services above this leve, but we use the historical policy given it is more in line with the taxes of other cities. The policy signals the interest of city officials to tax previously untaxed services. The tax revenue generated from the tax are then allowed to be spent in various ways.[14] First, we allow the tax revenue to be rebated lump-sum to the residents of Chicago. In this scenario, to close the model, tax revenue is returned to households as a lump sum return. Each household receives the same amount and this increases annual income. This allows us to isolate the effect of taxing

[14] Parry and Bento (2001), Parry and Bento (2002), and Bento et al. (2009) emphasize the critical importance of considering what the tax revenue is used for.

Uber without any endogenous investment in public services. This scenario is also realistic from a policy perspective: cities need not earmark their revenue to transit ridership and may instead use the revenue to benefit all citizens by letting the tax revenue from TNCs to accrue to the general fund. A lump-sum transfer would capture this if general public services are valued at par with increase in private income.

As an alternative to a lump-sum rebate, we allow the tax revenue to be invested in public transit in order to improve the frequency of trains, which reduces average waiting time. This case follows the proposals of many cities, which specifically earmark taxes on Uber to improve public transportation infrastructure or frequency. In a final scenario, tax revenue is used to reduce the one way ticket cost of public transit rather than to improve the quality of public transportation. This policy holds the quality of infrastructure fixed, but adjusts the transit price. Such a policy is also in place in many cities around the United States.

We then proceed in subsequent tables by considering different tax policies. In Table 4 we allow for the city, county and state sales tax (9.25%) to be applied to each fare at a rate of the 9.25%[15] As a third tax policy, we consider a 20 cent per mile tax. This policy attempts to tax road ware that may be caused by an increase in Uber rides in recent years.

All of the taxes only apply to TNCs and do not apply to taxis or other modes of transportation. The $0.67 flat tax is the historical policy in Chicago and is in place in other cities around the United States at a similar rate. The alternative policies are policies implemented in at least one other city in the United States. In particular, many cities and states apply the sales tax. Finally, cities have considered taxing on a per mile basis as a way of taxing the road ware caused by ride-hailing aps.

In latter sections of the paper, we consider additional policies in place in several cities: subsidies for Uber as a last-mile provider of public transit services and congestion tolls.

Figure 3 visually shows the breakdown by transit choice to get to work for the laissez-faire equilibrium and for each of the policies that we show subsequently. We will discuss each of these cases in turn.

## 5.3 A Fixed Tax on TNCs

Before discussing the results, the intuition of the effects can be seen in how the tax policy shifts the transport curves in Figure 4. While these policies also shift/pivot bid rent curves

[15]In this scenario, we assume that all of the revenue from the county and state sales tax on Uber rides within the city of Chicago's limits are transferred to the city of Chicago via intergovernmental grants. These funds are used as a lump-sum transfer to the city government, to improve public transit alongside the city sales tax revenue, or to reduce fares. We have also considered the application of the city tax rate alone, but given this is a slightly smaller tax than the flat we, it has similar, but muted, effects relative to the prior scenario.

as in the standard monocentric city model, the effects on the transport curves represent the *direct* effect of the taxes and the novel mechanism in our model. In the first two panels of Figure 4, we show the fixed tax with a lump sum rebate and a fare reduction, respectively. For simplicity, we show the effects for individuals zero miles from the transit station, as the shifts are qualitatively similar for other values of $j$ in this scenario.

In both scenarios that are depicted, the unit tax directly shifts up the Uber to work and Uber to transit curves. In the latter scenario, with a fare reduction, the Uber to transit curve is muted by the lower fare and the cost of walking and taking public transit shifts down slightly. With a lump sum rebate, the upward shift of the Uber cost curve is irrelevant because individuals living near transit stations never take Uber directly to work. However, recall that as distance to transit, $j$, increases, this leftward shift will be relevant as the cost of walking to public transit is prohibitive (for example, for individuals 0.4 miles from transit in Figure 2 would be affected). Thus, we can see that the decline in Uber usage from the tax comes from individuals sufficiently far from public transit. With a fare reduction, this in turn, mildly increases transit usage.

Based on our general equilibrium model, the tax on Uber raises 70 million dollars which is approximately 5% percent of the operating budget of the entire Chicago Transit Authority.

To compare results for various spending policies, consider the various commuting modes in Table 3. Of course, adding the fixed tax to Uber rides lowers the share of ridership taking Uber to work. Even when the tax revenue is entirely used to improve the frequency of public transportation or to reduce its fare, given the elasticity of transit is relatively small, taxing Uber still results in a corner solution where no individuals take Uber to public to transit.[16] However, some of the riders that previously took Uber to work substitute toward public transportation, but also toward solo driving. Given the tax is small, results where the government simply burns the tax revenue are qualitatively similar to the lump sum rebate case given that the income effect is small.

With respect to Uber's outcomes, all the different spending policies lower the average trip time and distance. Intuitively, trips become shorter because drivers that are relatively far away are more likely to substitute toward solo driving. As we assume that the incidence of the tax works via the share of revenues that accrue to Uber, Uber responds to the tax by lowering the share of profits paid to Uber in order to maintain equilibrium in the labor market.

The approach for the welfare analysis follows Sullivan (1985) and Borck and Brueckner (2018). There are several components in our aggregate welfare analysis. First, imposing taxes

[16] For example, in this case, the flat fee, which raises the most revenue, is able to improve transit wait times by less than a minute and only results in a transit subsidy of $0.29.

leads to welfare loss for landowners. The welfare loss experienced by landowners is measured by the reduction in aggregate land rent (residential plus agricultural). To aggregate this, the total land area used for the city and agriculture is held constant at a 40 mile radius. With a lump sum return, aggregate land rent declines by \$4.9 millions. Second, the imposition of the tax results in behavioral responses, but the income effect increases household's utility in the lump sum return scenario. The welfare change experienced by households is measured based on the compensation variation (CV) associated with the adoption of the tax policy. The wage CV is calculated by the change in income required to achieve the same utility as before tax is imposed. To compute the compensation variation in earnings, the model is re-simulated holding households' utility level constant in an open-city model framework. After the tax policy is introduced, wage rate per household is \$56,067, which is \$2 less than the original wage rate at \$56,069. Thus, the aggregate wage compensation is \$71.4 million. Thirdly, assuming each Uber driver is a self-employed entrepreneur, their profit is a part of the welfare change. The net profit for each Uber driver is the difference between the total revenue from Uber rides and the driver's operating cost. The operating cost includes the variable cost of operating a car and gasoline cost. Under the lump sum return scenario, Uber drivers' net profit is reduced by \$162 millions. In our analysis, the firm's profit does not enter into the welfare analysis because it is assumed that each firm has zero economic profit. In aggregate, imposing a fixed tax rate with lump sum return leads to a welfare loss of \$94.86 million. Interestingly, the welfare decline resulting from using the revenue to improve or subsidize public transit is larger in absolute value. This is because public transit is not valuable for many individuals, and the elasticity of improving it implies that speed or fare reductions have relatively small effects.

### 5.4 Sales Tax on TNCs

The bottom panels of Figure 4 show the effect of a sales tax on TNCs. Unlike the unit tax, the ad valorem tax pivots the transportation cost curves. Otherwise, all effects are qualitatively similar to the prior analysis. Again, the upward pivot of the Uber to work curve will only reduce Uber usage for individuals sufficiently far away from a transit line, where the Uber to work curve is part of the lower envelope forming the aggregate transport cost curve.

In this counter-factual, we levy state and local sales taxes on each Uber trip. At the average price of an Uber trip, this sales tax rate results in a tax payment that is slightly smaller than the fixed tax considered in the last section. The sales tax raises approximately ten million dollars less revenue than the fixed tax. Comparing across the columns in table 4, the results are qualitatively similar to the prior section: welfare declines, but moreso when the tax is used to finance public transit rather than returned lump-sum. For this reason, in this section, we focus on comparing the results to those results in table 3.

Interestingly, although the sales tax raises less revenue, it reduces the share of people taking Uber to work more than the flat fee. This is due to the sales tax having a higher rate on longer rides. This can be seen by the larger decline in driving times on Uber trips. Thus, the larger quantity response lowers tax revenue relative to the prior scenario. Moreover, larger declines in Uber ridership amplifies the fall in the fraction of revenues that accrues to Uber.

Critically, this counterfactual highlights an important policy difference. A sales tax, which is a percent of the fare, will more stringently penalize drivers with longer trips on Uber. This in turn, will amplify the substitution away from Uber at longer distances, which then has important implications for congestion and the revenue efficiency of the tax. The flat fee will have the largest consequences on short trips, which will dampen the inter-modal substitution of the tax, allowing it to raise more tax revenue.

## 5.5 Mileage Tax on TNCs

Table A1 shows the results of recently debated mileage taxes on Uber. The reasons given for a mileage tax is that it pays for damage to the roads by Uber and discourages excesively long trips. Relative to the other two tax policies, note that the mileage tax raises substantially less revenue. The reason for this is that the average Uber trip is about 1.5 miles. Thus, a $0.20 cents tax per mile does not raise much revenue. As a result, the results in this section are dampened relative to the prior taxes. In particular, the mileage tax is less effective than the sales tax at reducing the length of Uber trips, but is approximately equally effective as the flat tax on Uber rides.

## 5.6 Comparing Across Policies

For all policies, the share using public transportation always increases by more when the revenue funds fare reductions than when it funds transit improvements. Intuitively, lowering wait times in a meaningful way require a massive amount of investment and given the revenues raised in general equilibrium are relatively similar, price reductions induce more substitution. Given the reductions in wait times in column (2) of table 3 and a median wage rate of approximately $28 per hour, the improvements of public transportation are valued at $0.08 per trip. If the revenue is used to reduce fares directly, the fare reduction is $0.28, which explains the larger increase in public transit usage. As a result, welfare falls less when fares are reduced. This pattern is consistent across all three tax policies.

From this exercise, if city officials wish to use Uber taxes to fund public transportation, subsidizing the fares with tax revenues are more efficient than improving the wait times for public transportation.

Perhaps most interesting are the results on transit choice. In the prior tables, the increase in public transportation are due to two effects: "push factor" where individuals substitute away from Uber due to the higher taxes and a "pull factor" where individuals substitute toward public transit because its quality improves or fare decreases. If the income effect from the lump sum rebate is small, we isolate the pure "push factor." Simulating the model in a scenario where the government "burns" all tax revenue verifies this is the case for the prior three scenarios. Notably, under all policies, public transport rises in popularity relative to the no-tax equilibrium. When comparing revenue that is used lump-sum to revenue that is used to improve transit, the substitution toward transit is very small. Thus, much of the increase in transit ridership is due to the tax pushing people away from Uber and not the improvements due to public transit when the revenue is used to fund quality improvements. Comparing the lump-sum to the fare reduction scenario, we see that the latter case results in a much larger increase in transit ridership. Thus, when the revenue is used to fund fare decreases, much of the transit increase is explained by the "pull factor" over lower fares.

