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ABSTRACT

Ride-hailing applications create new challenges for governments providing transit services, but also create new opportunities to raise tax revenue. To shed light on the effect of taxing or subsidizing ride-hailing services, we extend a pseudo-monocentric city model to include multiple endogenously chosen transportation modes, including ride-hailing applications and endogenous car ownership. We show that most tax and spending programs that cities have currently adopted mildly increase public transit usage. However, the model predicts more significant increases in public transit ridership when ride-hailing applications are subsidized as a “last-mile” provider. Our model indicates that whether ride-hailing services and public transit are substitutes or complements is a policy choice.

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1. Introduction

Ride-hailing applications (apps) including Uber, Lyft and Via, have revolutionized transportation in cities around the world. While the effects of these platforms on the labor market and pricing strategies are well-studied,² the effects of ride-hailing apps on government finances as well as expenditures on related public ser-

vices such as public transportation remain uncertain. Taxing Uber services or changing expenditures on related public services, will affect the transit choices of individuals, possibly altering the business models of these platforms, and in the long-run, will affect urban form.³ Given many policymakers have argued that ride-hailing applications lead to added congestion within city limits⁴ or are crowding out public transit services, government regulations and policies are critical tools to alter the urban transit choice landscape. We study various policy options discussed in cities around the world related to taxing or subsidizing ride-hailing applications, as well as changes in government spending on possibly complementary or substitute modes of transit such as buses or subways (Hall et al., 2018; Gonzalez-Navarro et al., 2022).

Given the surge in the popularity of ride-hailing apps,⁵ they pose challenges for policymakers, including how to update anti-

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² See Angrist et al., 2021; Berger et al., 2018; Chen et al., 2019; Cramer and Krueger, 2016; Ge et al., 2020; Hall and Krueger, 2018; Cohen et al.; Hall et al., 2019.

³ Fox (2020) highlights the role of autonomous vehicles on governments.

⁴ See Erhardt et al. (2019) and Cairncross et al. (2021).

⁵ About a third of Americans have used applications like Uber and Lyft for rides. In 2016, ride-hailing apps 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.

quated tax systems to deal with platform marketplaces. Despite these challenges, many policymakers view ride-hailing apps as an attractive source of revenue. As a result, some states and cities have recently reformed their tax laws to raise revenue from ride-hailing applications. The motives for these new taxes vary from expanding the sales tax base as consumption shifts to services,⁶ seeking a way to raise revenue that can be earmarked to fund public infrastructure or public transit, or, often due to political economy reasons (Brueckner and Selod, 2006), to help level the playing field for traditionally taxis. At the same time, other cities are subsidizing ride-hailing services as a means of improving the mobility and employment opportunities of low-income houses or as a way to provide “last-mile” services for individuals to get from their house to public transit stations.

The expansion of ride-hailing apps may threaten publicly provided transportation networks, but privately-provided services such as Uber may also complement public services (Hall et al., 2018; Gonzalez-Navarro et al., 2022; Erhardt et al., 2019). Hall et al. (2018) outline several possible mechanisms. Uber may be a substitute because its convenience provides value to the consumer, even if the monetary price of Uber is higher. Moreover, adding another mode choice option may make transit less attractive. On the other hand, Uber may be a complement to transit because Uber can fill coverage gaps (geographic, time of day) in public transit coverage. Further, Uber reduces the need to entirely rely on a fixed transit schedule in the presence of bad weather or other shocks, implying that individuals will be more likely to use transit in one direction, if they know they can get back home via an alternative mode, Uber.⁷ Of these possibilities, our model will focus on the convenience of Uber lowering the cost relative to other modes of transit and Uber filling geographic coverage gaps in transit. In addition, we verify the robustness of the model to including idiosyncratic trip-specific benefits of taking Uber to transit. Finally, an additional mechanism in our model is endogenous car ownership: higher Uber prices may increase car ownership, which may in turn affect transit usage for some trips. Thus, our model sheds light on the channels discussed in the prior literature (Hall et al., 2018) by showing how policies on ride-hailing apps and related services influence modal choice and the long run development of cities.

While the literature on commodity taxes is well-developed, the taxation of ride-hailing apps poses challenges not traditionally found in standard (pre-digital economy) products. First, the taxation of ride-hailing apps will affect modes of transportation, land use, and public infrastructure investment in the long-run (Larson and Zhao, 2020). As a result, these taxes will have important general equilibrium effects and standard reduced form empirical analysis is not sufficient to determine the long-run effect of taxing ride-hailing apps. Second, ride-hailing apps are a platform. The business model of platforms, like Uber, Facebook and Amazon 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 increase. 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 (Kind et al., 2008; Koethenbueger, 2021).

We answer several questions. First, how does taxing/subsidizing ride-hailing services change car ownership and the mode of

transit in our cities? Second, focusing on the goal of many urban planners, what is the “optimal” way for cities to tax/subsidize ride-hailing apps? 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 ride-hailing policy, we consider several policies debated by cities: flat unit taxes per ride, ad valorem sales taxes on rides, mileage taxes, subsidies on rides to and from 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: transfers to non-residents (perhaps the policy is implemented by the state rather than city), lump-sum rebates to residents, reductions in the fares for public transportation, and improvements in the quality of public transportation. Given many of these policies were implemented only recently, and it would be nearly impossible to harmonize data across cities, 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.

We extend the standard monocentric city model (Brueckner, 1987) to allow for various transportation modes for commuting to work, leisure trips to central points of agglomeration (downtown), and “idiosyncratic” leisure trips to random points in the city. Although we use the structure of the monocentric city model for commuting and leisure trips to downtown, the addition of non-commuting leisure trips to various points throughout the city makes our city pseudo-monocentric.⁹ Although some models of the monocentric city include transit choice (e.g., Arnott and MacKinnon, 1977; Anas and Moses, 1979; Sasaki, 1989; Sasaki, 1990; Borck and Wrede, 2008; Brueckner and Franco, 2018), these models are limited in their applicability to our setting. In particular, these models usually 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, consumer heterogeneity in the proximity to transit stations, along with trips to non-central locations in the city, making the model realistic for our setting but also tractable for other researchers. In addition, our model features a multi-stage process by which individuals decide to own a car or not, allowing us to capture the long-run effects of transit prices via more permanent decisions regarding vehicles.

In our model, ride-hailing apps can be used for two choices with respect to trips downtown for either commuting or leisure purposes: as a direct means of transportation or as a means of transportation to the nearest public transit station instead of walking or buses. In addition, ride-hailing apps can be used as an alternative to driving or taking buses on local leisure trips to “random” (non-central) points. While these types of leisure trips have an exogenous distance, the distance of downtown leisure trips taken on Uber is endogenous. Our model necessarily makes several assumptions. One assumption is that we assume that trips can be discretely separated into commuting trips subject to congestion forces, leisure trips downtown at off-peak hours, and other local

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).

⁹ The monocentric city model was 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.

⁶ This fits in a broader debate of how tax systems should evolve in the presence of technological change (Agrawal and Wildasin, 2019). For example, Thummel (2022) considers the tax treatment of robots.

⁷ It is also possible that Uber will not affect transit, particularly, if transit riders and Uber riders are distinct segments of the population. Moreover, individuals might not experiment with different modes unless forced to do so (Larcom et al., 2017). Given our model does not feature income heterogeneity, this is not a channel we can accurately capture, but to the extent it exists, it would likely mute the changes.

trips where those local trips have a more limited range of transit options, while for trips to downtown we heavily rely on the structure of the monocentric city. Given the importance of Uber for trips outside the city center, these leisure trips to non-CBD (Central Business District) points turn the model into a pseudo-monocentric model.

The model is 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 ride-hailing apps and are most likely to face a tradeoff between ride-hailing apps and public transit modes. We first study the equilibrium without any government intervention and then with it. By focusing on a large city, we likely underestimate the “last-mile” effect of Uber. Rather than focusing on many different city sizes, we have elected to focus on many different policies. We will discuss whether the magnitudes of the effects depend on characteristics of the city, such as income or transit coverage. One may also wonder whether the key results would extend to cities that are polycentric. We will discuss what additional modeling issues would arise in polycentric cities. Ultimately, we argue that these added complications may change the magnitudes of our effects, but are unlikely to alter the sign or the qualitative conclusion that policy choices influence whether Uber and transit are complements or substitutes.

The first set of results concern taxes on Uber as they are currently implemented. 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, even when the spending is earmarked to transit. Second, at the margin, what the tax revenue is used for matters for what mode of transit individuals substitute toward. If the goal of cities is to reduce congestion and increase transit usage, taxes on Uber that fund fare reductions are more successful at achieving the goal 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.

The second set of results focus on transit proposals adopted in a limited number of cities that aim at forming a link between ride-hailing apps and public transportation in order to use Uber to fill coverage gaps. First, we show that subsidies on Uber rides (to transit stations) are an extremely effective way of increasing public transit usage. Indeed, a three dollar subsidy for all rides to and from public transit, increases the usage of rapid transit by over 15%. If cities enact policies, such as flat taxes on Uber, then Uber and rapid transit are substitutes: Uber remains too costly to act as a last mile provider but Uber offers an alternative means of getting directly downtown than rapid transit. We estimate the cross-price elasticity of taking public rapid transportation with respect to the price of taking Uber to work as 0.41 when cities tax Uber. But, the relationship between buses and Uber is more nuanced: raising the price of Uber increases car-ownership which induces declines in bus usage as a means of going directly to the leisure destination. In this way, Uber may be a substitute for rapid transit but, simultaneously, a complement to buses. In contrast, the Uber and rapid transit become complements under the subsidy regime. The cross-price elasticity is -0.32 , when cities enact subsidy policies.

Lastly, we consider optimal congestion tolls (Hall, 2018; Hall, 2021; van den Berg and Verhoef, 2011). Many cities see this as a viable policy because ride-hailing apps are more supportive of a policy that treats all drivers in the same manner. The optimal congestion toll alone increases transit usage as Uber subsidies did. However, we show that suboptimal tolls—implemented to raise the same amount of revenue as the flat tax on Uber rides—result in smaller increases in transit usage and driving speeds than taxing Uber directly.

A critical lesson from this paper is that transit elasticities are determined by the policy environment. In other words, these elasticities are not structural parameters, but rather are policy choices. Critically, and in contrast to the conventional wisdom, our results imply that standard transit elasticities and cross-price elasticities are not just a function of individual preferences. Therefore, they are not immutable and governments can choose these elasticities through the appropriate policies. Thus, the choice of various policy instruments can result in governments choosing the “optimal” transit elasticities. Policy commentators and government officials often worry that Uber is eroding public transit, but our results indicate that if this is true, it may be a result of policymakers failing to set an appropriate policy environment for the co-existence of Uber and transit. Our paper provides a guide forward.

Ride-hailing apps create many challenges and opportunities for cities; our paper provides policy guidance with respect to these tradeoffs. Critically, whether ride-hailing apps and public transit are substitutes or complements is a policy choice.

2. Institutional details

Taxes on ride-hailing services vary dramatically across cities. In January 2018, the city of Chicago passed a \$0.67 per trip tax on ride-hailing services in the city of Chicago – a rate similar to a few other cities around the country. 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. 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.

Chicago is not alone in its unit tax per trip, though the amount of the tax differs substantially across cities. For example, as of 2020, 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 ad valorem 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 unit tax, 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 applications, for example, 1.4% in Philadelphia. In the case of many of these taxes, cities and states differ in their implementation, including whether they apply uniformly to both ride-hailing applications and taxis.

Finally, other cities are instead providing subsidies for Uber riders. The rationale for the subsidy is to induce ride-hailing apps to be a “last-mile” provider for individuals wishing to take public transportation. It is often not cost effective for cities to have a high density transportation network. However, Uber can be prohibitively costly for low-income households. One urban area that has extensively used subsidies is the Pinellas Suncoast Transit Authority (PSTA). For rides starting or ending at a designated stop during daytime hours, the PSTA subsidizes the ride by 50% up to a maximum of \$3. The PSTA also provides free ride-hail rides for low income qualifying riders between 9 pm and 6 am. 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 rapid transit stations.

3. Model structure

In order to model the general equilibrium effects of tax policy, we first construct a baseline city that represent a present-day city before ride hailing services are introduced. The city is pseudo-monocentric and lies on a featureless plane without geological constraints and housing regulations. We assume that land is owned by absentee landlords. We assume a closed city model: Uber's taxation should not result in intercity migration.

The complexity of extending the baseline model to include public transportation, ride-hailing, multiple trip types, car ownership and tax policy requires the model be solved numerically. The goal of numerical simulation models 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 calibrate it to a given present-day city.

Given the monocentric city model has come under some criticism as employment has suburbanized, it is useful to discuss its applicability to our setting. Empirical evidence that our calibrated city—Chicago—conforms to the predictions of the monocentric city model abounds. The key prediction of the model is that population density, structure density and land value decline substantially from the city center. Regarding employment density and land rents, Rosenthal et al. (2022) document that transit cities including Chicago display a monotonic decline in employment density and land rent as one moves away from the CBD. The decline is steep at first and then quickly flatten out, which is a characteristic of a monocentric city with a dominant central business district. McMillen (2006) shows, what is obvious from observing the Chicago skyline, that the city center still dominates urban spatial patterns in terms of structure density, which declines exponentially from the core.¹⁰ Thus, the monocentric city model remains a useful tool to analyze Chicago. But, obviously other cities are not monocentric, and the important question is whether our results using Chicago as a case study extend more generally. We return to this issue later in the paper.

3.1. Theoretical framework

Summary. Firms are located in the CBD and pay the same exogenous wage rate to identical workers, which are fixed in population. Workers, who commute to the CBD reside in a residential district between the CBD and city boundary. The city boundary is determined endogenously by the reservation rent of agricultural land. Utility is endogenous and allowed to vary under different policy scenarios. Households engage in commuting, downtown leisure trips, and other leisure trips using various transport modes. Mode choice is determined endogenously. In contrast to existing models of urban areas where households are only heterogeneous in distance to the city center, in our model, 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 station. Land and housing prices vary across locations so that in equilibrium, households are indifferent across all locations.

3.1.1. The central business district

All employment is concentrated in the CBD, which is at the center of the circle. Because this is a closed city model, total employ-

ment 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 for the CBD and the potential effects of ride hailing transportation services on parking or the formation of employment sub centers. These simplified assumptions are necessary to facilitate simulation analysis. However, unlike the standard model, as will become clear, not all trips are to downtown and so many trips will not rely on this structure.