Our model has several important implications for policy. First, in a world where no one uses Uber to get to transit stations, Uber is a mild substitute for public transportation: an increase in the price of Uber increase transit ridership even without improving public transit. However, the cross-price elasticity is small. We can calculate the cross-price elasticity of public transit with respect to the price of taking to Uber to work. At the average Uber price of \$7.15, the fixed free represents a 9.37% change in the price. The change in public transit shares implies a 2.80% increase in transit usage. This is a cross-price elasticity of 0.30.[17] Although not huge, this elasticity is larger than many cross-price elasticities for food products (Harding and Lovenheim 2017). Second, taxes on TNCs alone cannot dramatically increase transit ridership. Rather, how the tax revenue is spent, is critical. Our results suggest that some uses are more effective than others.

[17] Cohen et al. (2016) estimate the own-price elasticity of Uber to be approximately -0.60. This estimate is smaller than our implied own-price elasticity of Uber which applies only to using Uber to drive to work. Given driving to work entails many substitutes, the own-price elasticity should be higher.

# 6 Alternative Policies and Counterfactual Results

## 6.1 Subsidy Policies

In the prior sections, we show that Uber is a substitute for public transportation: exogenous increases in the price of Uber via a tax induce substitution toward public transportation. In this section, we consider whether an appropriate combination of government policies can shock the system such that Uber and public transit are complements. Before turning to the results, we explain how we model the subsidy.

This scenario also aims to simulate the effects of different subsidy policies considered in several cities in the U.S. targeting at increasing public transit usage.[18] The comparison between tax policy and subsidy policies shed light on which type of policies are more effective to increase public transit usage and reduce traffic congestion. The first subsidy policy is a flat rate off the cost of taking Uber to public transit per trip. Therefore, given the flat rate $subsidy_{flat}$ the cost of taking Uber to transit stations become

$$T_{uberpub}(k,j) = -subsidy_{flat} + f_0 + f_1 j + f_2 \cdot j/V_{res} + awt_{uber} \cdot \tau_{uber} \cdot W + \tau_{uber} W \cdot j/V_{res} + awt \cdot \tau_{pub} W + publicfare + \tau_{pub} W \cdot k/V_{metro}, \quad (32)$$

This subsidy aims to encourage people, especially those who live in reasonable proximity from the transit station, to take Uber to public transit.

In the second subsidy policy, riders could get a discount rate off of the cost of taking Uber to public transit. Given the discount rate $subsidy_{discount}$, the cost of taking Uber to a transit station is

$$T_{uberpub}(k,j) = (1 - subsidy_{discount})(f_0 + f_1 j + f_2 \cdot j/V_{res}) + awt_{uber} \cdot \tau_{uber} \cdot W + \tau_{uber} W \cdot j/V_{res} + awt \cdot \tau_{pub} W + publicfare + \tau_{pub} W \cdot k/V_{metro}, \quad (33)$$

In the simulation, the discount rate is set at 20% off.

In the third subsidy policy, the government subsidizes the public transit system directly for everyone who takes public transit. It is free to take public transit in this scenario. Free public transit has been debated in the media and among policy makers. Given free public transit, $publicfare = 0$, people have more incentives to take public transit and perhaps

[18] For work on subsidy policies more generally, see Brueckner (2005). Given we focus on the city of Chicago, we ignore spillovers to other municipalities (Brueckner 2015).

taking Uber to transit stations. The cost of walking to public transit becomes

$$T_{walkpub}(k,j) = \tau_w \cdot W \cdot (j/V_{walk}) + awt \cdot \tau_{pub} \cdot W + \tau_{pub} \cdot W \cdot (k/V_{metro})\,, \tag{34}$$

The cost of taking Uber to public transit is

$$\begin{aligned} T_{uberpub}(k,j) = f_0 + f_1 j + f_2 \cdot j/V_{res} + awt_{uber} \cdot \tau_{uber} \cdot W + \tau_{uber} W \cdot j/V_{res} \\ + awt \cdot \tau_{pub} W + \tau_{pub} W \cdot k/V_{metro}, \end{aligned} \tag{35}$$

In order to provide the subsidy, the government deducts a lump sum tax from each household's income. In equilibrium, households' aggregate income deductions equal to the aggregate subsidy. The lump sum income deduction is determined endogenously in equilibrium.

#### 6.1.1 Results

Figure 5 shows the intuition of the subsidy for various distances. The upper panels show a fixed Uber subsidy for rides to transit statons, while the lower panels show the effect of making transit free. The Uber subsidy dramatically lowers the cost of taking Uber to public transit, making it a viable option for drivers that are sufficiently far away from public transit. This increased transit usage than has general equilibrium effects that mildly shift down the driving cost curves. However, this scenario raises the cost of transit for people who walk to transit because of the added congestion to public transit from more riders. Unlike the Uber subsidy, making transit free has identicial shifts, with the exception of people who walk to transit stations. Unlike the Uber subsidy, the free transit offsets the added congestion time on the transit, shifting the walking to public transit curve downward. This increases this mode choice, especially at higher distances from transit.

Table 5 shows the results. Critically, and unlike the tax policies considered previously that fund transit improvements, all three of the subsidy policies we consider are sufficiently large to induce some individuals to use Uber as a last-mile service to get to public transportation. The flat rate \$3 dollar deduction has the biggest effect: 22.7% of people are induced to take Uber to a transit station and overall transit ridership increases by more than 1.5 times relative to the baseline scenario. Given the large increase in transit ridership, public transit overcrowding is critical to dampening the effect: transit wait times increase from 7.5 minutes to 11.7 minutes. In particular, we re-simulate the model in the absence of such overcrowding; our model would predict that transit ridership would increase 2.5 times relative to the baseline scenario, suggesting that transit limitations are critical to the policy landscape.

Critically, a decline in the price of Uber rides to public transit raises public transit ridership. For the flat-rate subsidy, much of this increase is due to new riders who use public transit but a small part of it may also be due to some riders substituting walking toward Uber as their last-mile service. Overall, the dramatic increase in transit ridership reduces solo driving and also reduces the number of people that take Uber directly to work, and thus are unable to receive the subsidy.

In the case of the 20% subsidy on Uber rides, the subsidy is just large enough to induce some individuals to utilize Uber as a means of transport. Transit congestion does not increase. In particular, the subsidy in this case is less than half of the $3 dollar subsidy. Key to both of these subsidies is that riders only receive the subsidy on fares to and from public transit.

In the last column, we consider the case of free public transportation. In this case, transit fares fall to zero and there is a surge in transit ridership, but in this case, individuals who are able to walk to public transportation drive the surge rather than individuals taking Uber. In practice, this raises interesting equity issues, if income is a monotonic function of distance to transit stations. Nonetheless, the decline in public transit fares also increases the number of individuals that take Uber to public transit. This suggests that Uber and public transit are complements with respect to the price of transit ridership. However,note that the decline in transit fares induces a very small substitution (and almost unchanged) away from using Uber as a means of driving to work. Again, public transit congestion is critical. Were there no transit congestion, the share of individuals taking Uber to work would have fallen to 7.28% but the share taking Uber to transit would have increased to 8%.

These results imply that using Uber to get directly to work is a substitute product for taking transit to work. However, even without transit congestion, the decline in individuals taking Uber to work is small relative to the increase in individuals that take Uber to public transit. With congestion, this decline is almost nonexistent. As a result, we can conclude that overall, Uber is a complement to public transit. As in the prior section, we can calculate a cross-price elasticity when the system is at a corner solution where no one uses Uber as a last-mile provider. Here, we use the free public transit scenario as an exogenous shock to the price of transit and trace out the elasticity of Uber with respect to this shock. Given price falls from 2.50 to 0, this corresponds to a 100% change. With transit congestion, the total change in Uber usage is 1.83 percentage points, which corresponds to a 21% change in use of Uber for any purpose. The implied cross-price elasticity of total Uber usage (direct to work plus to transit stations) with respect to transit prices is -0.21. Notice, if we calculated the elasticity of taking Uber to directly work with respect to this price, it would be positive but close to zero, 0.002. In a case with no transit congestion, the cross-price elasticity of taking Uber directly to work is 0.17. This, suggest that for different sets of drivers and different combinations of policies and whether or not transit is overcrowded, the cross-price elasticity may differ in sign. We could do a similar exercise with respect to subsidy policies and would reach similar conclusions.

Reconciling this result with the prior section, governments need to create an appropriate policy environment to induce complementary between these means of transit – critically, the polices must induce the equilibrium away from the corner solution where no individuals take Uber to public transit. Critically, in all but one of these policies, welfare in the metropolitan area increases.

## 6.2 Optimal Congestion Toll Policy

Congestion tolls have been imposed in different cities around the world to relieve traffic congestion. Studies such as Liu and McDonald (1998) and Liu and McDonald (1999) have shown that congestion tolls is effective in relieving traffic congestion and Agrawal et al. (2019) show that they are theoretically an important instrument for local tax policy. Uber has opposed city-level tax policies like those considered previously but politically supports a congestion toll policy applied widely and equally to all drivers. After imposing congestion tolls, transportation costs increase, which discourages solo driving as well as the demand for taking Uber to work. The comparison between tax policy and congestion toll policy adds insights into which policy is more effective at reducing traffic congestion.

In this scenario, optimal congestion tolls are imposed on each car driving through the highways. The toll is not levied on Uber rides to transit stations because these rides only drive through residential results. Following the simple congestion model in Mcdonald (2004), optimal congestion toll is calculated based on the externalities created by each additional driver on the highway. Each additional driver on the highway can delay every commuter that is already on the highway and therefore increases marginal commuting cost for each driver. As a result, each driver's gasoline cost and time cost of driving increase. It is calculated based on

$$toll(k) = \overrightarrow{N}(k) * \frac{dMC(k)}{d\overrightarrow{N}(k)} \tag{36}$$

where $MC(k)$ is the marginal commuting cost for each driver in annulus $k$, which is equal to $m_1 + p_g \frac{1}{G(V(\overrightarrow{N}(k)))} + \tau W \frac{1}{V(\overrightarrow{N}(k))}$. $\overrightarrow{N}(k)$ is the traffic volume at radius $k$. The effect of an added vehicle on marginal commuting cost is

$$\frac{dMC(k)}{d\overrightarrow{N}(k)} = p_g \frac{d(1/G(V(\overrightarrow{N}(k))))}{d\overrightarrow{N}(k)} + \tau W \frac{d(1/V(\overrightarrow{N}(k)))}{d\overrightarrow{N}(k)} \tag{37}$$

Therefore, after congestion toll is imposed, the total commuting cost for each solo driver is

$$T_{drive}(k,j) \;=\; m_0 \,+\, parking_{CBD} \,+\, \left[m_1 k + p_g \int_{k_{CBD}}^{k} \frac{1}{G(V(\kappa))} d\kappa\right] \,+\, \int_0^k toll(\kappa) d\kappa, \tag{38}$$

The cost for taking Uber to work becomes

$$\begin{aligned} T_{uber}(k,j) = f_0 + f_1 \cdot k + f_2 \int_{k_{CBD}}^{k} \frac{1}{V(\kappa)} d\kappa + awt_{uber} \cdot \tau_{uber} \cdot W \\ + \tau_{uber} \cdot W \cdot \int_{k_{CBD}}^{k} \frac{1}{V(\kappa)} d\kappa + \int_0^k toll(\kappa) d\kappa, \end{aligned} \tag{39}$$

For carpools, tolls are split among riders, therefore, the cost for carpooling is

$$\begin{aligned} T_{carpool}(k,j) = m_0 + \tau_{carpool} \cdot W \cdot t_{carpool} + parking_{CBD}/n + (m_1/n)k + (p_g/n) \int_{k_{CBD}}^{k} \frac{1}{G(V(\kappa))} d\kappa \\ + \tau W \int_{k_{CBD}}^{k} \frac{1}{V(\kappa)} d\kappa + \int_0^k (toll(\kappa)/n) d\kappa. \end{aligned} \tag{40}$$

### 6.2.1 Results

Figure 6 shows the intuition from the optimal toll, for different distances from public transit. The upper panels show the toll with a lump sum rebate, while the latter panels show the toll revenue used for transit fare reductions. Unlike the prior figures, the largest upward shift is for solo-driving, which also shifts up the carpool curve, but by less, due to the added number of drivers. Given the toll applies to drivers taking Uber to work, this curve also shifts upward. The public transit curves also shift upward as the added transit usage raises congestion on public transit. However, these latter two effects are offset and have downward shifts when the revenue is used to reduce the transit fare. Given the optimal congestion toll is at a high rate, public transit becomes free and this shifts the public transit curve downward. Note that this increased transit ridership mutes the effect of the increase from the toll on the Uber to work curve as there is less congestion on the roadway.

As expected, in Table 6, the optimal congestion toll raises the average speed on highways by as much as 5%. First consider the case with the toll revenue rebated to households. With respect to transit choice, total car ridership to work (solo, carpool, Uber) falls by approximately three percentage points. The substitution patterns are interesting. The fall in solo driving is dramatic, with some individuals switching to carpool and to public transit. Noticeably, there is an almost one percentage point increase in the share of households that take Uber directly to work. The optimal congestion toll raises the price of driving such that some marginal individuals take Uber to public transit. Overall, the increase in public transit usage is driven moreso by individual walk to public transit or take Uber to transit. This split would be more even if public transit crowding were not included in the model.

In other cases, where the toll revenue is used to improve public transit times or to reduce transit fares, the toll is even more effective at increasing transit usage. Like in the prior section with a tax, reducing public transit fares are more effective at increasing transit usage that using the revenue to fund wait time reductions. In the case of fare reductions, the optimal congestion toll almost doubles transit usage and results in over 5% of households taking Uber to public transit. The optimal toll combined with reduced transit fares is the most effective policy – even moreso than Uber subsidies – of increasing public transit usage. This is because the optimal congestion toll induces a similar response of individuals walking to public transit, but a larger shift of Uber to transit given that the congestion toll is only assessed on highways and not on city roads used to get to transit stations. The $3 Uber subsidy is more effective at increasing Uber usage to public transit, but total transit usage does not increase as much because the limited effect on walking. However, unlike the highly targeted subsidies, the welfare effects of the congestion toll may come with some negative effects. Critically, although the marginal damage is internalized and less people are on the roadways, the average commuting time to work increases. This is partially a result of the congestion toll dramatically increasing urban sprawl.

Given the congestion toll provides the largest shock to the city, we can very clearly discuss some of the intuition using standard bid rent curves, housing demand, traffic, and other metrics as a function of distance the CBD and the nearest transit station. Relative to the no tax scenario, the bid rent pivots. Housing price near the CBD increases because public transit becomes a more appealing transit mode which creates incentives for households to live closer to the CBD as well as the transit stations. Commuting speed increases and commuting time falls at all distances. The decline in traffic congestion due to congestion tolls reduces the commuting cost of driving, which creates incentives for households to live further away from the CBD and transit stations. As a result, the city radius increases. As the demand for housing towards the city edge increases, the housing price for households who live further away from the CBD and transit stations goes up.

The results in this section show that cities have access to traditional policies that can spur TNCs to complement public transit. While targeted subsidies are also effective at doing this, congestion tolls have similar effects. In so much as cities may not want to pass policies that target specific sectors or companies, the use of congestion tolls may be a more politically viable option in some cities.

## 6.3 Tax vs. Fixed Congestion Toll Policy

In reality, it is difficult to implement optimal congestion toll policy. A fixed toll policy is more common and easier to implement. In this scenario, toll rate is fixed per car but the aggregate toll revenue is equivalent to the tax revenue under the Uber tax of \$0.67 per trip, which facilitates the comparison. Given a fixed toll rate per trip, $toll_{fixed}$, the commuting cost for each solo driver is

$$T_{drive}(k,j) \quad = \quad m_0 \; + \; parking_{CBD} \; + \; \left[m_1 k + p_g \int_{k_{CBD}}^{k} \frac{1}{G(V(\kappa))} d\kappa\right] \; + \; toll_{fixed}, \quad (41)$$

The cost for taking Uber to work becomes

$$T_{uber}(k,j) = f_0 + f_1 \cdot k + f_2 \int_{k_{CBD}}^{k} \frac{1}{V(\kappa)} d\kappa + awt_{uber} \cdot \tau_{uber} \cdot W + \tau_{uber} \cdot W \cdot \int_{k_{CBD}}^{k} \frac{1}{V(\kappa)} d\kappa + toll_{fixed}, \quad (42)$$

For carpools, tolls are split among riders, therefore, the cost for carpooling is

$$T_{carpool}(k,j) = m_0 + \tau_{carpool} \cdot W \cdot t_{carpool} + parking_{CBD}/n + (m_1/n)k + (p_g/n) \int_{k_{CBD}}^{k} \frac{1}{G(V(\kappa))} d\kappa + \tau W \int_{k_{CBD}}^{k} \frac{1}{V(\kappa)} d\kappa + toll_{fixed}/n. \quad (43)$$

### 6.3.1 Results

As shown in Table A2, if the optimal toll is set to equal the revenue generated from the fixed Uber tax in our prior simulation, the toll will be much less effective at reducing congestion than the optimal toll. The reason for this is that the optimal toll is much higher than the toll in this section. The fixed toll has limited effect on speed. In particular, the speed increase from the Uber tax is either the same or larger than under the fixed toll. Otherwise, the analytical results with respect to public transit mode choice are similar, but muted in magnitude, relative to the direct Uber tax. We conclude that a sub-optimal toll is less likely to be effective at reducing congestion externalities than a tax on Uber, which because of its targeted nature at particular drivers, causes a mildly larger increase in transit usage.

# 7 Conclusion

Technological changes create important new challenges and opportunities for cities and their public finances. Transportation network companies represent one of the most important technological changes of the last decade, but the effect of government policies on these companies remains unknown. We provide some of the first evidence and our results indicate that many of the existing policies adopted by cities are ineffective at meeting their stated goals of reducing congestion externalities and increasing public transit usage. Instead subsidies for TNCs or congestion tolls – even if inefficiently set – are more effective of meeting these two goals. Our results suggest that taking Uber directly to work is a substitute for public transit, but that overall Uber and public transit are complements if cities adopt appropriate policies to encourage Uber to be a "last-mile" service provider for the city.

While we have made much progress on study the taxation of TNCs, much more research is needed. Future research might consider how results differ depending on the size of the city. Given sufficient density is critical for public transit system, the results we identify are likely to be even more applicable in smaller cities where buses or other modes of transit do not readily cover suburban parts of the urban area. Thus, our results on subsidies may be a lower bound to the effects in smaller cities with extensive transit infrastructure with incomplete coverage.

In addition, given a large share of ride-hail is for going out to social activities and for going home, the effect of taxing or subsidizing these rides might also be studied. Given these rides are likely to be distinct from commuting, we expect the effect of policies on these rides will be in addition (rather than in conflict) with the results we have presented. One reason these rides might be important is that some spatial microstructure appears to be a response to search frictions: clusters of retail, entertainment, recreation and specialized services. In so much as ride-hail might disrupt these clusters, taxes or subsidies may have important effects on urban form via these smaller agglomerations. However, as rides for social activities are highly variable and what modes of transportation are viable alternatives may be highly context or activity dependent, modeling them will pose additional challenges for researchers. Nonetheless, our tax policy framework can provide a starting point for studying how these trips might be regulated.