3.1.2. Land use

Urban land use is divided among highways, residential streets, residential housing, and other uses (public transit, parks, etc.). It is assumed that a constant fraction, θ_R , of land area is allocated to highways, θ_S , of land area is allocated to residential streets, a fixed proportion, θ , 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 are along the circumference of each radius. The highway network is assumed to be dense. This eliminates the need to model households' commuting from home to the highway.

Residential streets are located at each radius. Residential roads are used to engage in local trips and to drive to the rapid transit lines. We assume that, unlike highways which follow *all* rays from the origin, the rapid transit lines are evenly distributed, i.e. the distance between transit lines is equal at a given annulus. Each rapid transit line offers a radial route that links the CBD with residential locations. Stops are located at each radius. We assume that the CBD stops are next to the final destination, such that no additional transit is necessary. Although rapid transit lines are radial, we assume that buses follow residential street roads—driving around the circle—and that bus stops are located at each point.

The city expands until the residential sector is outbid by the agriculture sector. At the city boundary \bar{k} , the residential land price $p_\ell(\bar{k})$ is equal to agricultural land price p^a . The ride-hailing industry has no effect on the 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 (Brueckner and Franco, 2017). The fixed proportions assumption is reasonable if land use regulations or zoning allocates development in fixed proportions.

3.1.3. Housing production

Recall individuals are characterized by a distance from the CBD and a distance from the public transit lines. Housing $H(k, j)$ at distance k from the CBD and distance j from public transit, is produced using structure (capital), S , and land, ℓ , as inputs under a constant returns to scale technology. The production function has a constant elasticity of substitution (CES) functional form with an elasticity of substitution equal to $1/(1 - \rho)$:

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

where structure inputs are perfectly elastically supplied. Then, A represents the housing production technology, α_1 is the structure input share, and α_2 is the land input share. 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. Developers choose structure inputs and land given a structure input price p_s and residential land prices $p_\ell(k, j)$. The structure input price is exogenous while residential land price is determined endogenously.

¹⁰ The dominance of the CBD in Chicago can also be seen from the pattern of the population density distribution shown in Fig.A1.

3.1.4. Households

Homogeneous households consume housing and a composite commodity to maximize:

$$U(k,j) = [\beta_1 y(k,j)^\eta + \beta_2 h(k,j)^\eta]^{1/\eta}, \tag{2}$$

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

Households have an exogenously given income, W . For a household living at distance k from the CBD and distance j from rapid transit, she spends income on the numéraire good, $y(k,j)$, housing, $h(k,j)$, and total transportation costs, $T(k,j)$. Housing expenditure depends on the housing rental price $r(k,j)$ and size $h(k,j)$, yielding the budget constraint:

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

In equilibrium, households' utility is identical at each distance, k , from the the CBD edge, and j from public transit. The assumption of homogeneous income implies there are no heterogeneous effects of ride hailing transportation services across different income groups. Survey results generally show that affluent Americans are more likely to adopt ride hailing.

3.1.5. Transportation technology

The model features three types of trips: commuting trips to the CBD, leisure trips to downtown, and idiosyncratic "local" trips for leisure. This wide variety of trip-types allows us to model various channels that policies may influence Uber or transit ridership. The total transportation cost for households at a distance pair (k,j) , $T(k,j)$, includes the total commuting cost for work, $T^{comm}(k,j)$, the non-commuting cost for leisure trips to the CBD, $T^{leisure}(k,j)$, and the total cost for "random" local trips, $T^{local}(k,j)$.

As will become apparent, both commuting and CBD leisure trips will rely on the structure of the monocentric city model, while "random" local trips will not. Commuting and leisure trips differ in terms of their time of day, thus influencing the available modes of transit, the costs of each mode, and the extent of traffic congestion on roadways. For example, households make non-commuting trips to downtown during non-rush hours or on weekend, while commuting trips occur at peak hours. Among different transportation modes individuals optimally choose one mode to minimize costs.¹¹

Commuting trips to the CBD. Workers choose from different transportation modes to commute to work including walking, public transit, driving, and carpooling. According to the American Community Survey in 2010, over 90% of the U.S. population commute through these four modes. Workers may arrive at public rapid transit lines by walking or bus. After the ride hailing service is introduced, workers have the option to either take it directly to work or to the nearest public transit station. For ease of notation, given a fixed number of trips, we define transport costs as annualized measures.

For households living at distance k from the CBD and distance j from the public transit station, the total transportation cost for walking $n_{commute}$ number of commuting trips is:

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

where the time cost of walking is a fraction τ_w of the wage rate per hour, 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 includes the fixed cost of owning a car, m_0 , an annual parking fee at the CBD, $parking_{CBD}$, costs propor-

tional 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 . Then, gasoline consumption per mile G^{-1} depends on vehicle velocity, V . The velocity at each distance k is determined jointly by the number of commuters and road capacity. The time-cost of commuting depends on the value of time as a fraction, τ , of the wage rate per hour, w , and the travel time $\int_k^j \frac{1}{V(\kappa)} d\kappa$, where k represents the edge of the CBD and κ represents the argument in the integrand. We assume parking is next to the office. Taken together, the total commuting cost of driving is:

$$T_{drive}(k,j) = m_0 + \left[parking_{CBD} + m_1 k + p_g \int_k^j \frac{1}{G(V(\kappa))} d\kappa + \tau w \int_k^j \frac{1}{V(\kappa)} d\kappa \right] \cdot n_{commute}. \tag{5}$$

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 for velocity is

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

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

Households living further away from the CBD have greater incentives to carpool because costs could be shared among riders. If workers choose to carpool, each carpool has n riders, who alternate driving trips, implying that all carpoolers will own a car. 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 . 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, the time cost of scheduling carpooling is $\tau_{schedule} \cdot w \cdot z_{carpool}$, where $\tau_{schedule}$ is the time cost of coordinating and scheduling carpooling as a fraction of wage rate. Similarly, $\tau_{carpool}$ is the time cost of driving. Therefore, the total commuting cost for workers who carpool is:

$$T_{carpool}(k,j) = m_0 + [\tau_{schedule} \cdot w \cdot z_{carpool} + parking_{CBD}/n + (m_1/n)k + (p_g/n) \int_k^j \frac{1}{G(V(\kappa))} d\kappa + \tau_{carpool} w \int_k^j \frac{1}{V(\kappa)} d\kappa] \cdot n_{commute}. \tag{7}$$

As mentioned previously, transit lines are evenly distributed. Each transit line offers a radial route that links the CBD with residential locations. Stops are located at each radius for workers to enter a transit line to the CBD. Buses follow residential roads and thus can be used on trips from home to transit stations.¹² Thus, if households choose to take public transit, in the absence of ride-hailing apps, they could walk or take bus to the nearest public transit station and then take public transit. Therefore, for households walking to the public transit, the transportation cost is:

$$T_{walkpub}(k,j) = [\tau_w \cdot w \cdot (j/V_{walk}) + awt \cdot \tau_{pub} \cdot w + publicfare + \tau_{pub} \cdot w \cdot (k/V_{metro})] \cdot n_{commute}, \tag{8}$$

¹¹ Individuals at a given distance k from the CBD and distance j from the public transit station will commute using the same mode for all commuting trips.

¹² Given buses and rapid transit have similar prices in Chicago, we assume individuals would never want to take a bus directly to downtown given the speed improvements of using rapid transit.

where the first term represents the time cost of walking to the nearby transit station. Then, awt is the average waiting time. The time cost of transit is measured as a fraction, τ_{pub} , of the wage rate and $publicfare$ is the ticket cost. Then, 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. For households taking a bus to the public transit, the transportation cost is:

$$T_{buspub}(k,j) = [\tau_{bus} \cdot w \cdot (j/V_{bus}) + t_{buswait} \cdot \tau_{bus} \cdot w + busfare + awt \cdot \tau_{pub} \cdot w + transferfare + \tau_{pub} \cdot w \cdot (k/V_{metro})] \cdot n_{commute}, \tag{9}$$

where τ_{bus} is the time cost of taking the bus, V_{bus} is the average speed of the bus, and $t_{buswait}$ is the time spent waiting for the bus, and $busfare$ is the bus fare. Then, the first term in this equation is the total time cost of taking the bus accounting for its speed, the second term is the time cost of waiting for the bus, and the third term is the bus fare. The remaining terms parallel that of the prior equation related to taking rapid transit, except the fare for a transfer to rapid transit is given by $transferfare$, which may be less than the direct fare of taking rapid transit. In this way, taking a bus is similar to walking to transit, but potentially incurs different time costs, waiting costs, and the bus fare.

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 (Osuna and Newell, 1972; Esfeh et al., 2020). 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 half of the headway. Therefore, $awt = \frac{1}{2}\Gamma$, where Γ is the headway or the frequency of the train. However, if overcrowding is an issue, passengers who are not able to board the first-arriving train have to wait another time period of Γ . 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 Γ is \bar{Z} , it implies that the trains could fit a population of \bar{Z} comfortably. If the number of passengers using public transit, Z , is greater than \bar{Z} , the public transit is overcrowded. There are $(Z - \bar{Z})$ 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

$$awt = \frac{\bar{Z}}{Z} \cdot \frac{\Gamma}{2} + \left(1 - \frac{\bar{Z}}{Z}\right) \cdot \left(\frac{\Gamma}{2} + \Gamma\right). \tag{10}$$

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

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 night shift workers. Because Uber is a major player in the ride hailing industry, this paper uses the fare structure of Uber to represent ride-hailing apps. The cost of taking Uber to work includes the payment to Uber, the time cost of waiting, and the time cost of traveling, given by:

$$T_{uber}(k,j) = \left[f_0 + f_1 \cdot k + f_2 \int_k^j \frac{1}{V(\kappa)} d\kappa + awt_{uber} \cdot \tau_{uberwait} \cdot w + \tau_{uber} \cdot w \cdot \int_k^j \frac{1}{V(\kappa)} d\kappa \right] \cdot n_{commute}, \tag{11}$$

where f_0 represents the base fare, f_1 represents the price per mile, f_2 represents the price per hour, awt_{uber} is the average waiting time for Uber drivers to arrive, and $\tau_{uberwait}$ is the time cost of waiting for Uber. To simplify, the fare structure of taking Uber is set exoge-

nously without surge pricing. The time cost of commuting is a fraction, τ_{uber} , of the wage. We assume $\tau_{uber} < \tau$, because while in the Uber, individuals can spend time working or other productive uses. “Dead trips” where the driver needs to find the next passenger also do not cause added congestion, given they must always be in the opposite direction on the highway.

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

$$T_{uberpub}(k,j) = (f_0 + f_1j + (f_2 + \tau_{uber}w) \cdot [(j - \bar{j})/V_{res} + \bar{j}/\bar{V}_{res}] + awt_{uber} \cdot \tau_{uberwait} \cdot w + awt \cdot \tau_{pub} \cdot w + publicfare + \tau_{pub}w \cdot k/V_{metro}) \cdot n_{commute}, \tag{12}$$

where the first five terms represent the cost of taking Uber to transit and the last three terms represent the cost of taking public transit. To get to transit lines, Uber drives on residential streets.¹³ As more people start to take Uber to transit stations, the speed on local roads could fall. This congestion is likely to be most salient near transit stations, possibly a result of Uber causing congestion in the dropoff area. Thus, we model this congestion within a given distance \bar{j} of transit stations to capture congestion near the Uber arrival and departure points. To capture this, V_{res} represents the driving speed on residential streets without congestion caused by Uber, while \bar{V}_{res} represents the speed on residential streets within \bar{j} miles of transit stations. Then the term within square brackets implies added personal time costs due to congestion and added costs of Uber, as a result of the app pricing per minute of travel.

To model congestion near transit, we assume it is based on the average Uber speed rather than the precise amount of congestion at each distance.¹⁴ The average Uber speed with congestion, \bar{V}_{res} , is a function of the number of Uber cars on the road and the residential road capacity, taking a similar functional form as (6) except replacing a, b and c with residential road specific congestion parameters, a_{res}, b_{res} , and c_{res} , and replacing $M(k)$ with $\frac{N_{uberpub}}{R_{res}}$. In this last term, $N_{uberpub}$ is the the number of Uber trips to transit and R_{res} represents the residential road capacity. We have verified the results are robust to the distance threshold that we specify congestion starts at.¹⁵

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

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

Car Ownership. We allow for endogenous car ownership, such that Uber and the policy regime can change the number of car owners. Car ownership decisions are made in two stages. In the first stage, households choose their commuting mode to work. If they choose to drive or carpool, they must own a car, incurring the fixed costs of owning a car. In the second stage, households choose their mode choice for leisure trips discussed below. Households who choose not to own a car for commuting purposes may decide to own a car for non-commuting trips if the total costs of doing so are less than the total costs of those trips without a car. This theoretical innovation sheds light on the effects of Uber on the car ownership rate. The two stage process is a simplification, but facilitates solving

¹³ In contrast to Uber trips to public transit, all highway trips are radial. In addition to driving to transit stations, residential streets are used for other purposes such as shopping or errands besides commuting.

¹⁴ This simplifies computations considerably, with little expense. Moreover, this allows us to interpret the congestion as a fixed cost near the station rather than something that accumulates over distances.

¹⁵ Intuitively, as this distance increases and congestion occurs over a longer space, then the response of individuals willing to switch to Uber as a way to get to public transit is muted.

the model. Moreover, such a process is not unreasonable given the heavy reliance on driving to commute to work.

Households choose to own a car for commuting purposes if households choose to drive or carpool to work, that is, if $T^{com}(k, j) = T_{drive}(k, j)$ or $T^{com}(k, j) = T_{carpool}(k, j)$.

Transport Cost Curves. Much of the intuition of the model can be seen using the transportation cost curves defined above—and those defined subsequently for leisure trips. 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, Fig. 1 shows the transport cost curves (per trip) with respect to distance to the CBD, conditional on various distances to transit lines. Appendix A.1 extensively discusses the differences between the fixed (shifts) and marginal cost

(pivots) of each mode of transit and explicitly demonstrates how the optimal transit cutoff rules are derived in partial equilibrium.

Focus on Panel 1a. The vertical intercept shows the fixed cost conditional on a given distance from the transit station. Based on our calibration discussed subsequently, 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 costs. 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 options. Finally, the fixed cost of walking to transit is lower than taking the bus and Uber to transit. However, note these conclusions depend on distance from the transit station.