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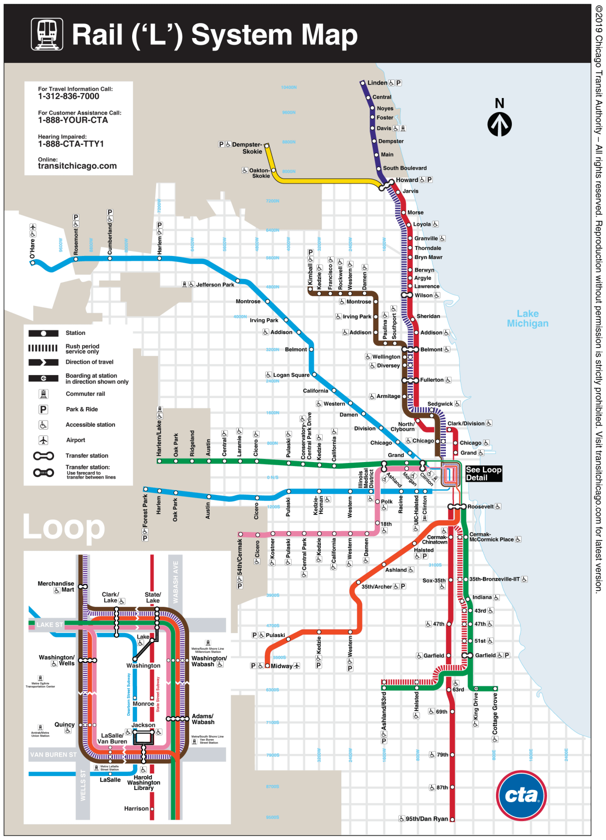
Figure 1: Chicago public transit system, Actual and Simulated

(a) Public Transit Map




(b) Simulated

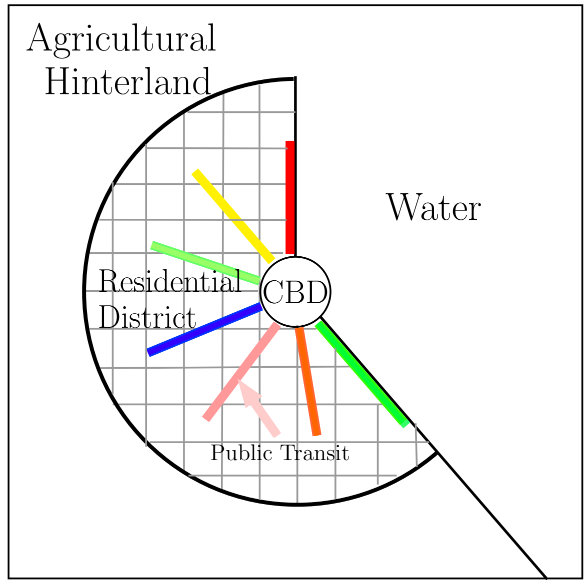
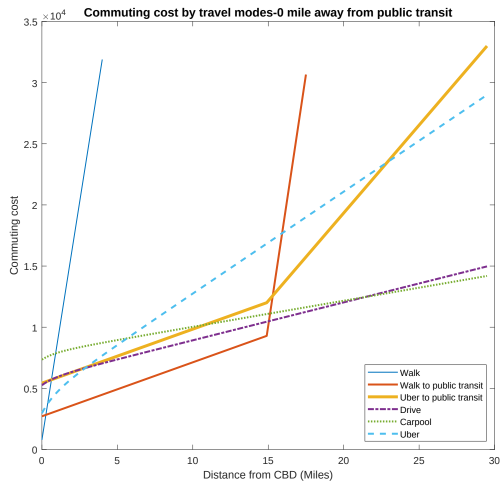
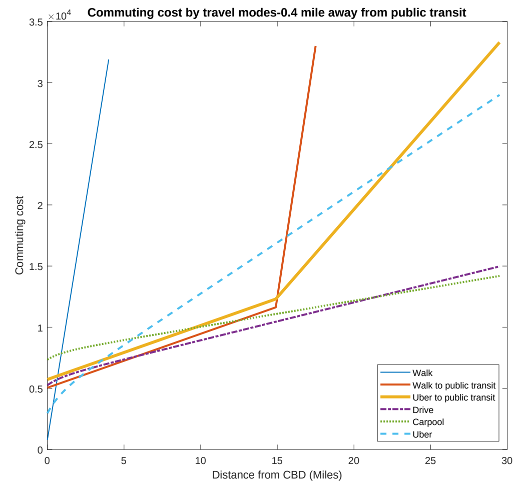


Figure 2: Transportation Cost Curves (By Distance to Transit Stations)

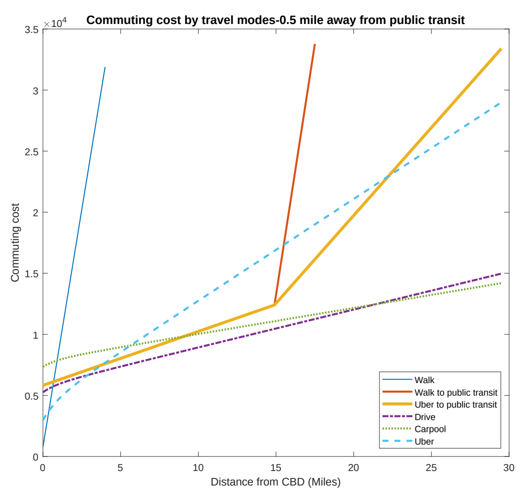
(a) 0 Miles from Transit




(b) 0.4 Miles from Transit




(c) 0.5 Miles from Transit




(d) 0.8 Miles from Transit

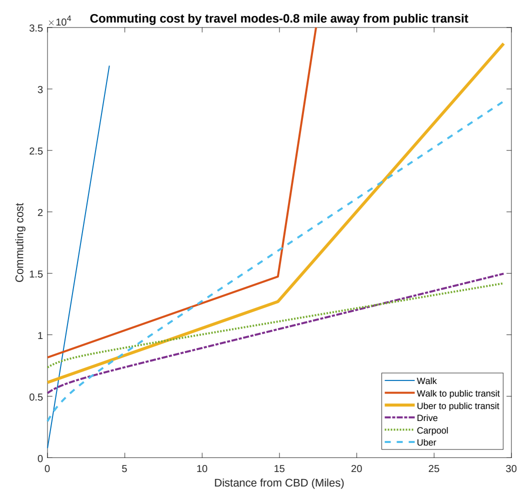
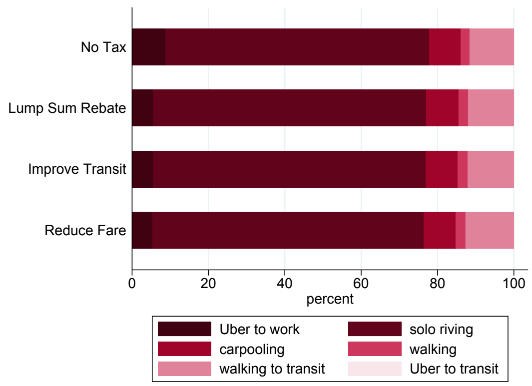
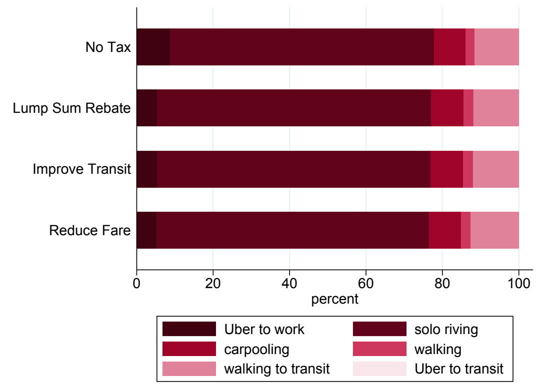


Figure 3: Different Polices and Commuting Mode

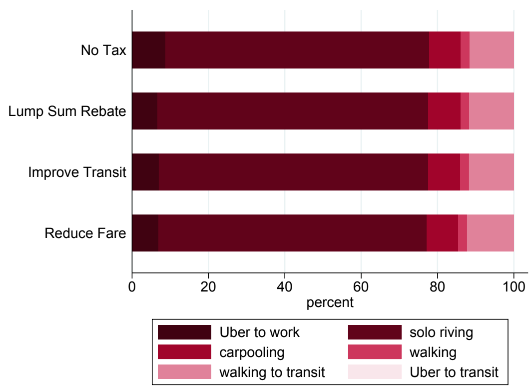
(a) Flat Tax on Uber



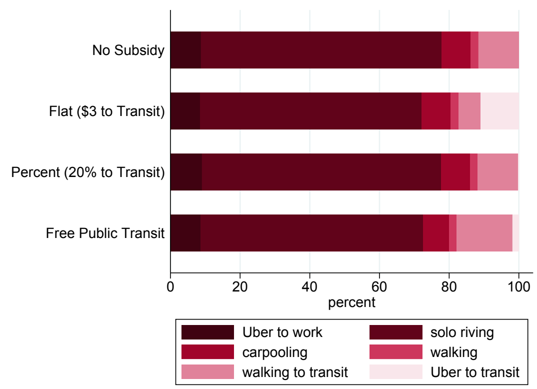

(b) Sales Tax on Uber



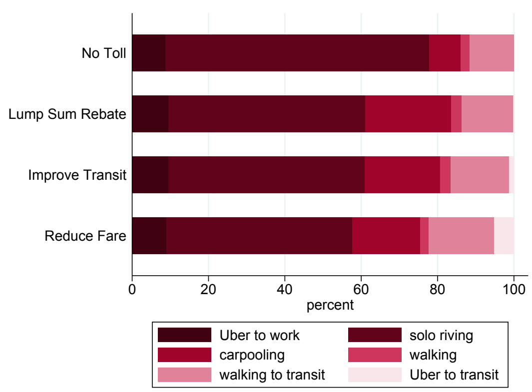

(c) Mile Tax




(d) Subsidy Policies




(e) Optimal Congestion Policies




(f) Fixed Toll

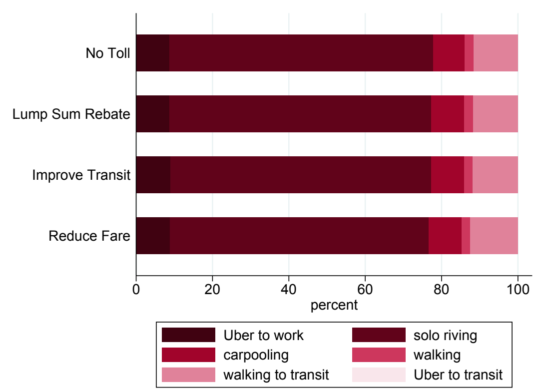
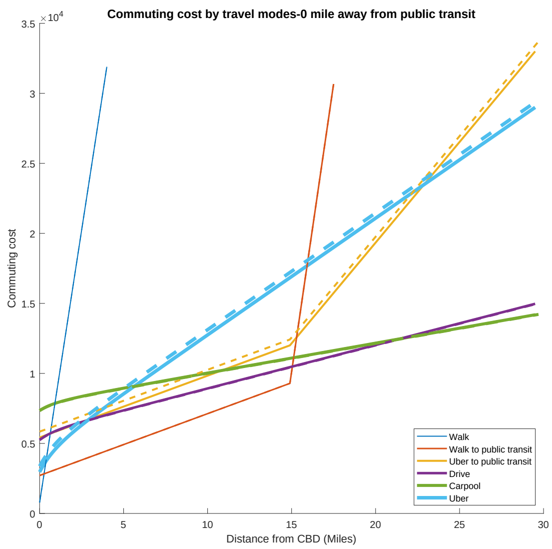
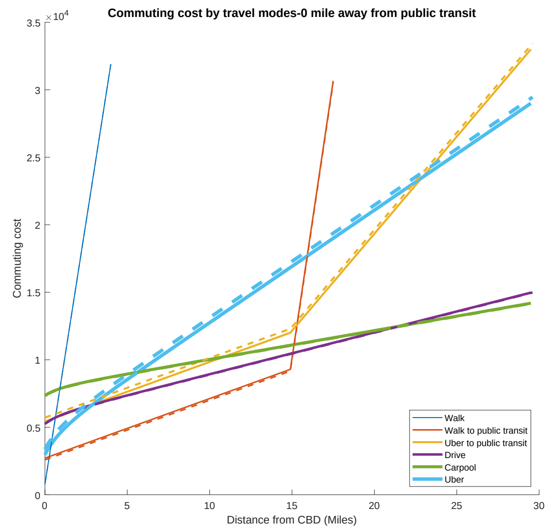