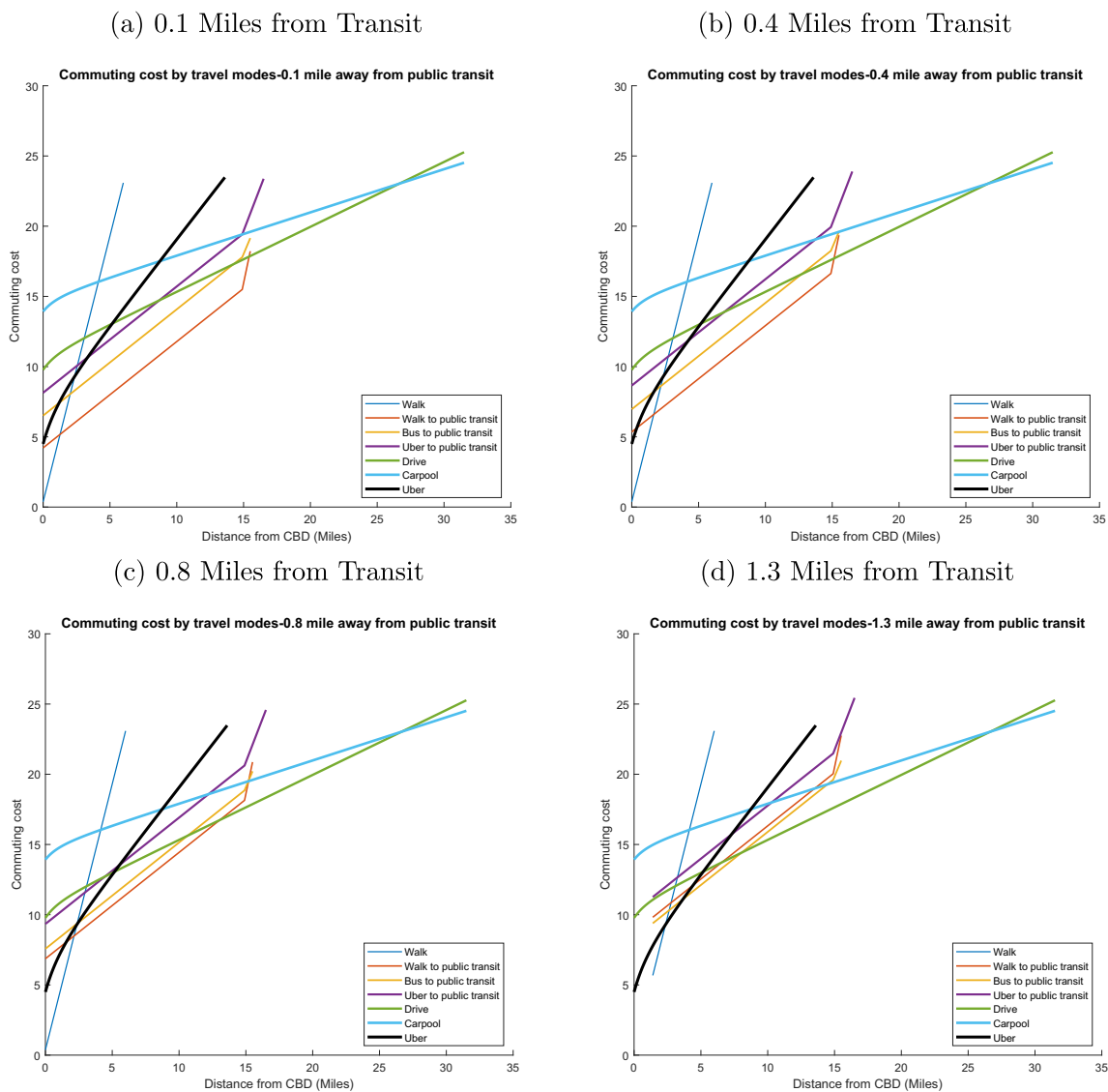


Fig. 1. Transportation Cost Curves (By Distance to Transit Stations). This figure shows the transportation cost curves for commuting purposes. Similar figures could also be drawn for leisure trips. Recall that transportation cost curves vary by distance to the CBD (horizontal axis) and distance to the nearest transit line (each panel). Rather than present a 3D surface, we show the transport cost curves in a series of panels. The horizontal axis of each figure corresponds to the distance to the CBD, while each panel corresponds to a given distance from the transit line. We truncate transit lines at 15 miles from the CBD, as is the case in Chicago, and as a result the labels on the figures are the distance to transit lines for individuals no further than 15 miles from transit. Those individuals further than 15 miles from the CBD will have different distance to transit, which explains the kinks in those cost curves. The intercepts represent fixed costs, while the slopes represent marginal costs. The numerical values of the costs are based on our calibration to the city of Chicago.

With respect to marginal costs, note that because each graph fixes the distance to transit, the marginal cost is only related to terms relating to distance to the CBD. The marginal cost of walking is the highest. Uber's marginal cost is the second highest because it charges a higher fare per mile and minute than would be realized by using one's own car. 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 transit is the same by assumption in our calibration. Each of these curves have a kink after 15 miles, where the Chicago rapid transit line reaches its endpoint.

The transport cost curve accounting for optimal individual choices is the *lower envelope* of all of the curves. The intersections of each individual curve along this lower envelope partitions 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, taking bus or 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. Critically, as distance to transit increases, public transit becomes too costly, and given Uber directly to work has a relatively low fixed cost, Uber directly to work becomes a viable option (see the last panel). Taking Uber to transit is never viable unless subsidized. Thus, the four panels 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.

Leisure Trips to Downtown. Our model will feature two types of leisure trips, the first of which will borrow some of the structure of commuting trips. Households make non-commuting trips to downtown (shopping, nightlife, concert venues) during non-rush hours or weekends for leisure purposes. As noted in Hall et al. (2018), there can be idiosyncratic reasons such as the weather or time of day that alter why individuals take Uber. To model this, for each leisure trip i , there is a random benefit (negative cost) associated with taking Uber to downtown. We could also model a random benefit of taking Uber to transit, but given we do not have data to calibrate the parameters of that distribution, we leave this as a robustness exercise for later in the paper.

Households have the same three options to get to public transit for non-commuting trips to downtown, but the cost functions have different parameters due to being off-peak hours. For example, for households walking to rapid transit, the non-commuting cost has the same per-trip form as (8) except that awt is replaced with $awt_{nonrush}$, the average waiting time for transit during non-rush hours or weekends. Due to lower transit frequency at night and on weekends, we assume $awt_{nonrush} > awt$. The same modifications to average waiting times are made for the cost functions of taking the bus and Uber to public transit. Uber to public transit also has an additional modification: because these trips are not during rush hour, we assume there is no congestion near transit stations, achieved by setting $\bar{j} = 0$ in (12).

If households take Uber directly to their centrally located leisure activity, there is a random benefit (negative cost) of taking Uber that is trip-specific, $randuber(i)$ which follows a Pareto type 1 distribution, with scale parameter normalized to one. This random term captures any psychic benefits of engaging in activities, such as the ability to avoid drunk driving or the role of time-of-day or weather in changing the relative cost of Uber. The Pareto distribution is ideal because it implies many trips will have small benefits, but some trips will have very large Uber benefits. As discussed in the calibration section, we set the Pareto parameter such that it pins down the appropriate share of Uber trips by trip purpose. Given individuals optimize the mode for each trip separately,

the non-commuting cost for trip i of taking Uber downtown for leisure is:

$$T_{uber}^{leisure}(k, j, i) = randuber(i) + f_0 + f_1 \cdot k + f_2 \frac{k}{V_{norush}} + awt_{uber} \cdot \tau_{uber} \cdot W + \tau_{uber} \cdot W \cdot \frac{k}{V_{norush}} + f_1 \cdot k + f_2 \frac{k}{V_{CBD}} + \tau_{uber} \cdot W \cdot \frac{k}{V_{CBD}}, \tag{14}$$

In addition, the cost differs from (11) because V_{norush} is the driving speed during non-rush hours. Furthermore, a critique of ride-hailing apps is that they generate congestion downtown due to many trips to common points of interest. For leisure trips, these rides must travel a distance within the CBD to get to the final destination. We allow for Uber to generate downtown congestion by assuming that V_{CBD} is the driving speed downtown in the CBD, so that the last terms capture the extra cost associated with downtown congestion caused by Uber drivers.

We model downtown congestion on the roads within the CBD. Similar to congestion near transit stations, after a car enters into the downtown area, its speed becomes a function of the number of Uber drivers. In practice, we interpret this penalty as a cost of taking an Uber into the downtown area, which could capture extra waiting, drivers stopping in the road or idle driving by Uber drivers who are looking for pickups. The number of Uber drivers affects car drivers as well. This cost only arises on leisure and not commuting trips: first, as the calibration will make clear, leisure trips using Uber are more common than commuting trips and, second, employment might be more spread out in the CBD than points of leisure such as the symphony and bar district. The downtown driving speed again takes a similar form as (6) except replacing a, b and c with downtown-leisure congestion parameters $a_{les}, b_{les},$ and c_{les} . Further, we replace $M(k)$ with $\frac{N_{CBDleisure}}{R_{CBD}}$, where $N_{CBDleisure}$ is the number of Uber trips into the CBD and R_{CBD} represents the road capacity in the CBD.

Households can also drive to the city center for leisure purposes. Here, the cost will depend on whether the household has already purchased a car for commuting. If households own a car for commuting purpose, the non-commuting cost for driving is:

$$T_{drive}^{leisure}(k, j) = parking_{pertrip} + m_1 k + p_g \frac{k}{G(V_{norush})} + \tau_w \frac{k}{V_{norush}} + m_1 \cdot k + p_g \frac{k}{G(V_{CBD})} + \tau_w \frac{k}{V_{CBD}}, \tag{15}$$

where $parking_{pertrip}$ is the per-trip cost of parking downtown during off-hours. This equation differs from (5) because Uber drivers impose an externality on other drivers in the CBD.

Given our model features endogenous car ownership, if households don't own a car for commuting purposes, households need to pay the fixed cost to buy a car for leisure purpose. Thus, for an individual who does not already own a car, the per trip cost of driving for leisure trips becomes $T_{drive, buycar}^{leisure}(k, j)$ which equals the fixed cost of car ownership (m_0) divided by the number of leisure trips plus all of the terms on the right-hand-side of (15).

For simplicity, we assume individuals do not carpool or walk directly to the destination for leisure trips. Then, for each trip i , an individual will pick the mode of transportation that minimizes the cost of that trip after accounting for the fact that the cost of driving will be different depending if they already own a car for commuting purposes, they will buy a car for leisure purposes only, or they will never own a car. Unlike commuting trips mode choice is trip-specific due to the presence of random Uber benefits.

Car Ownership for Leisure Trips. For individuals who already own a car for commuting purposes, they make no additional own-

ership decision and instead simply pick the mode that minimizes each trip cost. But for individuals who do not already own a car, we first calculate their decision for each trip i assuming they will buy a car (including the added fixed costs). We then aggregate their total leisure trip costs (public transport via walking/Uber/bus, driving, or Uber direct) by summing over all trips i , yielding a sum $T_{buycar}^{leisure}(k, j)$. We then repeat this procedure assuming households never buy a car thus facing only the choice set walking/Uber/bus to transit or Uber direct to downtown for each trip. After aggregating, this yields a total cost of $T_{nocar}^{leisure}(k, j)$. If not already owning a car for commuting, a household will purchase a car if:

$$T_{buycar}^{leisure}(k, j) < T_{nocar}^{leisure}(k, j). \tag{16}$$

Idiosyncratic Local Trips. Uber is also an important transit mode for trips related to shopping/social activities outside of the CBD and possible within-CBD trips. By definition, these trips can be quite “random” in terms of distance, time, and frequency, depending on proximity to retail agglomerations, social centers, and other sub-centers within the city. Moreover, whether an individual drives, takes public transit, or takes Uber on these trips may depend on numerous factors. Nonetheless, we make significant progress by imposing some simplifying assumptions on the nature and cost of these trips. Adding them to the model allows for a more realistic, psuedo-monocentric city that allows us to more accurately study the effect of ridehailing taxes.

The first assumption is that local trips can only be made by taking Uber, driving or bus.¹⁶ Second, individual trips are heterogeneous in their fixed costs of driving or taking the bus. Finally, the average distance of local trips is $Dist_L$ per trip, trip-specific parking costs are $parking_L(i)$, and the average driving speed is V_{res} . Only individuals that have decided to purchase a car, either for commuting or leisure trips, can drive on these trips; individuals without a car must take the bus or Uber. If choosing to drive, the total cost is a function the same variables defined previously, except including idiosyncratic parking costs:

$$T_{drive}^{Local}(i) = parking_L(i) + \left[m_1 \cdot Dist_L + p_g \cdot \frac{Dist_L}{G(V_{res})} + \tau \cdot w \cdot \frac{Dist_L}{V_{res}} \right]. \tag{17}$$

Instead, if choosing to take a bus, the local trip cost is:

$$T_{bus}^{Local}(i) = randomwait(i) + \frac{Dist_L}{V_{bus}} \cdot \tau_{bus} \cdot w + busfare, \tag{18}$$

where $randomwait(i)$ is a trip-specific waiting time for the bus. This might include idiosyncratic costs relating to the extent of the bus transfers necessary.

If choosing to take Uber, the cost function is:

$$T_{uber}^{Local} = f_0 + f_1 \cdot Dist_L + f_2 \cdot \frac{Dist_L}{V_{res}} + awt_{uber} \cdot \tau_{uberwait} \cdot w + \tau_{uber} \cdot w \cdot \frac{Dist_L}{V_{res}}. \tag{19}$$

For households who own a car, they choose a mode from driving, bus or Uber to minimize the cost for each trip i . For households who choose not to own a car, their local trip cost is determined by picking from a choice set that only includes buses or Uber.

Given local trips are heterogeneous and idiosyncratic, we need a flexible way to model the costs of each local trip. To do this, rather than introduce heterogeneity in the distance of these trips, we instead allow for heterogeneity in the parking costs and bus waiting times of each local trip.¹⁷ Generally speaking, idiosyncratic park-

ing costs can have a broad interpretation: they could include the dollar costs of actual parking, any time costs of finding street parking, and any psychic or monetary costs of engaging in activities such as drunk driving. Although the dollar cost of parking may be low on average, the total fixed cost for some trips may be very high. The same is true for bus waiting times: the idiosyncratic cost could be due to uncertainty of waiting, the numbers of bus transfers necessary to reach different destinations, or a cost of a bus being late.

Thus, to model the possibility that some trips have very high fixed costs of driving or taking the bus, we again assume the distribution of parking cost and bus costs follows Pareto type 1 distributions, with scale parameter normalized to one. For each local trip, we separately draw a new random parking cost and bus waiting time from the distribution. Then, as above, $parking_L$ has a CDF of $1 - (1/parking_L)^\alpha$, where the Pareto parameter is α , with a similar function for bus wait times. As discussed in the calibration section, we set the Pareto parameter to pin down the the share of Uber trips that are taken to non-CBD locations to match data on the destination (CBD/non-CBD) of all Uber trips within Chicago, classifying all trips that are not to or from the CBD as a “local” trip.

Individuals endogenously determine the optimal mode for each trip i . The aggregate local trip cost per household, T^L is the sum of all individual trip costs.

3.1.6. Tax policy

There have been several tax policies proposed in the past years: a flat tax, an ad valorem tax, and a mileage tax. Here we consider each of these policies in turn.

Flat Tax. Chicago historically imposed a constant unit tax per Uber trip regardless of the distance or cost. The historical constant tax rate per Uber trip, $t_{triptax}$, was \$0.67 per trip in Chicago. Using, (11), the tax-inclusive transportation cost for taking Uber to work adds $t_{triptax}$ to each trip. Similarly, using (12), the cost of Uber to transit adds $t_{triptax}$ to each trip. The tax also similarly shifts upward any leisure trip costs that involve Uber.

Sales Tax. Another tax policy that has been implemented in other places such as New York City is a sales tax, which is proportional to the monetized cost of each Uber trip. This is a potential alternative tax policy for Chicago to adopt. If a sales tax policy is adopted, at a sales tax rate, $t_{salestax}$, the tax inclusive price of taking Uber to work becomes $(1 + t_{salestax}) \cdot (f_0 + f_1 \cdot k + f_2 \int_k^k \frac{1}{v(x)} dx)$. This then replaces the price of Uber in (11), where all non-monetized costs are obviously not affected by the tax. The sales tax similarly pre-multiplies the price of Uber for all other mode and trip types involving Uber.

Mileage Tax. Finally, a mileage tax is another policy that has been proposed to tax Uber and other driving (Davis and Sallee, 2020). It is a tax rate that is imposed on the driving distance by Uber trips. Given the tax rate per mile, $t_{miletax}$, the only term in (11) that is affected is the second term relating to Uber’s per mile part of its pricing scheme, which now becomes $f_1 \cdot k \cdot (1 + t_{miletax})$. Similarly, the distance-based parts of the fares also increase by the mileage tax rate for all other trips types and destinations involving Uber.

3.1.7. Tax return scheme

We consider four spending plans to balance the budget: external transfers, lump sum rebates, improvement to public transit, and fare reductions.¹⁸ The amount of tax revenue, TR , raised is determined endogenously. Under the constant tax rate t_{tax} per trip, the aggregate tax revenue is $t_{tax} \cdot Trips_{uber}$, where $Trips_{uber}$ are the total

¹⁶ Given these trips do not involve travel to downtown, radial modes of public transit are not included in the choice set.

¹⁷ Note that we do not need heterogeneity on all three trips, which would be redundant. Any two trips could have the idiosyncratic component to make our point.

¹⁸ 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.

trips on Uber. Under the sales tax, aggregate tax revenue is $t_{\text{salestax}} \cdot \text{Revenue}_{\text{salestax}}$, where $\text{Revenue}_{\text{salestax}}$ is the aggregate sale revenue from all Uber trips. Under the mileage tax policy, the aggregate tax revenue is $t_{\text{miletax}} \cdot \text{Distance}_{\text{miletax}}$, where $\text{Distance}_{\text{miletax}}$ is the aggregate Uber driving distance.

External Transfers. First, we assume that the state government levies this tax only in Chicago and then spends the revenue such that it only benefits nonresidents of the city. While Chicago's tax involves local spending, in many other states the tax is levied by the state government, which then implicitly use the revenue to subsidize rural parts of the state.

Lump Sum. The second spending scheme is to return the tax revenue lump sum to each resident household, which increases households' income. This scenario is realistic from a policy perspective: cities need not earmark their revenue to transit ridership and may instead use the revenue to benefit all citizens via a general fund. A lump-sum transfer would capture this if general public spending is valued at par with increase in private income.

Transit Improvements. A third spending plan is to invest the total tax revenue to improve the public transit system by increasing train frequency, which reduces average waiting times. We assume that the average waiting times is a function of the total budget devoted to operating the public transit system. The elasticity of average waiting times with respect to the public transit budget is assumed to be a constant, ϵ_{metro} . Therefore,

$$awt = C_{\text{metro}}(\text{basebudget} + TR)^{\epsilon_{\text{metro}}}, \tag{20}$$

where C_{metro} is a constant, *basebudget* is the baseline operating budget, and *TR* is the tax revenue raised. This tax return scheme has the potential to increase public transit usage by lowering the cost of transit due to lower waiting times. There may be increasing returns to improving transit that the constant elasticity assumption suppresses. If so, then the transit model responses we estimate would be smaller than those with increasing returns.

Reduce Fares. A final spending program is to invest the total tax revenue in the public transit system by reducing the one way ticket cost of taking metros or buses. In equilibrium, the aggregate tax revenue should equal to the aggregate public transit fare reduction. This policy holds the quality of infrastructure fixed, but adjusts the transit price.

3.1.8. Labor market of Uber

An important part of Uber's role as a platform is connecting riders and drivers. We model the driver labor market to incorporate the incidence of the tax: Uber drivers will share some of the incidence of the tax. Presumably, drivers make labor supply decisions on expected hourly wages rather than the realized wage. Given expected wages are unobserved, we proxy for it using driver revenue net of the Uber commission. To proceed, and be consistent with empirical labor supply elasticities, we assume that the hours L_S of Uber driving time supplied per driver depend on pay per hour, which equals total revenue, $\text{Revenue}_{\text{uber}}$ paid to all drivers divided by L_S times the number of drivers. We assume the number of drivers, Dr , is fixed, so all adjustments occur on the intensive margin.

For each Uber trip, the driver revenue depends on the base fare, cost per mile, cost per minute, trip length, and the driving time. Aggregate revenue is the sum of revenues from trips to downtown, to transit, and local trips. Let l index a household-trip that is from location $(k(l), j(l))$. Then, aggregate revenue from commuting trips is

$$\begin{aligned} \text{Revenue}_{\text{uber}}^{\text{com}} &= \sum_{l \in \mathcal{N}_{\text{uber}}} f_0 + f_1 \cdot k(l) + f_2 \int_k^{k(l)} \frac{1}{V(\kappa)} d\kappa \\ &+ \sum_{l \in \mathcal{N}_{\text{uberpub}}} f_0 + f_1 j(l) + f_2 \cdot \frac{j(l)}{V_{\text{res}}} \end{aligned} \tag{21}$$

where $\mathcal{N}_{\text{uber}}$ and $\mathcal{N}_{\text{uberpub}}$ are the sets of household-trips taking Uber directly to the CBD and to public transit for commuting purposes. Similar expressions can then be derived for leisure trips to downtown and for local leisure trips. Summing revenue from leisure trips with revenue from commuting trips yields total Uber revenue, $\text{Revenue}_{\text{uber}}$. However, the company of Uber takes a certain fraction, π_{uber} , of drivers' revenue as fees. Although it can vary by city or driver, on average, this is about 30% of drivers' revenue. Therefore, Uber drivers' net revenue is $(1 - \pi_{\text{uber}})\text{Revenue}_{\text{uber}}$.

We assume that the labor supply function $L_S = ((1 - \pi_{\text{uber}})\text{Revenue}_{\text{uber}} / (L_S \cdot Dr))^{\epsilon_{\text{labor}}}$ has a constant elasticity, ϵ_{labor} . Then, rearranging, the labor supply function yields:

$$L_S = C_{\text{uber}}((1 - \pi_{\text{uber}})\text{Revenue}_{\text{uber}})^{\epsilon_{\text{labor}} / (1 + \epsilon_{\text{labor}})}, \tag{22}$$

where C_{uber} is a constant. Multiplying by Dr , or total potential Uber drivers, gives total Uber hours, with Dr absorbed into the constant. Critically, π_{uber} adjusts to maintain equilibrium in the labor market. Some discussion is in order. In particular, for driver revenue, we only deduct Uber's commission and, following standard practice among empirical studies estimating this elasticity, do not deduct driver capital/operating costs.¹⁹

A household who chooses to take Uber demands driving service from an Uber driver. The demand is measured by the driving time for all Uber trips. Similar to the supply side, summing across all household-trips using Uber, the demand is given by

$$\begin{aligned} L_D &= \sum_{l \in \mathcal{N}_{\text{uber}}^{\text{com}}} \int_k^{k(l)} \frac{1}{V(\kappa)} d\kappa + \sum_{l \in \mathcal{N}_{\text{uberpub}}^{\text{com}}} \frac{j(l)}{V_{\text{res}}} + \sum_{i \in \mathcal{N}_{\text{uber}}^{\text{local}}} \frac{\text{Dist}_i}{V_{\text{res}}} \\ &+ \sum_{l \in \mathcal{N}_{\text{uber}}^{\text{leisure}}} \left(\frac{k(l)}{V_{\text{res}}} + \frac{\text{CBD}}{V_{\text{CBD}}} \right) + \sum_{l \in \mathcal{N}_{\text{uberpub}}^{\text{leisure}}} \left(\frac{j(l) - \bar{j}}{V_{\text{res}}} + \frac{\bar{j}}{V_{\text{res}}} \right) \end{aligned} \tag{23}$$

where each \mathcal{N} is the number of Uber trips for that trip type.

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

After the 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 movement along the supply curve, which decreases Uber supply. This disrupts market equilibrium. Note that because Uber is a two-sided platform any policy change both *shifts* the demand curve and induces a *movement along* the labor supply curve. Depending on the relative size of the demand shift versus the extent of movement along the labor supply curve, this may result in a shortage or surplus of drivers if Uber's commission is held constant. If there is a surplus [shortage] of drivers, then π_{uber} increases [decreases]. To ensure supply meets the demand, the company of Uber has to change the fraction taken from drivers' revenue.

Critically, the households' mode choices are not a function of π_{uber} and thus the way we model the labor market does not affect the equilibrium transit choices in the model.²⁰ Our approach is important for modeling the incidence of the tax: drivers share some of the cost of the policy changes because the policies now affect their

¹⁹ Hall et al. (2017) do not net out driver costs, and so the measure of the hourly earning rate is a gross flow to both the driver's labor and capital. This is consistent with how empirical studies estimate the labor supply elasticity of Uber drivers: Chen et al. (2019) do not net out driver costs from revenue and Angrist et al. (2021) define the wage as the hourly farebox net of only the Uber fee.
²⁰ Alternatively, we could simply assume that supply is perfectly elastic.

net profits. This means that driver welfare is affected by policies, consistent with reality.

Discussion First, in our model, Uber's labor market clears by drivers adjusting hours worked. This implicitly assumes there is no extensive margin of labor supply. This assumption is necessary because the literature we draw on to calibrate the elasticity (Chen et al., 2019), estimates labor supply elasticities in terms of hours worked. However, we can explore what would change if drivers also responded along the extensive margin. In particular, given the labor market need only clear in aggregate, the functional form of (22) would be similar, simply needing to replace the hours elasticity with a number capturing both responses, and adjusting the constant appropriately. If allowing for both extensive and intensive labor supply responses increases the elasticity then it can easily be shown that the changes to the Uber commission rate will change by more than in our current model. Given the demand-side is not affected by this, there will be no effect on modal choices. But because driver profits enter into the welfare function, welfare changes becomes more positive (or less negative).

Second, Uber adjusts the driver share of revenue rather than the fare to restore equilibrium. In practice, Uber could change the driver's commission, the base fare, the time fare, or the fare per mile (or a combination of the four). We have elected to use the commission because of its simplicity in equilibrating the supply of drivers in contrast to a multi-dimensional pricing problem. Moreover, there is some evidence that ride-hailing apps do this in practice, as commission rates appear to vary by location. The *New York Times* notes that Uber has adjusted driver commissions in response to New York levying its sales tax on Uber rides, though there is disagreement as to whether Uber's contract actually allows this (Scheiber, 2017). Lyft, on the other hand, appears to explicitly deduct a percentage from the fares drivers receive (Scheiber, 2017). Given the complex multi-dimensional incidence problem underlying this, we leave alternative incidence assumptions to future work. However, any fare change that is absorbed by Uber because it is not passed on to consumers will mitigate the modal choice responses relative to our results.

3.2. Model solution

The model is solved numerically. To solve the model, the city is discretized into a grid of uniform squares. 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 radially uniform and symmetric with respect to transit lines, it is sufficient to examine half the market area for one line. After this market area's solution is obtained, it is aggregated across all market areas.

Given the initial values for the housing price and the fraction of people who choose to drive, then the cost for each transit mode, the optimal mode choice for each type of trip, and the population density, along with housing and land prices at each location are solved recursively. We check if the following equilibrium conditions are achieved for spatial equilibrium. If any one of these equilibrium conditions is not met, the simulation is re-initialized and simulated until subsequent iterations achieve an equilibrium.

First, all households achieve the same utility level and all housing producers earn zero economic profit. Second, the land price at the city edge must be equal to the agricultural land rent $p_\ell(\bar{k}) = p_\ell^a$.

This condition is used to determine the city boundary, \bar{k} , in equilibrium. The city expands until the residential land price falls to the agricultural land rent.

Second, 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:

$$N = \int_{\bar{k}}^{\bar{k}} \int_0^{J(k)} \theta \cdot D(k, j) dj dk, \quad (24)$$

where $D(k, j)$ is the endogenous household density at distance k from the CBD edge and distance j from public transit, which is derived from $\frac{H(k, j)/\ell(k, j)}{h(k, j)}$, where $H(k, j)$ is total housing production, $h(k, j)$ is housing demand per household and $\ell(k, j)$ is total land, as defined previously. Recall θ is the fixed fraction of land devoted to housing and $J(k)$ is the maximum distance to the public transit at each radius k .