Figure 4: How a Fixed Uber Tax and a Sales Tax Change Transport Curves (Post-reform: Dashed Lines)

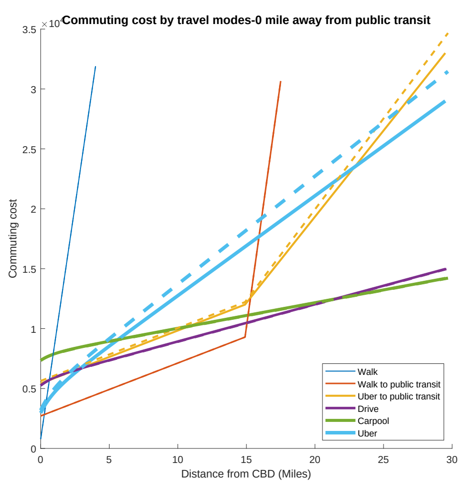
(a) Fixed Tax, Lump Sum Rebate




(b) Fixed Tax, Reduce Fare




(c) Sales Tax, Lump Sum Rebate




(d) Sales Tax, Reduce Fare

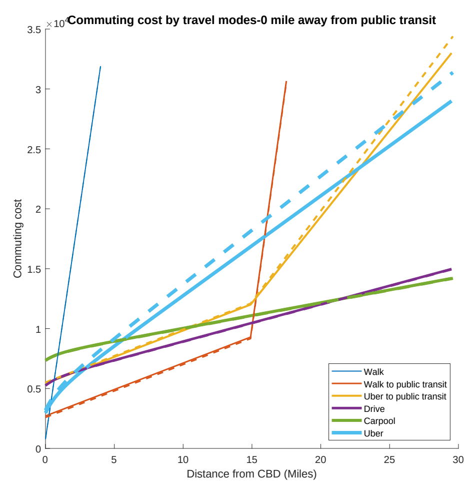
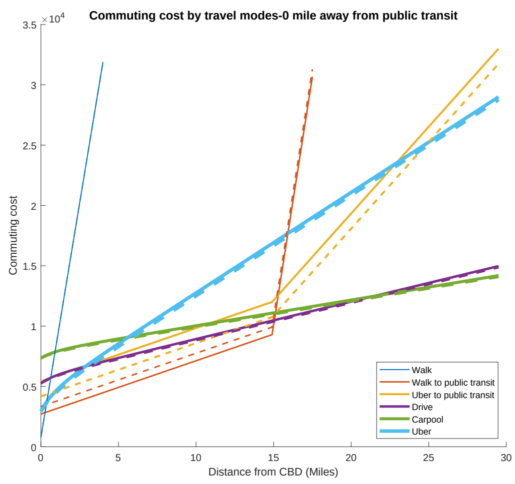
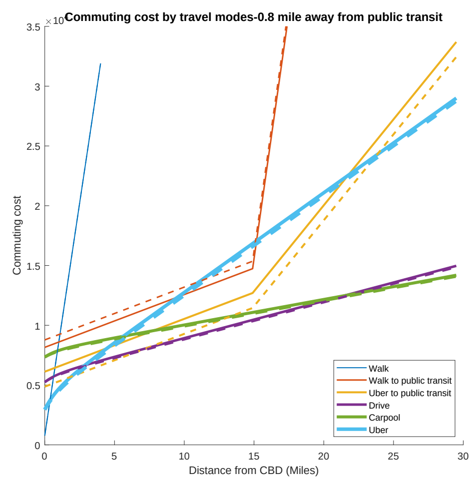


Figure 5: Subsidy Policies (Post-reform: Dashed Lines)

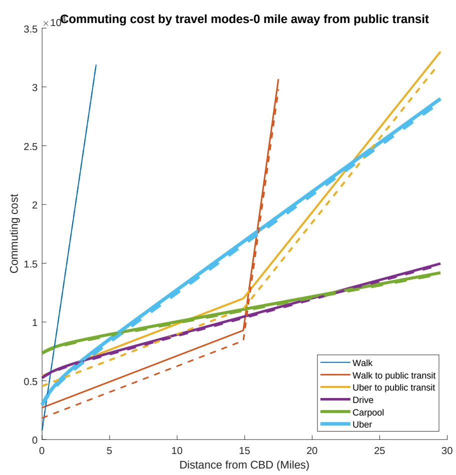
(a) Fixed Subsidy, 0 Miles




(b) Fixed Subsidy, 0.8 miles




(c) Free Transit, 0 Miles




(d) Free Transit, 0.8 Miles

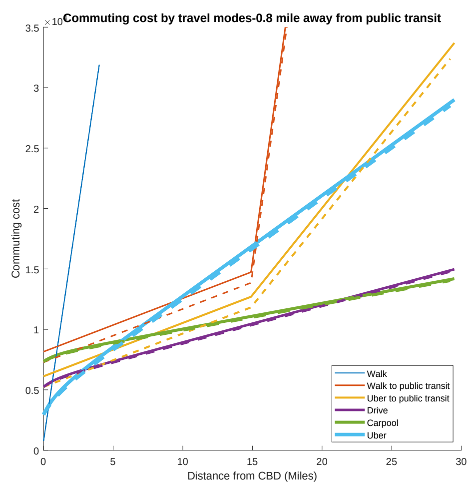
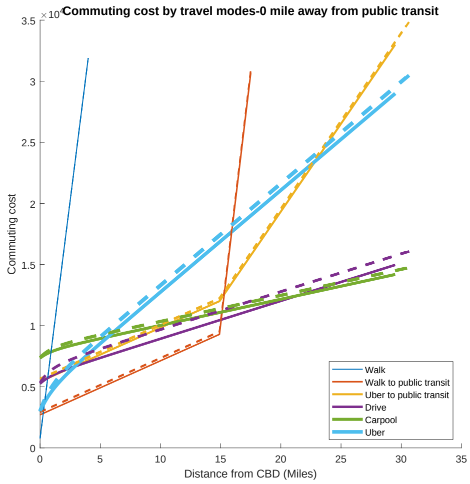
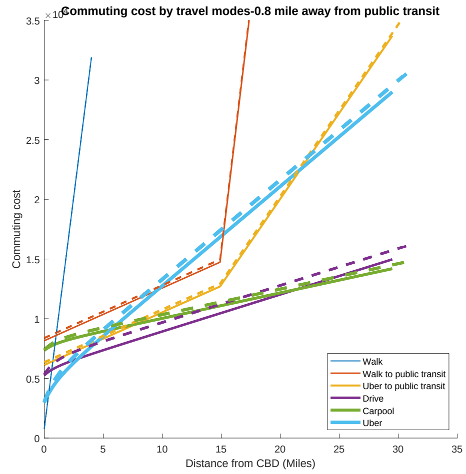


Figure 6: Optimal Toll (Post-reform: Dashed Lines)

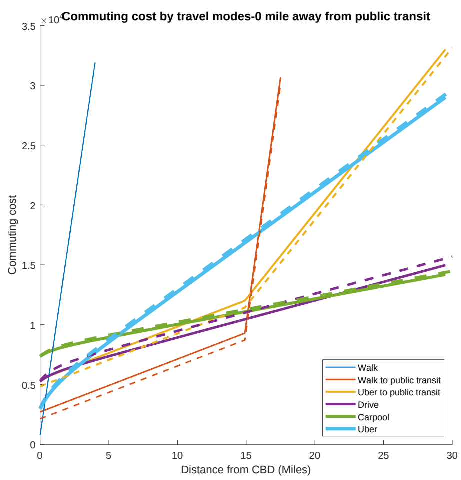
(a) Optimal Toll, Lump Sum Rebate, 0 Miles




(b) Optimal Toll, Lump Sum Rebate, 0.8 miles




(c) Optimal Toll, Reduce Transit Fare, 0 Miles




(d) Optimal Toll, Reduce Transit Fare, 0.8 Miles

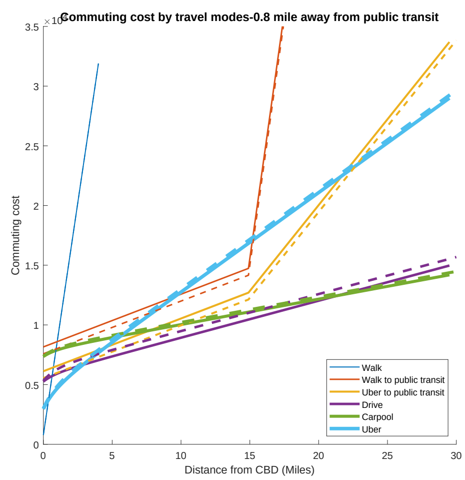


Table 1: Simulation Parameters

| 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) |
| $\alpha_1$ | 1 | Structure share | Muth (1975); Altmann and DeSalvo (1981) |
| $\alpha_2$ | 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) |
| $\beta_1$ | 1 | Numéraire share | Numéraire |
| $\beta_2$ | 0.168 | Housing share | Bureau of Labor Statistics (2010), Calculated |
| *Land Use* | | | |
| $\theta$ | 0.46 | Fraction of land used for housing | Overman et al. (2008) |
| $\theta_R$ | 0.1 | Fraction of land used for highways | Encyclopedia of Chicago |
| $\theta_s$ | 0.15 | Fraction of land used for local streets | Encyclopedia of Chicago |
| $k_{CBD}$ | 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 |
| *Driving* | | | |
| $v_{low}$ | 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 |
| $\tau$ | 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) |
| $V_{res}$ | 30 | Driving speed limit on residential streets | Statutory speed limit in Chicago |
| $V_{res}^{min}$ | 1 | Minimum average speed on residential streets | Assumed |
| $\tau_w$ | 1.11 | Time cost of walking | Calibrated |
| $\tau_{carpool}$ | 0.767 | Time cost of coordinating carpool | Calibrated |
| $t_{carpool}$ | 15 | Time for coordinating carpool in minutes | Calibrated |
| *Walking* | | | |
| $V_{walk}$ | 2.5 | Average walking speed | Assumed |
| $\tau_w$ | 1.11 | Time cost of walking | Calibrated |
| *Public Transit* | | | |
| $awt$ | 7.5 | Average waiting time in minutes at the transit station | Chicago Transit Authority |
| $publicfare$ | 2.5 | Metro ticket per trip | Chicago Transit Authority |
| $V_{metro}$ | 20 | Average metro speed per hour | Chicago Transit Authority |
| $\tau_{pub}$ | 0.5 | Time cost of taking public transit | Calibrated |
| *Uber* | | | |
| $f_0$ | 3.64 | Uber basefare | Uber |
| $f_1$ | 0.81 | Uber cost per mile | Uber |
| $f_2$ | 0.28 | Uber cost per minute | Uber |
| $\tau_{uber}$ | 0.24 | Time cost of commuting using Uber | Calibrated |
| *Uber Labor Market* | | | |
| $\epsilon_{labor}$ | 1.72 | Uber supply elasticity | Chen et al. (2019) |
| $\theta_{uber}$ | 30% | Fraction of Uber takes from drivers' revenue | Assumed |