Third, the total number of cars on the highway is determined by the population who choose to drive, carpool, or take Uber to downtown, which must equal to the total traffic volume passing through the CBD edge. This determines the traffic volume on highways. Similar conditions apply with respect to the volumes on local roads and within the CBD.

Fourth, to clear the Uber labor market, labor supply is equal to labor demand in equilibrium. This condition determines the endogenous Uber commission rate.

Finally, aggregate tax revenue is equal to the spending of that revenue, balancing the government budget constraint. This condition determines the improvement in public transit, fare reduction, or the amount of the lump sum return endogenously.

3.3. Baseline calibration and simulation

The calibration of the 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 to calibrate the model due to its size and the presence of a public transit system.²¹ The relatively strong CBD in Chicago also facilitates our simulations, but we will discuss the external validity of our results to cities of other sizes and to cities that are polycentric.

For the transit system in Chicago, the total route length is 102.8 miles with several transit lines. The route length for each line ranges from 5.1 miles to 26.9 miles. In the simulation, we assume there are 7 lines with equal route length of 15 miles. These 7 lines divide the city into equal pieces. The simulated city has a CBD, a residential district, and an agricultural hinterland, which occupy 60% of the circular area.²² The rapid transit system, the simulated city geometry, and simulated public transit system are shown in Fig. 2.

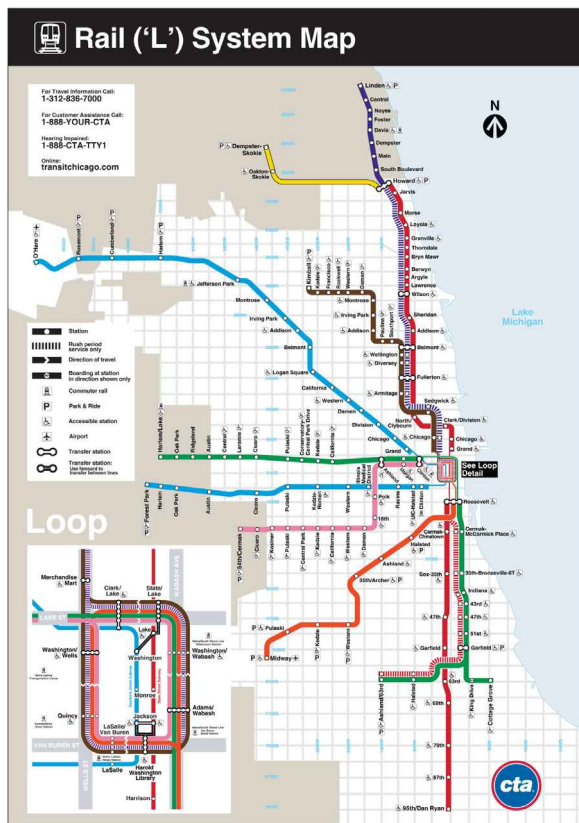
Parameter calibration follows the literature on numerical urban simulations. These parameter values are shown in Table A1. Additional discussion of some parameters is given in Appendix A.2. Here we discuss important parameters.

According to National Household Travel Survey (2017), the average annual person trips to and from work per household is approximately 1/2 the number of vehicle trips for shopping, family/personal errands, school or church, and social and recreation purpose. We assume that all social/recreational trips in the National Household Travel Survey are CBD leisure trips, while all remaining shopping, personal, and school trips are idiosyncratic local trips. Given this, 25% of leisure trips are to the CBD and 75% are idiosyncratic. From these same data, the average trip length for local trips is 7.15 miles. In the simulation, we assume each indi-

²¹ 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.

²² Saiz (2010) estimates that 60% of city area is available for development due to Lake Michigan.

(a) Public Transit Map



(b) Simulated

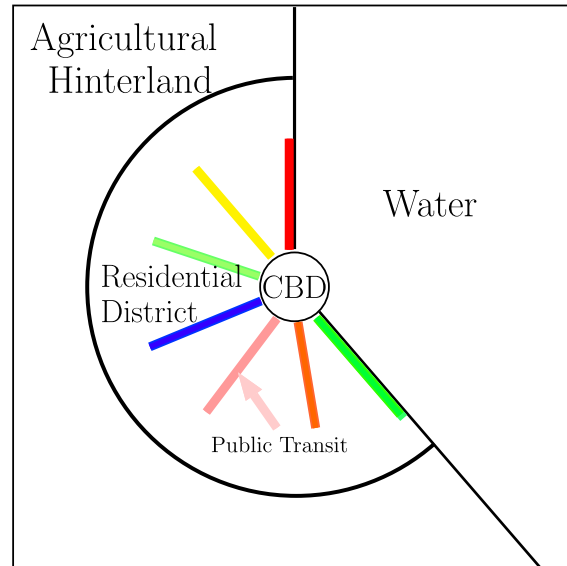


Fig. 2. Chicago Public Transit System, Actual and Simulated. This figure shows the layout of Chicago’s “L” System. While there are many transit lines, the Panel (a) shows that the lines move in approximately seven different distinct directions. Panel (b) shows the equal spacing of these lines for our simulated model. Panel (a) is sourced from the Chicago Transit Authority website <https://www.transitchicago.com/ma/ps/>.

vidual works 5 days per week for 50 weeks. Given 1.25 people per household, the number of commuting trips is 625 per year per household. Given the survey data, the total number of leisure trips to the CBD is 295, with the annual number of local trips set to 859 per household.

Next, we need to determine the benchmark share of Uber trips by trip type. We use the Chicago Data Portal “Transportation Network Providers - Trips” to determine this. We define a local trip as any trip that is not from outside the CBD to the CBD, or vice versa. This dataset provides information on the origin and destination of trips within the city from 2018 to 2020. Alex Mucci cleaned and geolocated these data, and counts the number of ridehailing trips that start/end in the downtown congestion zone.²³ These data indicate that 2/3 of trips have either only an origin or a destination within the downtown zone. See Fig.A2. According to survey data in Young and Farber (2019), 17.7% of ride-hailing trips are for work, but this number is larger for younger workers and night shift workers. We then assume that any trip entirely within downtown or that is entirely outside of downtown is a local trip. Combining these data, we calibrate the model such that (approximately) 18% of Uber trips are for commuting trips, 48% are CBD leisure trips, and 34% of all Uber trips are for local trips. To achieve these benchmarks, we set the Pareto parameter for the three distributions governing the local parking costs, bus waiting times, and random Uber benefits to match these shares. In other words, we pick the local trips Pareto param-

eters such that in our baseline simulation, 34% of total Uber trips in our model are “local” trips, i.e., not involving a trip to downtown. And we pick the Pareto parameter on Uber’s CBD leisure trips such that 48% of all Uber trips are leisure trips to downtown.

Uber drivers’ labor supply elasticity is set at 1.72, based on the elasticity at the median in Chen et al. (2019). The effective commission taken by Uber ranges from 20% to 50%. Therefore, in the simulation, the fraction that Uber takes from drivers’ revenue is set at 30%.

We assume that the transit system is near the load capacity per headway because some stations are overcrowded while others are not. Thus, \bar{Z} is set to 13% of population.²⁴

Results from simulating the calibrated model are shown in the final column of Table 1. Overall, the simulated baseline city matches the average characteristics of Chicago quite well. The model fits the modal choices, car ownership rates, and Uber trip shares well.

4. Results and counterfactual scenarios

In this section, we discuss the effect of various tax policies. Our focus is on the mode of transit and congestion metrics such as speed. The main tables in the text present the results of mode choice for all trips (commuting, CBD leisure, local leisure) combined, while the online appendix tables present mode choices disaggregated by trip type.

²³ The boundaries of the downtown congestion zone are given by Business Addairs and Consumer Protection website on “City of Chicago Congestion Pricing”https://www.chicago.gov/city/en/depts/bacp/supp_info/city_of_chicago_congestion_pricing.html.

²⁴ The assumption on \bar{Z} is consistent with rush hour patterns on many lines, but not on off-peak demand.

Table 1
Calibration of the Simulation.

City Characteristics	Chicago Urbanized Area	Simulated Characteristics
Total Occupied Units	3,012,005	3,010,616
Median Income	56,069	56,069
Median Lot Size (Acres, 1 unit structure)	0.17	0.23
Median Unit Size	2000.00	2016.62
City Radius (miles)	33.56	34.10
Land area (square miles)	2122.81	2179.01
Time to work (Residential Average)	30.70	29.41
Percent housed in 1 unit structures	58.80%	59.38%
Percent housed in 2–4 unit structures	14.60%	14.71%
Percent housed in 5 + unit structures	26.60%	25.91%
Means of Transportation to Work		
Walked	3.30%	3.37%
Public transportation	12.40%	12.94%
Drove alone	69.40%	71.60%
Carpooled	8.70%	9.14%
Other/WFH	4.50%	0.00%
Uber	–	2.95%
Types of Trips		
Uber share for CBD leisure trips	9.60%	10.17%
Uber share for local trips	2.30%	3.00%
Car Ownership		
Total ownership rate	87.10%	89.85%
Car ownership for commuting	78.10%	80.74%
Car ownership for leisure	9.00%	9.11%

The table shows the results of our calibration. The first numerical column shows actual data for the Chicago urbanized area. The second numerical column shows the simulated characteristics from our model. Sources for city data in the first column: American Community Survey 1 year estimates (2010); American Housing Survey (2009). Sources for car ownership: American Community Survey. Sources for Uber Trips: Author calculation from Fig.A2 according to procedure in text.

4.1. 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 2 presents this case. With respect to transit choice, solo driving is the most common means of transportation. In addition, just over 4% of people take an Uber directly to their destination. The share of individuals taking Uber is non-trivial. Among individuals taking public transportation, the model initially predicts a corner solution: no individuals will take Uber to public transportation and all individuals walk or take the bus. The reason for this is that Uber charges a base fare that is too high to make Uber a viable option. We will relax this subsequently. Even if the time and distance to the train station are small, the base fare of is larger than the fare to use the L-train. Given no Uber rides are used to get to public transit, the average Uber trip is 23 min, is at a distance of about 8 miles, and costs about \$16. Car ownership rates are almost 90%, with most households owning a car for commuting purposes.

4.2. Counterfactual exercises with taxes

In the remainder of Tables 2/A2, we consider Chicago's fixed tax of \$0.67 on Uber.²⁵ As discussed previously, the tax revenue generated is then allowed to be spent in various ways.

²⁵ Recently, Chicago raised this tax on ride-hailing services above this levee, but we use the historical policy given it is more in line with the taxes of other cities.

We then proceed in subsequent tables by considering different tax policies. In Tables 3/A3 we allow for the city, county and state sales tax to be applied to each fare at a rate of the 9.25%.²⁶ As a third tax policy in Tables A4/A5, we consider a 20 cent per mile tax. This policy attempts to tax road wear that may be caused by an increase in Uber rides.

Fig.A3 visually previews the results of transit choice for the laissez-faire equilibrium and for each of the policies. We will discuss each of these cases in turn.

4.2.1. Results: a fixed tax on Uber

Fig. 3 shows the intuition with respect to how the tax policy shifts the transport curves for commuting trips. Similar figures could be made for leisure trips. While these policies also shift/pivot bid rent curves as in the standard monocentric city model, the effects on the transport curves represent the direct effect of the taxes and spending and thus we present the intuition using them. In the first two panels, we show the fixed tax with a lump sum rebate or a fare reduction, respectively. For simplicity, we show the effects for individuals $j = 0.1$ miles from transit stations; shifts are qualitatively similar for other values of j in this scenario. The only difference for other values of j is which curves form the lower envelope.

In both depicted scenarios, 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 shift is muted by the lower fare; additionally, the cost of walking to 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 upward shift will be relevant as walking/transit are no longer dominant options (e.g., for individuals 1.3 miles from transit in Fig. 1). 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.

Now turn to the simulation results in Tables 2/A2. Based on our general equilibrium model, the tax on Uber raises about 115 million dollars which is approximately 14% of the Chicago Transit Authority rapid transit budget. To compare results for various spending policies, consider the various policies in Table 2. Of course, adding the fixed tax to Uber rides lowers the share of ridership taking Uber to directly to the destination. Even when tax revenue is entirely used to improve the frequency of public transportation or to reduce its fare, taxing Uber still results in a corner solution where no individuals take Uber to public transit.²⁷ Most substitution away from Uber is toward solo driving. Given this, car ownership mildly increases. However, in situations where transit becomes cheaper due to the Uber tax revenue funding transit fees, some of the riders that previously took Uber to work substitute toward public transportation. Only in the latter scenario does car ownership mildly decline. Finally, speeds on highways and downtown mildly increase.

Critically, in Table A2, Uber trips to the CBD are more elastic than leisure Uber trips.²⁸ Intuitively, Uber is used for leisure trips to downtown with high idiosyncratic benefits of Uber and for local trips that have high idiosyncratic fixed costs of other means. These

²⁶ With the exception of the case of external rebates, we assume that all of the revenue from the county and state sales tax on the city's Uber rides are transferred to the city of Chicago via intergovernmental grants.

²⁷ For example, in this case, the flat fee is able to improve transit wait times to work by at most only a few seconds and only results in a transit subsidy of \$0.40.

²⁸ This can be calculated using Table A2, noting that in the baseline scenario, the average price of Uber for commuting, Uber leisure trips to downtown, and Uber local trips are \$9.91, \$21.37, and \$14.22, respectively.

Table 2
Fixed Taxes.