Table 2: Calibration of the Simulation

| **City characteristics** | **Chicago urbanized area** | **Simulated characteristics** |
|---|---|---|
| Total Occupied Units[1] | 3,012,005 | 3,011,326 |
| 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 | 1995.5 |
| City Radius (miles)[1] | 33.56 | 32.10 |
| Land area (square miles)[1] | 2122.8 | 1930 |
| Time to work (Residential Average)[1] | 30.7 | 24.34 |
| Fraction housed in 1 unit structures[1] | 58.8% | 58.24% |
| Fraction housed in 2-4 unit structures[1] | 14.6% | 15.16% |
| Fraction housed in 5+ unit structures[1] | 26.6% | 26.6% |
| **Means of transportation to work**[1] | | |
| Walked | 3.30% | 2.24% |
| Public transportation | 12.40% | 11.62% |
| Drove alone | 69.40% | 69.14% |
| Carpooled | 8.70% | 8.27% |
| Uber | 0% | 8.74% |
| 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: Fixed Tax Rate

| **Scenario** | **Uber (Laissez Faire)** | **Tax (67 cents per trip)** | | |
|---|---|---|---|---|
| **Tax return** | | **Lump sum return** | **Improve transit** | **Reduce transit fare** |
| | | **Urban Form** | | |
| City Radius (assuming circle) | 32.10 | 32.3 | 32.20 | 32.20 |
| Median Residential Struct./Land ratio | 0.523 | 0.520 | 0.520 | 0.52 |
| Residential Density (hh per sq. mile) | 1559.87 | 1541.19 | 1550.14 | 1550.14 |
| Average Commuting Time to work | 24.34 | 24.243 | 24.21 | 24.33 |
| | | **Fraction of population by Commuting Mode** | | |
| Walking | 2.24% | 2.57% | 2.57% | 2.56% |
| Public transit | 11.62% | 11.94% | 12.09% | 12.69% |
| *Walking to public transit* | 11.62% | 11.94% | 12.09% | 12.69% |
| *Taking Uber to public transit* | 0.00% | 0.00% | 0.00% | 0.00% |
| Solo driving | 69.14% | 71.48% | 71.40% | 70.97% |
| Carpooling | 8.27% | 8.49% | 8.42% | 8.37% |
| Taking Uber to work | 8.74% | 5.52% | 5.52% | 5.41% |
| | | **Traffic Congestion and Public Transit Crowding** | | |
| Average speed on highways | 37.92 | 38.14 | 38.118 | 38.11 |
| Public trasit average waiting time (minutes) | 7.50 | 7.50 | 7.32 | 7.85 |
| | | **Uber Outcome** | | |
| Aggregate uber dirver income revenue (Millions) | 803.48 | 594.64 | 594.68 | 587.68 |
| Uber driver supply (millions hours) | 34.71 | 20.68 | 20.68 | 20.27 |
| Average Uber driving time per trip (minutes) | 7.66 | 6.94 | 6.94 | 6.95 |
| Average Uber driving distance per trip (miles) | 1.68 | 1.43 | 1.43 | 1.44 |
| Average Uber price per trip | 7.15 | 6.74 | 6.74 | 6.75 |
| Fraction of profit that Uber takes | 30.00% | 13.17% | 13.17% | 12.42% |
| | | **Tax Revenue and Tax Return** | | |
| Aggregate tax revenue (millions) | **0.00** | 69.64 | 69.65 | 68.17 |
| Tax return per household | 0.00 | 23.20 | 0.00 | 0.00 |
| Public transit headway (minutes) | 15.00 | 15.00 | 14.64 | 15.00 |
| Public transit one way ticket cost | 2.50 | 2.50 | 2.50 | 2.21 |
| | | **Welfare** | | |
| Wage rate | 56069.00 | 56069.00 | 56069.00 | 56069 |
| Utility | 11354.83 | 11360.70 | 11355.76 | 11357.43 |

Table 4: Sales Tax

| **Scenario** | **Uber (Laissez Faire)** | | **Salestax (9.25%)** | |
|---|---|---|---|---|
| **Tax return** | | **Lump sum return** | **Improve transit** | **Reduce transit fare** |
| **Urban Form** | | | | |
| City Radius (assuming circle) | 32.10 | 32.3 | 32.30 | 32.2 |
| Median Residential Struct./Land ratio | 0.523 | 0.520 | 0.520 | 0.52 |
| Residential Density (hh per sq. mile) | 1559.87 | 1541.19 | 1541.19 | 1550.60 |
| Average Commuting Time to work | 24.34 | 24.212 | 24.19 | 24.28 |
| **Fraction of population by Commuting Mode** | | | | |
| Walking | 2.24% | 2.57% | 2.57% | 2.56% |
| Public transit | 11.62% | 11.90% | 12.02% | 12.61% |
| *Walking to public transit* | 11.62% | 11.90% | 12.02% | 12.61% |
| *Taking Uber to public transit* | 0.00% | 0.00% | 0.00% | 0.00% |
| Solo driving | 69.14% | 71.74% | 71.65% | 71.24% |
| Carpooling | 8.27% | 8.48% | 8.45% | 8.36% |
| Taking Uber to work | 8.74% | 5.31% | 5.31% | 5.23% |
| **Traffic Congestion and Public Transit Crowding** | | | | |
| Average speed on highways | 37.92 | 38.14 | 38.143 | 38.12 |
| Public trasit average waiting time (minutes) | 7.50 | 7.50 | 7.34 | 7.74 |
| **Uber Outcome** | | | | |
| Aggregate uber dirver income revenue (Millions) | 803.48 | 577.07 | 577.11 | 572.15 |
| Uber driver supply (millions hours) | 34.71 | 19.64 | 19.64 | 19.35 |
| Average Uber driving time per trip (minutes) | 7.66 | 6.78 | 6.78 | 6.79 |
| Average Uber driving distance per trip (miles) | 1.68 | 1.38 | 1.38 | 1.38 |
| Average Uber price per trip | 7.15 | 6.65 | 6.65 | 6.66 |
| Fraction of profit that Uber takes | 30.00% | 11.24% | 11.25% | 10.69% |
| **Tax Revenue and Tax Return** | | | | |
| Aggregate tax revenue (millions) | **0.00** | 60.14 | 60.15 | 59.26 |
| Tax return per household | 0.00 | 20.14 | 0 | 0.00 |
| Public trasit headway (minutes) | 15.00 | 15.00 | 14.69 | 15.00 |
| Public transit one way ticket cost | 2.50 | 2.50 | 2.50 | 2.25 |
| **Welfare** | | | | |
| Wage rate | 56069.00 | 56069.00 | 56069.00 | 56069.00 |
| Utility | 11354.83 | 11360.38 | 11356.09 | 11357.64 |

Table 5: Subsidy Policies

| **Scenario** | **Uber (Laissez Faire)** | **Subsidy (flat rate $3 off Uber to public transit)** | **Subsidy (20% off Uber to public transit)** | **Free public transit** |
|---|---|---|---|---|
| **Source of subsidy** | | **Lump sum income reduction** | **Lump sum income reduction** | **Lump sum income reduction** |
| **Urban Form** | | | | |
| City Radius (assuming circle) | 32.10 | 32.10 | 32.10 | 31.80 |
| Median Residential Struct./Land ratio | 0.523 | 0.520 | 0.523 | 0.537 |
| Residential Density (hh per sq. mile) | 1559.87 | 1559.87 | 1559.87 | 1590.34 |
| Average Commuting Time to work | 24.34 | 25.04 | 24.25 | 24.79 |
| **Fraction of population by Commuting Mode** | | | | |
| Walking | 2.24% | 2.27% | 2.23% | 2.07% |
| Public transit | 11.62% | 17.32% | 11.77% | 17.88% |
| *Walking to public transit* | 11.62% | 6.39% | 11.55% | 16.03% |
| *Taking Uber to public transit* | 0.00% | 10.93% | 0.22% | 1.85% |
| Solo driving | 69.14% | 63.60% | 68.69% | 63.78% |
| Carpooling | 8.27% | 8.27% | 8.28% | 7.55% |
| Taking Uber to work | 8.74% | 8.54% | 9.03% | 8.72% |
| **Traffic Congestion and Public Transit Crowding** | | | | |
| Average speed on highways | 37.92 | 38.84 | 38.04 | 38.77 |
| Public trasit averagewaiting time (minutes) | 7.50 | 11.76 | 7.50 | 12.10 |
| **Uber Outcome** | | | | |
| Aggregate uber dirver income revenue (Millions) | 803.48 | 1011.73 | 824.02 | 830.49 |
| Uber driver supply (millions hours) | 34.71 | 51.59 | 36.25 | 36.74 |
| Average Uber driving time per trip (minutes) | 7.66 | 3.45 | 7.49 | 6.08 |
| Average Uber driving distance per trip (miles) | 1.68 | 0.97 | 1.69 | 1.58 |
| Average Uber price per trip | 7.15 | 5.39 | 7.11 | 6.63 |
| Fraction of profit that Uber takes | 30.00% | 48.23% | 31.87% | 35.84% |
| **Income Deduction for Subsidy** | | | | |
| Aggregate subsidy (millions) | 0.00 | 617.06 | 3.49 | 841.51 |
| Income deduction per household | 0.00 | 205.86 | 1.17 | 280.08 |
| **Welfare** | | | | |
| Wage rate | 56069.00 | 56069.00 | 56069.00 | 56069.00 |
| Utility | 11354.83 | 11325.58 | 11357.39 | 11327.65 |

Table 6: Optimal Congestion Policy

| **Scenario** | **Uber (Laissez Faire)** | **Optimal congestion tolls** | | |
|---|---|---|---|---|
| **Tax return** | | **Lump sum return** | **Improve transit** | **Reduce transit fare** |
| | | **Urban Form** | | |
| City Radius (assuming circle) | 32.10 | 33.70 | 32.90 | 32.60 |
| Median Residential Struct./Land ratio | 0.523 | 0.488 | 0.507 | 0.518 |
| Residential Density (hh per sq. mile) | 1559.87 | 1415.12 | 1485.18 | 1512.80 |
| Average Commuting Time to work | 24.34 | 26.43 | 25.37 | 26.99 |
| | | **Fraction of population by Commuting Mode** | | |
| Walking | 2.24% | 2.74% | 2.83% | 2.27% |
| Public transit | 11.62% | 13.66% | 16.53% | 22.31% |
| *Walking to public transit* | 11.62% | 13.57% | 15.23% | 17.09% |
| *Taking Uber to public transit* | 0.00% | 0.09% | 1.30% | 5.21% |
| Solo driving | 69.14% | 51.51% | 51.47% | 48.67% |
| Carpooling | 8.27% | 22.58% | 19.70% | 17.78% |
| Taking Uber to work | 8.74% | 9.51% | 9.46% | 8.98% |
| | | **Traffic Congestion and Public Transit Crowding** | | |
| Average speed on highways | 37.92 | 39.55 | 39.64 | 40.04 |
| Public transit average waiting time (minutes) | 7.50 | 8.89 | 6.81 | 14.14 |
| | | **Uber Outcome** | | |
| Aggregate uber dirver income revenue (Millions) | 803.48 | 820.12 | 838.68 | 893.69 |
| Uber driver supply (millions hours) | 34.71 | 35.95 | 37.36 | 41.68 |
| Average Uber driving time per trip (minutes) | 7.66 | 6.93 | 6.06 | 4.36 |
| Average Uber driving distance per trip (miles) | 1.68 | 1.90 | 1.73 | 1.38 |
| Average Uber price per trip | 7.15 | 7.12 | 6.73 | 5.98 |
| Fraction of profit that Uber takes | 30.00% | 35.07% | 37.52% | 43.35% |
| | | **Toll Revenue and Distribution** | | |
| Aggregate toll revenue (millions) | **0.00** | 3647.97 | 3411.72 | 2906.89 |
| Public transit headway (minutes) | 15.00 | 15.00 | 9.09 | 15.00 |
| Public transit one way ticket cost | 2.50 | 2.50 | 2.50 | 0.49 |
| Toll return Per Household | | 1207.81 | 0.00 | 0.00 |
| | | **Welfare** | | |
| Wage rate | 56069.00 | 56069.00 | 56069.00 | 56069.00 |
| Utility | 11354.83 | 11512.20 | 11245.74 | 11280.31 |

# A Online Appendix

## A.1 Commuting Mode Choice

Given many of the results hinge on how the transportation cost curves shift or pivot, in this section we characterize some of the properties of each of these curves. We emphasize the fixed costs and marginal costs of each mode, which lead to explicit two-dimensional cutoff rules for mode choice.

### A.1.1 Comparison of the Fixed Costs for Different Commuting Modes

Recall that $k$ represents the distance from the CBD and $j$ represents the distance from the nearest transit station. The fixed cost for walking is zero,

$$fc_{walk}(k, j) = 0. \tag{A1}$$

The fixed cost for walking to take public transit holding location $j$ constant is

$$fc_{walkpub}(k, j) = \tau_w \cdot W \cdot (j/V_{walk}) + awt \cdot \tau_{pub} \cdot W + publicfare. \tag{A2}$$

The fixed cost for using Uber to public transit holding location $j$ constant is

$$fc_{uberpub}(k, j) = f_0 + awt_{uber} \cdot \tau_{uber} \cdot W + f_1 \cdot j + f_2 \cdot j/V_{res} + \tau_{uber} W \cdot j/V_{res} + awt \cdot \tau_{pub} W + publicfare. \tag{A3}$$

It includes the fixed cost of taking Uber as well as the fixed cost of waiting for the train and transit fare tickets.

The fixed cost for driving is

$$fc_{drive}(k, j) = m_0 + parking_{CBD}. \tag{A4}$$

The fixed cost for taking Uber is

$$fc_{uber}(k, j) = f_0 + awt_{uber} \cdot \tau_{uber} \cdot W. \tag{A5}$$

The fixed cost for carpooling is

$$fc_{carpool}(k, j) = m_0 + \tau_{carpool} \cdot W \cdot z_{carpool} + parking_{CBD}/n. \tag{A6}$$

Comparing across commuting modes, the fixed cost for walking is the lowest. If $j$ is small, which means the individual is living close to the public transit station, then the fixed cost of walking to public transit is lower than taking Uber to the transit stations. However, as $j$ increases, the cost of walking to transit stations increases sharply due to the high time cost and slow speed of walking.

The fixed cost of taking Uber is much lower than the fixed cost of owning a car for driving or carpooling. Also, the fixed cost of taking Uber directly to work is lower than taking Uber to the public transit.

Whether the fixed cost of taking Uber is higher or lower than walking to public transit depends on where location $j$ is. If $j$ is small, because the basefare is higher than the public transit ticket fare, the fixed cost of taking Uber is higher than walking to public transit. However, as $j$ increases, the time cost of walking increases, thus the fixed cost of taking Uber becomes lower than walking to take public transit. In addition, the fixed cost of walking to take transit is lower than driving if living closer to the transit station, and becomes higher than driving as $j$ increases.

The fixed cost of carpooling is higher than the fixed cost of driving because the additional carpooling cost is higher than shared parking cost.

### A.1.2 Comparison of the Marginal Costs for Different Commuting Modes

The marginal cost for walking is

$$mc_{walk}(k,j) = \tau_w \cdot W \cdot (1/V_{walk}). \tag{A7}$$

The marginal cost for public transit holding location $j$ constant is

$$mc_{walkpub}(k,j) = \tau_{pub} \cdot W \cdot (1/V_{metro}). \tag{A8}$$

The marginal cost for using Uber to public transit holding location $j$ constant is

$$mc_{uberpub}(k,j) = \tau_{pub} \cdot W \cdot \frac{1}{V_{metro}}. \tag{A9}$$

The marginal cost for driving is

$$mc_{drive}(k,j) = m_1 + p_g \frac{1}{G(V(k))} \cdot \frac{-1}{G^2} \cdot G'(V(k)) \cdot V'(k) + \tau W \cdot \frac{1}{V(k)} \cdot \frac{-1}{V^2} \cdot V'(k). \tag{A10}$$

The marginal cost for taking Uber is

$$mc_{uber}(k,j) = f_1 + f_2 \frac{1}{V(k)} \cdot \frac{-1}{V^2} \cdot V'(k) + \tau_{uber} \cdot W \cdot \frac{1}{V(k)} \cdot \frac{-1}{V^2} \cdot V'(k). \tag{A11}$$

The marginal cost for carpooling is

$$mc_{carpool}(k,j) = m_1/n + (p_g/n)\frac{1}{G(V(\kappa))}\cdot\frac{-1}{G^2}\cdot G'(V(k))\cdot V'(k) + \tau W\frac{1}{V(\kappa)}\cdot\frac{-1}{V^2}\cdot V'(k). \quad \text{(A12)}$$

In contrast to the fixed costs, the marginal cost for walking is the highest because the time cost of walking is highest and the speed of walking is lowest. Given zero fixed cost, if workers live closer to the CBD, the optimal commuting mode is walking. However, as workers live further away from the CBD, the cost of walking increases rapidly due to steep marginal cost curve. Therefore, there exists a boundary, $\overline{k_{walk}}$, such that people choose walking within $\overline{k_{walk}}$ and choose other commuting modes beyond $\overline{k_{walk}}$.

Uber has the second highest marginal cost because Uber charges a higher fare per mile, $f_1$, and fare per minute, $f_2$, to make a profit compared to the variable maintenance cost and gasoline cost of owning a car. Because Uber has a lower fixed cost, even if the marginal cost is higher, for workers living closer to the CBD, the total commuting cost of taking Uber could be lower than other commuting modes. However, if workers live further away from the CBD, it is not cost effective to take Uber because the total cost increases rapidly due to a high marginal cost. Therefore, there exists a boundary $\overline{k_{uber}}$ such that beyond this boundary, there are not any workers choosing to take Uber.

The marginal cost of carpooling is smaller than the marginal cost of driving because riders share the maintenance cost and gasoline cost. Because carpooling has a higher fixed cost and a lower marginal cost compared to driving, there exists a carpooling boundary $\overline{k_{pool}}$ such that beyond the boundary, workers will choose carpooling over solo driving.

The marginal costs of walking to public transit and taking Uber to public transit are the same. They are higher than driving because of the slower speed of trains and the higher time cost of taking train. The boundary for public transit will depend not only on distance from the CBD, but also distance from the transit station.

### A.1.3 Optimal Commuting Mode Choice

There exists a boundary $\overline{j_1}$ such that people living within the boundary choose to walk to public transit. We solve for $\overline{j_1}$ using

$$T_{walk}(k,j) = T_{walkpub}(k,j) = T_{uber}(k,j) \quad \text{(A13)}$$

At $j = 0$, right next to the transit station, Uber is not a viable option. As $j$ increases, we could imagine that the public transit curve starts to shift up as the commuting cost of walking to transit station increases. As soon as $j > \overline{j_1}$, taking Uber becomes more cost effective for workers who live closer to the CBD. When the cost curve for walking to public transit passes the point where $T_{walk}(k,j) = T_{uber}(k,j)$, some workers start to take Uber to work.

For workers living beyond $\overline{k_{walk}}$ but close to the transit station, which is within the boundary $\overline{j_1}$, the dominate commuting mode is walking to public transit. The walking boundary $\overline{k_{walk}}$ is determined where the cost of walking is equal to the cost of walking to take public transit. Holding $j$ constant, $\overline{k_{walk}}$ is solved as

$$\overline{k_{walk}} = \frac{\tau_w \cdot W \cdot (j/V_{walk}) + awt \cdot \tau_{pub} \cdot W + publicfare}{\tau_w \cdot W/V_{walk} - \tau_{pub} \cdot W/V_{metro}}. \tag{A14}$$

Because the public transit lines end after 15 miles from the CBD, the marginal cost of taking public transit increases sharply because workers have to walk a longer distance to get to the transit line if they live more than 15 miles away from the CBD. For any $j < \overline{j_1}$, the public transit boundary $\overline{k_{walkpub}}$ is determined by the following:

$$T_{walkpub}(k,j) = T_{drive}(k,j), \tag{A15}$$

where workers choose to take public transit if living between $\overline{k_{walk}}$ and $\overline{k_{walkpub}}$. Workers choose to drive solo within the carpooling boundary $\overline{k_{pool}}$ and beyond the public transit boundary $\overline{k_{walkpub}}$. At the carpooling boundary, $T_{carpool}(k,j) = T_{drive}(k,j)$. Workers choose to carpool if $k > \overline{k_{pool}}$.