Scenario	Laissez Faire	Tax (\$0.67 per trip)			
		No lump sum rebate	Lump sum to HH	Improve transit	Reduce transit fare
Mode Shares: All Trips					
Walking	1.18%	1.24%	1.24%	1.24%	1.20%
Total public transit (L train)	5.87%	5.97%	5.97%	6.02%	6.49%
Walking to public transit	4.82%	4.76%	4.76%	4.77%	4.88%
Taking bus to public transit	1.04%	1.22%	1.21%	1.26%	1.61%
Taking Uber to public transit	0.00%	0.00%	0.00%	0.00%	0.00%
Bus to final destination	4.66%	4.51%	4.51%	4.58%	5.05%
Taking Uber direct	4.17%	3.22%	3.22%	3.20%	3.02%
Solo driving	80.90%	81.80%	81.80%	81.74%	80.88%
Carpooling	3.21%	3.26%	3.27%	3.22%	3.36%
Uber Outcomes: All Trips					
Driving time per trip (minutes)	23.48	24.42	24.42	24.48	24.91
Driving distance per trip (miles)	7.91	8.67	8.68	8.71	9.07
Average Uber price per trip (pre-tax)	16.04	17.09	17.10	17.14	17.60
Car Ownership					
Total car ownership rate	89.85%	90.29%	90.29%	90.16%	89.14%
Car ownership rate for commuting	80.74%	81.87%	81.89%	81.84%	81.50%
Car ownership rate for noncommuting trips	9.11%	8.42%	8.41%	8.31%	7.65%
Driving Characteristics					
Average speed on highways	45.05	45.45	45.45	45.42	45.46
Average commuting time to work	29.41	29.25	29.26	29.22	29.67
Maximum commuting distance	31.60	31.70	31.70	31.60	31.80
Public transit average waiting time (minutes)	5.00	5.24	5.24	5.18	5.92
Public transit headway (minutes)	10.00	10.00	10.00	9.76	10.00
Downtown driving speed	12.50	13.19	13.19	13.22	13.37
Uber speed near transit	25.00	25.00	25.00	25.00	25.00
Equilibrium in Ride Hail Market					
Percent of profit that Uber takes	30.00%	25.11%	25.11%	24.98%	24.44%
Tax Revenue					
Aggregate tax revenue (millions)	0.00	115.61	115.58	114.71	108.56
Welfare					
Utility per household	1274.93	1276.41	1277.63	1276.13	1275.19

The table shows the model solution for the fixed tax on Uber. The columns correspond sequentially to the no tax case, fixed tax with external spending, fixed tax with a lump sum return, fixed tax with transit improvements, and fixed tax with reduced public transit fare. The rows represent select endogenous variables. Other endogenous variables are omitted from the table.

trips are in the upper tail of the Pareto distribution, which mutes the response. Moreover, commuting trips have many other substitutes not possible for local trips. With respect to Uber's outcomes, all the different spending policies raise the average trip time and distance. Intuitively, trips become longer because the fixed cost of taxing Uber becomes higher. As we assume that the incidence of the tax works partly via Uber's commission, Uber lowers its commission to maintain equilibrium in the labor market. Intuitively, the tax shifts down demand for drivers, but driver revenues also fall, which causes a movement along the labor supply curve. Given our calibration, if Uber did nothing, there would be a shortage of drivers. So to maintain equilibrium, Uber lowers the commission rate (Fig. A4 for intuition). However, the Figure makes it clear that even after the adjustment to the commission, after-tax driver revenue falls, implying drivers are worse off.²⁹

4.2.2. Results: sales tax on Uber

The bottom panels of Fig. 3 show the effect of a sales tax on ride-hailing apps. 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, e.g., only when the Uber to work curve is part of the lower envelope of the overall cost curve.

²⁹ The change in the commission only dampens the fall in driver revenue, but driver revenue is declining.

At the average price of an Uber trip, this sales tax rate results in a tax payment that is more than the fixed tax considered in the last section, with the ad valorem tax on leisure trips being substantially higher in dollar terms. Thus, because of these local trips, the sales tax raises more revenue than the fixed tax. Comparing across the columns in Tables 3/A3, the results are qualitatively similar to the prior section. For this reason, in this section, we focus on comparing the results to those results in Table 2.

Given the sales tax raises more total revenue, it reduces the share of people taking Uber to their destination by more than the flat fee, but this reduction is not the same for all trips. Given the composition of riders, Uber trips to CBD and local leisure trips generally have lower prices than leisure trips to downtown. This can be seen in the comparing the driving times on Uber trips with the prior table: trips are shorter under the sales tax. Leisure trips to the CBD are, on average, more expensive and thus face a higher tax in dollars under the sales tax regime. Thus, the larger decline in Uber trips are mainly driven by this trip type. Moreover, larger declines in total Uber ridership amplifies the fall in the Uber commission.

Critically, this counterfactual highlights an important policy difference. A sales tax, which is a percent of the fare, will more stringently penalize riders 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.

Table 3
Sales Tax.

Scenario	Laissez Faire	Sales tax (9.25%)			
		No lump sum rebate	Lump sum to HH	Improve transit	Reduce transit fare
Spending					
Mode Shares: All Trips					
Walking	1.18%	1.29%	1.29%	1.27%	1.17%
Total public transit (L train)	5.87%	6.03%	6.02%	6.13%	7.03%
Walking to public transit	4.82%	4.77%	4.76%	4.79%	5.03%
Taking bus to public transit	1.04%	1.26%	1.26%	1.34%	2.00%
Taking Uber to public transit	0.00%	0.00%	0.00%	0.00%	0.00%
Bus to final destination	4.66%	4.41%	4.39%	4.53%	5.50%
Taking Uber direct	4.17%	2.90%	2.89%	2.86%	2.63%
Solo driving	80.90%	82.18%	82.16%	82.01%	80.27%
Carpooling	3.21%	3.19%	3.25%	3.20%	3.40%
Uber Outcomes: All Trips					
Driving time per trip (minutes)	23.48	24.29	24.31	24.41	25.09
Driving distance per trip (miles)	7.91	8.76	8.77	8.84	9.42
Average Uber price per trip (pre-tax)	16.04	17.16	17.17	17.26	17.98
Car Ownership					
Total car ownership rate	89.85%	90.59%	90.62%	90.33%	88.25%
Car ownership rate for commuting	80.74%	81.95%	82.00%	81.93%	81.07%
Car ownership rate for noncommuting trips	9.11%	8.64%	8.62%	8.40%	7.18%
Driving Characteristics					
Average speed on highways	45.05	45.42	45.44	45.41	45.83
Average commuting time to work	29.41	29.26	29.32	29.28	29.76
Maximum commuting distance	31.60	31.60	31.70	31.60	31.80
Public transit average waiting time (minutes)	5.00	5.43	5.41	5.28	6.58
Public transit headway (minutes)	10.00	10.00	10.00	9.52	10.00
Downtown driving speed	12.50	14.04	14.04	14.10	14.43
Uber speed near transit	25.00	25.00	25.00	25.00	25.00
Equilibrium in Ride Hail Market					
Percent of profit that Uber takes	30.00%	22.23%	22.26%	22.07%	21.21%
Tax Revenue					
Aggregate tax revenue (millions)	0.00	246.28	246.46	244.63	233.94
Welfare					
Utility per household	1274.93	1276.56	1279.22	1276.10	1274.81

The table shows the model solution for the sales tax on Uber. The columns correspond sequentially to the no tax case, sales tax with external spending, sales tax with a lump sum return, sales tax with transit improvements, and sales tax with reduced public transit fare. The rows represent select endogenous variables. Other endogenous variables are omitted from the table.

4.2.3. Results: mileage tax on Uber

Tables A4/A5 show the results of mileage taxes on Uber. The reason given for a mileage tax are that it pays for damage to the roads by Uber. Relative to the other two tax policies, note that the mileage tax raises similar revenue as the sales tax. Moreover, the results are more similar to a sales tax rather than a flat fee. The reason for this is that the mileage tax more heavily taxes longer trips, which are also more expensive. Thus, a tax per mile does not raise much revenue from short trips, but raises most of the revenue from longer (higher price) trips. As a result, the effect of using Uber on trips to downtown is dampened, but is amplified for local trips. Interestingly, the mileage tax raises the average distance on Uber. But, this result is deceiving, because the tax individually lowers the distance of commuting trips, downtown leisure trips, and local leisure trips. The average only goes up because the relative shares of these trips change following the tax.

4.2.4. Results: comparing across tax 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 requires a massive amount of investment, and given the the magnitudes of tax revenues raised, are relatively ineffective at reducing headway. Thus, price reductions induce more substitution. Even with transit improvements, congestion at transit stations still causes wait times to rise relative to the baseline. However, the transit improvements reduce wait times relative to the lump sum rebate case. Given the reductions

in wait times from transit improvements in Table 2 and a median wage rate of \$28 per hour, the improvements of public transportation are valued at \$0.03 per trip. If the revenue is used to reduce fares directly, the fare reduction is \$0.40, which explains the larger increase in rapid transit usage.

From this exercise, if city officials wish to increase transit usage, subsidizing the fares with tax revenues are more efficient than improving wait times. But in practice, none of these tax policies is effective at increasing ridership substantially.

The increases in public transportation are due to two effects: a “push factor” where individuals substitute away from Uber due to the taxes and a “pull factor” where individuals substitute toward transit because its quality improves or fare decreases. With external rebates, there is no income effect from spending so, we isolate the pure “push factor” in that specification. This shows little difference from the lump sum rebate case, suggesting that income effect on transit is small, though it may have effects on other quantities—including externalities.

Notably, under all policies, public transport rises in relative popularity for commuting trips to the no-tax equilibrium, but for leisure trips it may rise or fall depending on how the money is spent. When comparing lump sum rebates to transit improvements, the added substitution toward transit is very small even for commuting trips. 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 quality improvements. Comparing the lump-sum to the fare reduction scenario, we see that the latter case results in a larger increase in transit ridership for

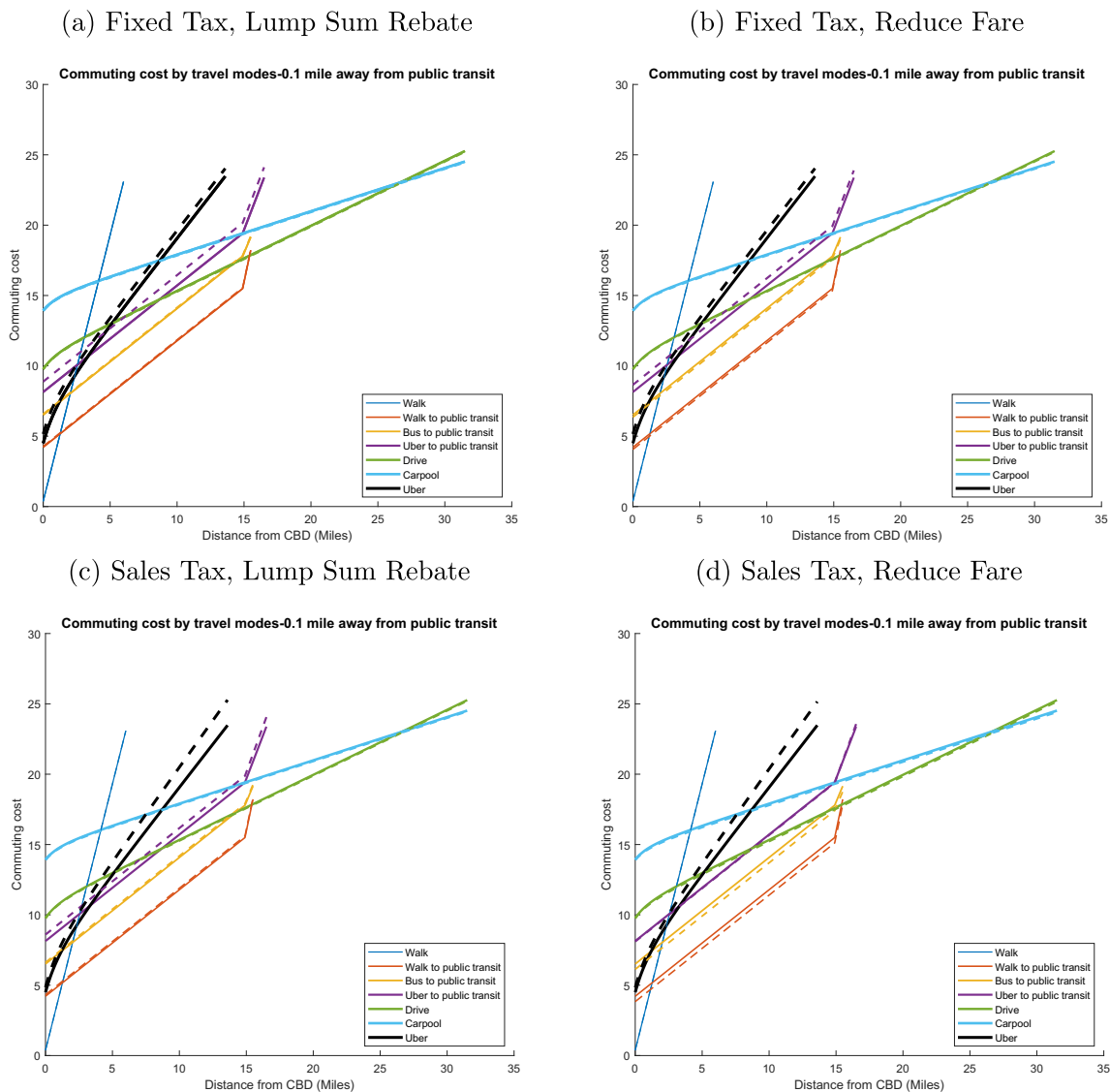


Fig. 3. How a Fixed Uber Tax and a Sales Tax Change Transport Curves (Post-reform: Dashed Lines). This figure shows how the commuting transportation cost curves shift in response to various tax policies. Panel (a) focuses on the fixed tax with a lump sum rebate, panel (b) focuses on the fixed tax with a fare reduction, panel (c) focuses on the sales tax with a lump sum rebate, and panel (d) focuses on the sales tax with a fare reduction. Recall that transportation cost curves vary by distance to the CBD and distance to the nearest transit line. The horizontal axis of each figure corresponds to the distance to the CBD, while each panel corresponds to a given distance from the transit line. We truncate transit lines at 15 miles from the CBD, as is the case in Chicago, and as a result the labels on the figures are the distance to transit lines for individuals no further than 15 miles from transit. Those individuals further than 15 miles from the CBD will have different distance to transit, which explains the kinks in those cost curves. For purposes of this policy counterfactual, we only show graphs for individuals near transit lines; the shifts are qualitatively similar at other distances, although which curves are the lower envelope are different. Pre-policy lines are solid and post-reform policy lines are dashed. Different colors denote different transit modes.

commuting purposes. Thus, when the revenue is used to fund fare decreases, much of the transit increase is explained by the “pull factor”.

Our model has several important implications for policy. First, in our model, Uber is a substitute for rapid transit: an increase in the price of Uber increases transit ridership on the L-train even without improving public transit. We can calculate the cross-price elasticity of public transit with respect to the price of taking to Uber. At the average Uber price of \$16.04, the fixed tax represents a 4.18% change in the price of those trips. For the lump sum case, the change in public transit shares implies a 1.70% increase in rapid transit usage. This yields a cross-price elasticity of 0.41.³⁰ On the other hand, Uber is a complement to buses as a

means of getting *directly* to the final destination, as an increase in the price of Uber lowers bus ridership by 3.2%. Intuitively, this mechanism works via endogenous car ownership. Higher taxes on Uber induce some individuals to buy a car. As a result of owning a car, buses become a less attractive mode of transportation for local trips. In this way, because Uber taxes moderately raise car ownership, they can harm public transit ridership. Why does this effect only induce buses to be complements and not rapid transit? These negative effects of car ownership on transit are more pronounced for buses than for rapid transit because rapid transit is not generally used for trips that do not have a radial direction. Moreover, combining all types of public transit (bus and L train), the effect of the Uber tax is a 0.47% decrease in transit. This implies that all public transit modes combined are a complement, with an elasticity of -0.11 . As a result, we conclude that endogenous car ownership is an important force that influences the cross-price elasticities.

³⁰ Cohen et al. estimate the own-price elasticity of Uber to be approximately -0.60 . As expected, our cross-price elasticity is smaller in absolute value.

Second, our model shows that taxes on ride-hailing apps 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. Nonetheless, if increasing transit ridership is a goal, simply taxing Uber and spending it on fare reductions raises overall ridership most.

4.3. Counterfactual exercises with subsidy policies

In the prior sections, we show that Uber is a substitute for rapid transit, but a complement for buses. Now, we consider whether an appropriate combination of government policies can shock the system such that both Uber and public transit are separately complements.

In order to provide the subsidy, the government deducts a lump sum tax from each household's income. The lump sum income deduction is determined endogenously in equilibrium to equal aggregate expenditures on the subsidy. In an alternative scenario, we assume the subsidy is externally financed by nonresidents of the city of Chicago, perhaps as a result of intergovernmental transfers. This scenario also aims to simulate the effects of different subsidy policies considered in several cities in the U.S.³¹ As they are currently implemented in most cities, subsidies only apply to rides to rapid transit stations.

Flat Subsidy. The first subsidy policy is a flat dollar value off the price of taking Uber to public transit. Given the subsidy only applies to Uber trips to transit stations, (12) is affected. Therefore, given the flat subsidy, $subsidy_{flat}$, the cost of taking Uber to transit stations for commuting purposes subtracts $subsidy_{flat}$ from the per trip cost, with a similar change applying for leisure trips. Currently, in cities with policies like this, to correctly levy the subsidies, Uber uses geolocation software that pinpoints whether the origin or destination of the ride is near a transit line. We use the prevailing rate of \$3.

Ad Valorem Subsidy. Riders get a percentage rate off of the price of taking Uber to public transit. Given the discount rate, $subsidy_{discount}$, assuming there is no congestion near transit stations, the monetary price of taking Uber to a transit station in (12) becomes $(1 - subsidy_{discount})(f_0 + f_1j + f_2 \cdot j/V_{res})$, with all non-monetary costs unaffected. The additional terms with congestion are also subsidized when they exist, and the subsidy similarly modifies leisure trips to transit via Uber. The discount rate is set at 50% off.

Free Public Transit. In the third subsidy policy, the government (completely) subsidizes the public transit (L-train) or any bus fare that involves a transfer to the L-train. Free public transit has been debated in the media and among policy makers. With free public transit, $publicfare = 0$, people have more incentives to take public transit, perhaps even increasing Uber ridership to transit stations. In addition, we set $busfare = 0$ and $transferfare = 0$ for individuals taking the bus to rapid transit.

4.3.1. Results

Fig. 4 shows the intuition of the subsidy for various distances j from transit. The upper panels show a fixed Uber subsidy for rides to transit stations, 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 riders that are sufficiently far away from public transit. This increased transit usage then has general equilibrium effects that mildly shift down the driving cost curves. However, this scenario raises the

cost of transit for people who walk or take the bus to transit because of the added congestion to public transit from more riders. Unlike the Uber subsidy, making transit free lowers the cost of all modes of public transit, though these declines are dampened by transit congestion. Unlike the Uber subsidy, free transit offsets the added congestion time on transit.

Tables 4/A6 show the results. Critically, and unlike the tax policies, the Uber 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 subsidy financed by a lump sum deduction has a large effect: 4.02% of people are induced to take Uber to a transit station and overall transit ridership is 1.2 times the baseline scenario. Given the large increase in transit ridership, public transit overcrowding is critical to dampening the effect: transit wait times increase from 5 min to over 6 min. Moreover, Uber congestion dampens speed near transit stations by about 5 miles per hour. We re-simulate the model in the absence of overcrowding. Our model would predict that transit ridership would increase much more without crowding, suggesting that transit limitations are critical for policy.

A decline in the price of Uber rides to public transit raises total public transit ridership. For the flat-rate subsidy, most of this increase is due to new riders who use public transit, but the increase is dampened from riders substituting from walking/buses to Uber as their last-mile service provider. Overall, the increase in transit ridership reduces solo driving and the number of people that take Uber directly to their final destination, and thus unable to receive the subsidy. Finally, the increase in speed on highways is larger than under the tax policies.

In the case of the 50% subsidy on Uber rides, the subsidy induces some individuals to utilize Uber as a means of transport to transit, but not as many as the flat rate. This is interesting because, given the mean price of an Uber ride to transit is about \$5.50, the average subsidy is only slightly lower than the \$3 flat rate. However, unlike the flat rate, the dollar equivalent of this ad valorem subsidy is low for short trips—which means the ad valorem subsidy is differently targeted than the flat subsidy. An ad valorem subsidy benefits longer trips and most trips to transit are short. Given the smaller increase in ridership, transit congestion does not increase as much under this specification.

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, particularly, if income is a monotonic function of distance to transit stations. Nonetheless, the decline in public transit fares results in a negligible share of individuals taking Uber to public transit because such a subsidy cannot differentially shift the Uber to transit cost curve. However, the decline in transit fares induces a substitution away from using Uber as a means of driving to the final destination. As noted previously, public transit congestion is critical. Were there no transit congestion—resulting from the dramatic increase of people who walk to transit—the shifts would be amplified.

Overall, the results again imply that using Uber to get directly to work is inversely related to taking transit to work. However, for the Uber subsidies, the decline in individuals taking Uber to work is small relative to the increase in individuals that take Uber to transit. As a result, we conclude that overall, Uber is a complement to public transit. As in the prior section, we can calculate a cross-price elasticity. Here, we use the ad valorem subsidy scenario as an exogenous shock to the price of Uber and trace out the elasticity of transit ridership. Recall the subsidy corresponds to a 50% decline in the price. Focusing first on the L-train, the total change in public transit ridership is 0.93 percentage points, which corresponds to a 15.8% change. The implied cross-price elasticity of total transit

³¹ 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).

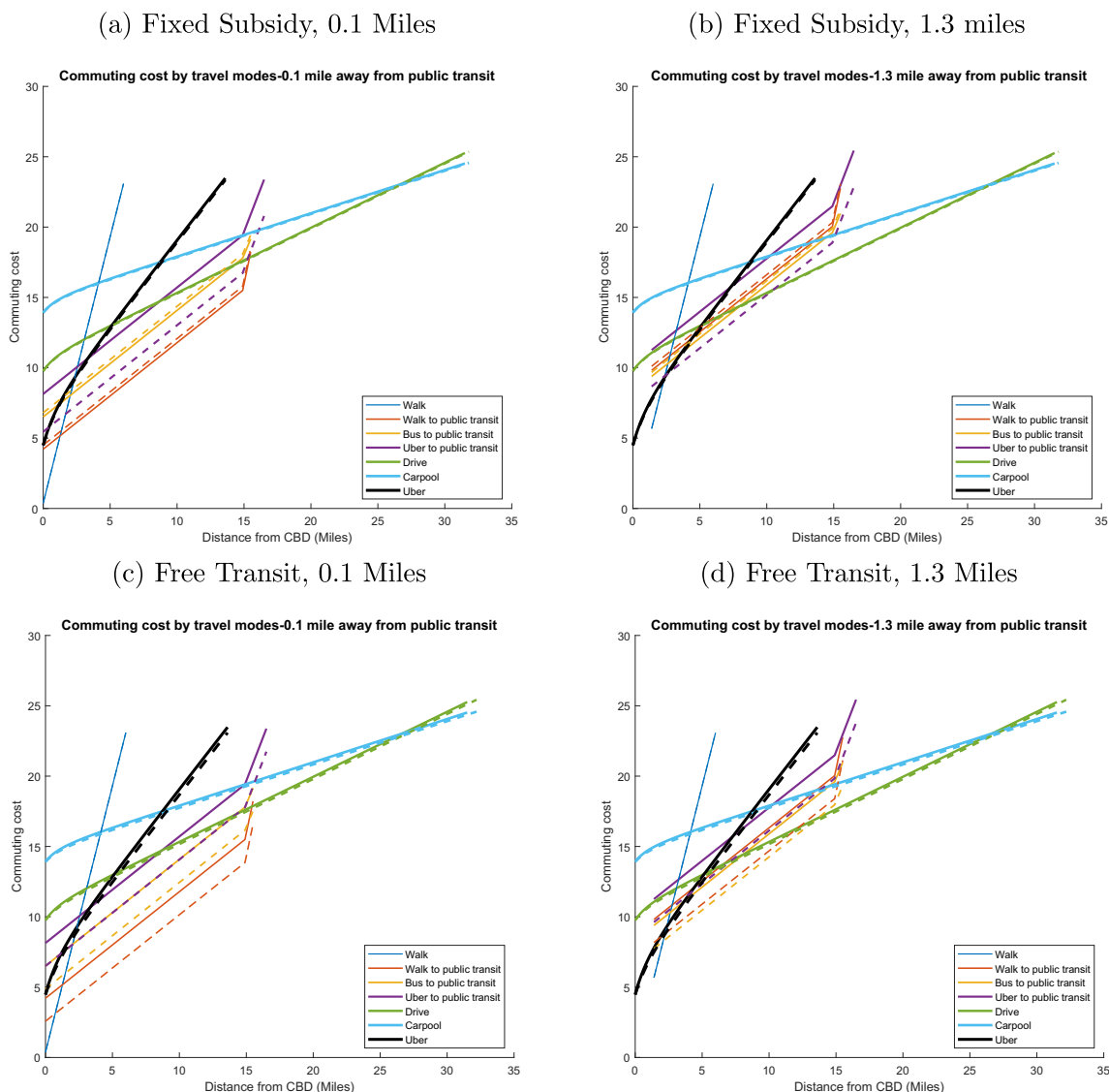


Fig. 4. Subsidy Policies (Post-reform: Dashed Lines). This figure shows how the commuting transportation cost curves shift in response to various subsidy policies—the fixed subsidy in panel (a) and (b) and free public transit in panel (c) and (d). Recall that transportation cost curves vary by distance to the CBD and distance to the nearest transit line. The horizontal axis of each figure corresponds to the distance to the CBD, while each panel corresponds to a given distance from the transit line. We truncate transit lines at 15 miles from the CBD, as is the case in Chicago, and as a result the labels on the figures are the distance to transit lines for individuals no further than 15 miles from transit. Those individuals further than 15 miles from the CBD will have different distance to transit, which explains the kinks in those cost curves. For purposes of these figures, panels (a) and (c) show the transport cost curves for individuals near transit lines, while panels (b) and (d) show the transport cost curves conditional on being 1.3 miles from transit lines. Pre-policy lines are solid and post-reform policy lines are dashed. Different colors denote different transit modes.

usage with respect to Uber prices is -0.32 . Interestingly, the sign of the cross-price elasticity for the L-train flips relative to the tax scenario. In the case of the L-train and buses combined, a 15.2% increase in all public transit implies a cross-price elasticity of -0.30 .

Reconciling this result with the prior section, governments can create an appropriate policy environment to induce (or amplify) complementarities between these means of transportation, especially with respect to rapid transit options that are likely to be used for trips to/from downtown. Critically, various policies can induce the equilibrium away from the corner solution where no individuals take Uber to public transit. In other words, the elasticities are endogenous to the policy environment, e.g., the elasticities are a policy choice.³²

³² Slemrod and Kopczuk (2002) make a similar argument for the elasticity of taxable income.

5. Alternative policies and counterfactual results

5.1. Toll policies

Congestion tolls have been imposed in different cities around the world to relieve traffic congestion externalities.³³ Uber has opposed city-level tax policies like those considered previously, but politically has been more supportive of a congestion toll policy applied widely and equally to all drivers. The comparison between tax policy and congestion toll policies adds insights into which policy is more effective at reducing traffic congestion. We consider two scenarios, the optimal congestion toll and a sub-optimal toll that raises the same revenue as the Uber tax.

³³ For studies, see as Liu and McDonald (1998) and Liu and McDonald (1999). Brinkman (2016) considers congestion in the presence of offsetting agglomeration externalities.

Table 4
Subsidy Policies.