If workers live too far away from the public transit, it becomes too costly to take public transit. Therefore, there exists a boundary $\overline{j_2}$ such that there is no one taking public transit beyond $\overline{j_2}$. The marginal cost of public transit is higher than driving, but lower than taking Uber. Then, $\overline{j_2}$ is determined using

$$T_{walkpub}(k,j) = T_{drive}(k,j) = T_{uber}(k,j) \tag{A16}$$

As $j$ increases, the public transit curve starts to shift up. As soon as the cost curve for walking to public transit pass the point where $T_{uber}(k,j) = T_{driver}(k,j)$, public transit is no longer an optimal option. Thus for $j > \overline{j_2}$, taking Uber or driving becomes more cost effective for workers.

Now, we can piece all the boundaries together to fully characterize the commuting mode. The walking boundary $\overline{k_{walk}}$ is determined by

$$T_{walk}(k,j) = T_{uber}(k,j). \tag{A17}$$

Workers choose to take Uber to work, if living beyond $\overline{k_{walk}}$ and within boundary $\overline{k_{uber}}$, where $\overline{k_{uber}}$ is determined by

$$T_{drive}(k, j) = T_{uber}(k, j). \tag{A18}$$

Beyond the Uber boundary $\overline{k_{uber}}$, workers choose to drive solo if living within carpooling boundary and choose to carpooling if living beyond carpooling boundary $\overline{k_{pool}}$.

Between $\overline{j_1}$ and $\overline{j_2}$, both public transit and Uber are viable options. If people live beyond $\overline{k_{walk}}$ but still close to the CBD, they choose Uber. Due to Uber's higher marginal cost, as workers live further away from the CBD, it is not cost effective to take Uber. Instead, people start to take public transit. The walking boundary is determined by $T_{walk}(k, j) = T_{uber}(k, j)$. The Uber boundary $\overline{k_{uber}}$ is determined by

$$T_{walkpub}(k, j) = T_{uber}(k, j), \tag{A19}$$

where people take Uber if living between $\overline{k_{walk}}$ and $\overline{k_{uber}}$.

The boundary for taking public transit $\overline{k_{walkpub}}$ is determined by

$$T_{drive}(k, j) = T_{walkpub}(k, j). \tag{A20}$$

Workers choose to take public transit if living between $\overline{k_{uber}}$ and $\overline{k_{walkpub}}$. Beyond $\overline{k_{walkpub}}$, worker choose to drive solo if within the carpooling boundary and carpool if living beyond the carpooling boundary.

Because taking Uber to public transit has a higher fixed cost as well as a higher marginal cost compared to walking to public transit. There exists a boundary $\overline{j_3}$ such that for $j < \overline{j_3}$, walking to public transit dominates taking Uber to public transit. However, if $j > \overline{j_3}$, the cost of walking to public transit is higher than taking Uber to public transit. It could be solved using $T_{walkpub}(k, j) = T_{uberpub}(k, j)$. That is, given any location $k$,

$$\tau_w \cdot W \cdot (j/V_{walk}) + awt \cdot \tau_{pub} \cdot W + publicfare + \tau_{pub} \cdot W \cdot (k/V_{metro}) =$$
$$f_0 + f_1 j + f_2 \cdot j/V_{res} + awt_{uber} \cdot \tau_{uber} \cdot W + \tau_{uber} W \cdot j/V_{res} + awt \cdot \tau_{pub} W + publicfare + \tau_{pub} W \cdot k/V_{metro}, \tag{A21}$$

Then $\overline{j_3}$ is solved,

$$\overline{j_1} = (f_0 + awt_{uber} \cdot \tau_{uber} \cdot W)/(\tau_w \cdot W/V_{walk} - f_1 - f_2/V_{res}) \tag{A22}$$

When $j > \overline{j_3}$, taking Uber to public transit starts to become cheaper than walking to public transit, however, public transit is not a cost effective option any more because the cost of driving is lower than either walking or taking Uber to public transit.

This explains why taking Uber to public transit is not an optimal option in our baseline simulation. However, taking Uber to public transit could become a viable option if subsidy policies target at taking Uber to public transit. From different subsidy policies, the cost curve for taking Uber to take public transit shifts downward due to a lower fixed cost or rotates with a flatter slope due to the reduction in marginal cost.

Different tax policies imposed on Uber change either the fixed cost or marginal cost of taking Uber. The cost curves for taking Uber directly to work or to transit stations shifts up due to increased fixed cost or rotates with steeper slope due to the increase in marginal cost.

## A.2 Additional Tables and Figures

In this section of the appendix, we present additional tables and figures, each of which is discussed in the text of the paper.

Table A1: Mile Tax

| **Scenario** | **Uber (Laissez Faire)** | **Tax per mile (20 cents per mile)** | | |
|---|---|---|---|---|
| **Tax return** | | **Lump sum return** | **Improve transit** | **Reduce transit fare** |
| **Urban Form** | | | | |
| City Radius (assuming circle) | 32.10 | 32.3 | 32.20 | 32.2 |
| Median Residential Struct./Land ratio | 0.523 | 0.519 | 0.519 | 0.52 |
| Residential Density (hh per sq. mile) | 1559.87 | 1541.19 | 1550.14 | 1550.843107 |
| Average Commuting Time to work | 24.34 | 24.248 | 24.12 | 24.17906116 |
| **Fraction of population by Commuting Mode** | | | | |
| Walking | 2.24% | 2.24% | 2.23% | 2.23% |
| Public transit | 11.62% | 11.73% | 11.76% | 12.27% |
| *Walking to public transit* | 11.62% | 11.73% | 11.76% | 12.27% |
| *Taking Uber to public transit* | 0.00% | 0.00% | 0.00% | 0.00% |
| Solo driving | 69.14% | 70.96% | 70.65% | 70.26% |
| Carpooling | 8.27% | 8.42% | 8.38% | 8.34% |
| Taking Uber to work | 8.74% | 6.66% | 6.99% | 6.90% |
| **Traffic Congestion and Public Transit Crowding** | | | | |
| Average speed on highways | 37.92 | 38.07 | 38.168 | 38.16 |
| Public transit average waiting time (minutes) | 7.50 | 7.50 | 7.40 | 7.50 |
| **Uber Outcome** | | | | |
| Aggregate uber dirver income revenue (Millions) | 803.48 | 662.48 | 682.07 | 677.52 |
| Uber driver supply (millions hours) | 34.71 | 24.90 | 26.19 | 25.89 |
| Average Uber driving time per trip (minutes) | 7.66 | 6.92 | 6.95 | 6.95 |
| Average Uber driving distance per trip (miles) | 1.68 | 1.42 | 1.47 | 1.47 |
| Average Uber price per trip | 7.15 | 6.73 | 6.78 | 6.78 |
| Fraction of profit that Uber takes | 30.00% | 19.57% | 21.65% | 21.28% |
| **Tax Revenue and Tax Return** | | | | |
| Aggregate tax revenue (millions) | **0.00** | 35.59 | 38.64 | 38.21 |
| Tax return per household | 0.00 | 11.72 | 0.00 | 0.00 |
| Public transit headway (minutes) | 15.00 | 15.00 | 14.79 | 15.00 |
| Public transit one way ticket cost | 2.50 | 2.50 | 2.50 | 2.33 |
| **Welfare** | | | | |
| Wage rate | 56069.00 | 56069.00 | 56069.00 | 56069 |
| Utility | 11354.83 | 11358.25 | 11358.58 | 11359.78 |

Table A2: Fixed Congestion Toll Policy

| **Scenario** | **Uber (Laissez Faire)** | **Fixed toll rate** | | |
|---|---|---|---|---|
| **Tax return** | | **Lump sum return** | **Improve transit** | **Reduce transit fare** |
| | | **Urban Form** | | |
| City Radius (assuming circle) | 32.10 | 32.20 | 32.10 | 32.20 |
| Median Residential Struct./Land ratio | 0.523 | 0.522 | 0.522 | 0.525 |
| Residential Density (hh per sq. mile) | 1559.87 | 1550.14 | 1559.87 | 1550.84 |
| Average Commuting Time to work | 24.34 | 24.41 | 24.28 | 24.30 |
| | | **Fraction of population by Commuting Mode** | | |
| Walking | 2.24% | 2.25% | 2.24% | 2.23% |
| Public transit | 11.62% | 11.76% | 11.83% | 12.53% |
| *Walking to public transit* | 11.62% | 11.76% | 11.83% | 12.53% |
| *Taking Uber to public transit* | 0.00% | 0.00% | 0.00% | 0.00% |
| Solo driving | 69.14% | 68.58% | 68.22% | 67.70% |
| Carpooling | 8.27% | 8.72% | 8.66% | 8.64% |
| Taking Uber to work | 8.74% | 8.70% | 9.05% | 8.90% |
| | | **Traffic Congestion and Public Transit Crowding** | | |
| Average speed on highways | 37.925 | 37.98 | 38.07 | 38.19 |
| Public transit average waiting time (minutes) | 7.50 | 7.50 | 7.32 | 7.66 |
| | | **Uber Outcome** | | |
| Aggregate uber dirver income revenue (Millions) | 803.48 | 800.26 | 819.14 | 808.18 |
| Uber driver supply (millions hours) | 34.71 | 34.47 | 35.88 | 35.06 |
| Average Uber driving time per trip (minutes) | 7.66 | 7.63 | 7.64 | 7.56 |
| Average Uber driving distance per trip (miles) | 1.68 | 1.68 | 1.73 | 1.73 |
| Average Uber price per trip | 7.15 | 7.14 | 7.18 | 7.16 |
| Fraction of profit that Uber takes | 30.00% | 29.88% | 31.42% | 31.04% |
| | | **Toll Revenue and Distribution** | | |
| Aggregate toll revenue (millions) | 0.00 | 69.65 | 69.65 | 69.65 |
| Public transit headway (minutes) | 15.00 | 15.00 | 14.64 | 15.00 |
| Public transit one way ticket cost | 2.50 | 2.50 | 2.50 | 2.21 |
| Toll return Per Household | 0.00 | 23.12 | 0.00 | 0.00 |
| Toll rate per car | 0.00 | 22.44 | 22.67 | 22.90 |
| | | **Welfare** | | |
| Wage rate | 56069.00 | 56069.00 | 56069.00 | 56069.00 |
| Utility | 11354.83 | 11355.86 | 11353.24 | 11357.86 |