Scenario	Laissez Faire	\$3 off Uber to transit	\$3 off Uber to transit	50% Uber to transit	Free public transit
Financing		No lump sum	Lump sum	Lump sum	Lump sum
Mode Shares: All Trips					
Walking	1.18%	1.22%	1.24%	1.23%	1.00%
Total public transit (L train)	5.87%	6.70%	6.76%	6.80%	9.56%
Walking to public transit	4.82%	2.73%	2.74%	3.56%	6.26%
Taking bus to public transit	1.04%	0.00%	0.00%	0.00%	3.30%
Taking Uber to public transit	0.00%	3.97%	4.02%	3.23%	0.00%
Bus to final destination	4.66%	5.55%	5.61%	5.33%	8.71%
Taking Uber direct	4.17%	3.59%	3.55%	3.47%	3.03%
Solo driving	80.90%	79.43%	79.41%	79.71%	73.97%
Carpooling	3.21%	3.51%	3.42%	3.46%	3.73%
Uber Outcomes: All Trips					
Driving time per trip (minutes)	23.48	15.74	15.73	16.91	25.73
Driving distance per trip (miles)	7.91	4.78	4.76	5.28	9.74
Average Uber price per trip (pre-tax)	16.04	10.98	10.96	11.77	18.33
Car Ownership					
Total car ownership rate	89.85%	87.91%	87.77%	88.39%	81.04%
Car ownership rate for commuting	80.74%	80.54%	80.48%	80.39%	77.47%
Car ownership rate for noncommuting	9.11%	7.37%	7.30%	8.00%	3.57%
Driving Characteristics					
Average speed on highways	45.05	45.67	45.45	45.67	46.47
Average commuting time to work	29.41	29.51	29.60	29.67	31.21
Maximum commuting distance	31.60	31.90	31.80	31.90	32.20
Public transit average waiting time (minutes)	5.00	6.07	6.14	6.36	8.39
Public transit headway (minutes)	10.00	10.00	10.00	10.00	10.00
Downtown driving speed	12.50	12.96	12.97	12.84	13.84
Uber speed near transit	25.00	20.19	20.11	20.95	25.00
Equilibrium in Ride Hail Market					
Percent of profit that Uber takes	30.00%	36.84%	36.78%	35.39%	26.14%
Tax Revenue					
Aggregate subsidy (millions)	0.00	638.08	646.26	507.70	1008.42
Welfare					
Utility per household	1274.93	1272.99	1264.99	1267.63	1259.04

The table shows the model solution for various Uber subsidy policies. The columns correspond sequentially to the no tax/subsidy case, a flat rate subsidy to transit that is externally financed, a flat rate subsidy on Uber rides to transit, an ad valorem subsidy on Uber rides to transit, and free public transit. The latter three are financed via lump sum income deductions. The rows represent select endogenous variables. Other endogenous variables are omitted from the table.

Optimal Toll. In this scenario, optimal congestion tolls are imposed on each car driving through the highways during rush-hour. The toll is not levied on Uber rides to transit stations or on local trips because these rides only drive through residential roads. Moreover, the tolls are not levied on leisure trips to downtown because they occur at off-peak hours. Following the simple congestion model in McDonald (2004), the 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. The toll is calculated as:

$$toll(k) = \vec{N}(k) * \frac{dMC(k)}{d\vec{N}(k)}, \tag{25}$$

where $\vec{N}(k)$ denote the traffic volume at radius k and $MC(k)$ is the marginal commuting cost for each driver at annulus k , which for solo drivers is equal to $m_1 + p_g \frac{1}{G(\vec{N}(k))} + \tau w \frac{1}{v(\vec{N}(k))}$. For simplicity, we use the marginal cost of a solo driver, rather than the marginal cost of the Uber consumer.³⁴ Then, the effect of an added vehicle on marginal commuting cost is

$$\frac{dMC(k)}{d\vec{N}(k)} = p_g \frac{d(1/G(v(\vec{N}(k))))}{d\vec{N}(k)} + \tau w \frac{d(1/v(\vec{N}(k)))}{d\vec{N}(k)}. \tag{26}$$

Therefore, the total commuting cost for each solo driver now adds $\int_0^k toll(\kappa) d\kappa$ per trip in (5). The same expression is added per trip in (11). For carpools, tolls are split among riders, therefore, it adds $\int_0^k (toll(\kappa)/n) d\kappa$ per trip in (7).

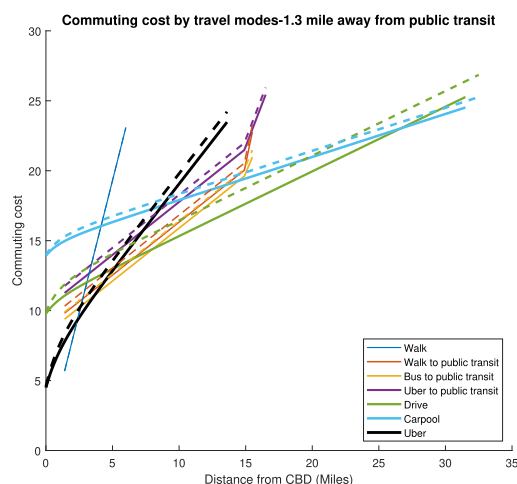
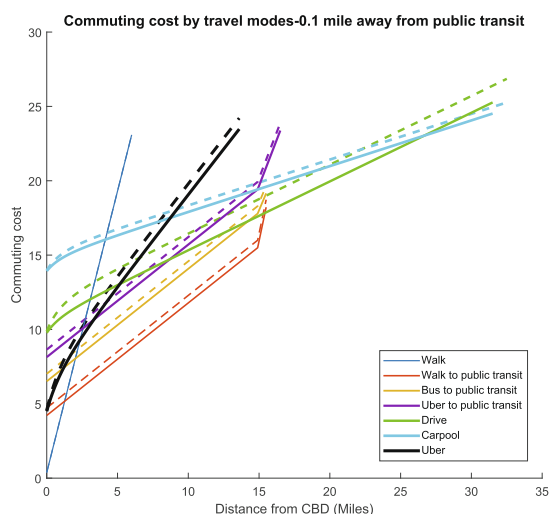
Fixed Toll. It can be difficult to implement an optimal congestion toll policy. A fixed toll policy is more common and easier to implement. In this scenario, the toll rate is fixed per car but the aggregate toll revenue is equivalent to the tax revenue under the Uber tax of \$0.67 per trip, which facilitates the comparison. Denote the fixed annualized toll as $toll_{fixed}$. Then, $toll_{fixed}$ is added to the commuting cost per trip in (5) and (11). For carpools, the toll is split, so $toll_{fixed}/n$ is added to the per trip cost of carpooling in (7). Again, leisure trips are unaffected.

5.1.1. Results: optimal toll

Fig. 5 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 lower panels show the toll revenue used for transit improvements. Unlike the prior figures, the largest upward shift is for solo-driving. Moreover, conditional on a given distance from the CBD, Uber and solo drivers pay the same toll. However, the upward shift in the Uber cost curve is muted by the fact that time enters Uber's pricing formula: individuals taking Uber save time from reduced congestion and thus are charged a

³⁴ Evaluating the toll at the consumer's marginal cost would be second order.

(a) Optimal Toll, Lump Sum Rebate, 0.1 Miles (b) Optimal Toll, Lump Sum Rebate, 1.3 miles



(c) Optimal Toll, Improve Public Transit, 0.1 Miles (d) Optimal Toll, Improve Public Transit, 1.3 Miles

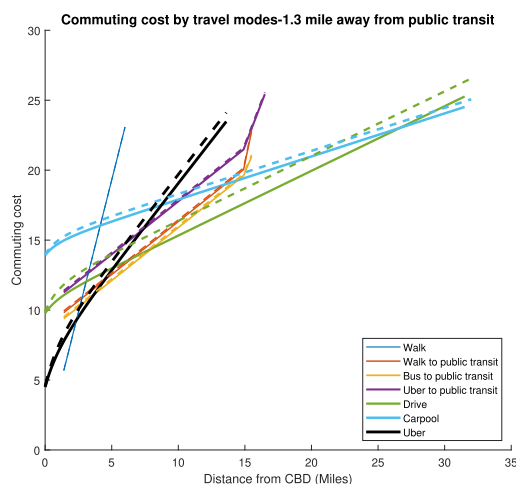
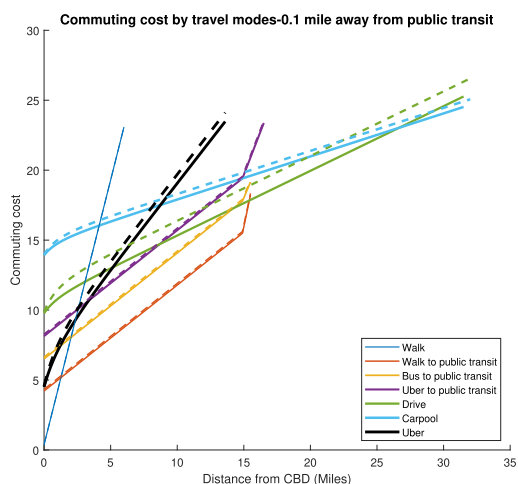


Fig. 5. Optimal Toll (Post-reform: Dashed Lines). This figure shows how the commuting transportation cost curves shift in response to various optimal toll policies—with lump sum rebates in panel (a) and (b) and with the revenue funding public transit improvements in panel (c) and (d). Recall that transportation cost curves vary by distance to the CBD and distance to the nearest transit line. The horizontal axis of each figure corresponds to the distance to the CBD, while each panel corresponds to a given distance from the transit line. We truncate transit lines at 15 miles from the CBD, as is the case in Chicago, and as a result the labels on the figures are the distance to transit lines for individuals no further than 15 miles from transit. Those individuals further than 15 miles from the CBD will have different distance to transit, which explains the kinks in those cost curves. For purposes of these figures, panels (a) and (c) show the transport cost curves for individuals near transit lines, while panels (b) and (d) show the transport cost curves conditional on being 1.3 miles from transit lines. Pre-policy lines are solid and post-reform policy lines are dashed. Different colors denote different transit modes.

lower price by Uber. The public transit curves also shift upward as the added transit usage raises congestion on public transit. However, these latter two effects are offset when the revenue is used to improve public transit. Note that the increased transit ridership mutes the effect of the increase from the toll on the Uber to work curve as well, because there is less congestion on the roads. If the revenue were used to reduce transit fares, these curves would shift down further as the toll is large enough to make transit free.

In Tables 5/A7, the optimal congestion toll raises the average speed on highways by as much as 7%. First consider the case where the toll revenue is rebated to households. With respect to transit choice, total car ridership (solo, carpool, Uber) falls by just over 1.5 percentage points, though this number is larger if not counting carpool trips. The substitution patterns are interesting. The fall in solo driving is dramatic, with some individuals switching to carpooling and to public transit. Noticeably, there is only a small

change in the share of households that take Uber directly to their destination, perhaps explaining Uber’s preference of the policy over taxes specifically targeting them. The optimal congestion toll is not sufficient to induce individuals to take Uber to public transit, however, as that cost curve does not shift downward relative to the two other means of getting to transit. Thus, the increase in public transit usage is driven by individuals walking or taking a bus to transit. Critically, given the toll is very high, this initial specification has a very large income effect from its rebate to households. Comparing this column with to column with external rebating of the toll, allows us to isolate the income effect of the policy on mode choice. Transit ridership is lower with the lump sum rebate to residents (higher income).

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. Again, reducing public transit fares

Table 5
Optimal Toll.

Scenario	Laissez Faire	Optimal congestion toll			
		No lump sum rebate	Lump sum to HH	Improve transit	Reduce transit fare
Mode Shares: All Trips					
Walking	1.18%	1.44%	1.38%	1.37%	1.13%
Total public transit (L train)	5.87%	7.18%	7.11%	8.15%	11.32%
Walking to public transit	4.82%	5.24%	5.16%	5.41%	6.51%
Taking bus to public transit	1.04%	1.94%	1.95%	2.74%	4.80%
Taking Uber to public transit	0.00%	0.00%	0.00%	0.00%	0.00%
Bus to final destination	4.66%	4.95%	4.80%	5.79%	9.10%
Taking Uber direct	4.17%	4.17%	4.08%	3.73%	3.06%
Solo driving	80.90%	74.42%	74.19%	72.98%	67.36%
Carpooling	3.21%	7.84%	8.44%	7.98%	8.03%
Uber Outcomes: All Trips					
Driving time per trip (minutes)	23.48	23.24	23.38	24.11	25.76
Driving distance per trip (miles)	7.91	7.98	8.11	8.52	9.71
Average Uber price per trip (pre-tax)	16.04	16.04	16.19	16.79	18.31
Car Ownership					
Total car ownership rate	89.85%	89.23%	89.56%	87.39%	80.19%
Car ownership rate for commuting	80.74%	76.63%	77.04%	75.97%	72.44%
Car ownership rate for noncommuting trips	9.11%	12.60%	12.51%	11.42%	7.75%
Driving Characteristics					
Average speed on highways	45.05	47.28	47.42	47.51	48.40
Average commuting time to work	29.41	31.65	32.28	32.04	34.15
Maximum commuting distance	31.60	31.90	32.60	32.10	32.60
Public transit average waiting time (minutes)	5.00	7.08	7.05	5.52	9.66
Public transit headway (minutes)	10.00	10.00	10.00	6.95	10.00
Downtown driving speed	12.50	12.33	12.43	12.66	13.66
Uber speed near transit	25.00	25.00	25.00	25.00	25.00
Equilibrium in Ride Hail Market					
Percent of profit that Uber takes	30.00%	30.42%	30.22%	28.88%	26.39%
Tax Revenue					
Aggregate tax revenue (millions)	0.00	3335.84	3307.15	3141.32	2530.44
Welfare					
Utility per household	1274.93	1257.71	1295.47	1257.16	1256.11

The table shows the model solution for the optimal congestion toll. The columns correspond sequentially to the no toll case, the optimal toll with external funding, the optimal toll with a lump sum return, the optimal toll with transit improvements, and the optimal toll with reduced public transit fare. The rows represent select endogenous variables. Other endogenous variables are omitted from the table.

are more effective at increasing transit usage than using the revenue to fund wait time reductions. Nonetheless, improving transit is more effective at increasing transit usage relative to the lump sum rebate. In the case of fare reductions, the optimal congestion toll doubles L-train and bus usage. The optimal toll combined with reduced transit fares is the most effective policy—even moreso than Uber subsidies—at increasing total public transit usage. However, unlike subsidies, it achieves the goal via more individuals walking to transit and not Uber ridership. The \$3 Uber subsidy is more effective at increasing Uber usage to public transit, but total transit usage does not increase as much.

Interestingly, car ownership declines only moderately in the toll experiments. Much of this decline is a result of less households owning a car for commuting purposes. Given this, however, more households buy a car for leisure purposes. Only in cases where the toll revenue funds transit fee reductions does overall car ownership decline substantially.

Given the congestion toll provides the largest shock to the city, we can discuss some of the intuition using standard bid rent curves, housing demand, and traffic, as a function of distance the CBD and the nearest transit station. Relative to the no tax scenario, housing prices near transit stations increase because public transit becomes a more appealing transit mode. 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. The city radius increases. As the demand for housing towards the city edge and transit stations increases,

the housing prices for households who live further away from the CBD and near transit stations go up.

5.1.2. Results: fixed tolls

As shown in Tables A8/A9, if the 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 fixed toll. The fixed toll has limited effect on speed. In particular, the speed increase from the Uber tax is either the same or larger than the fixed toll. Otherwise, the 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.

5.2. Robustness checks and model extensions

Robustness. Tables A10.1–A11.2 show the robustness of our results to changes in various parameters. We focus on the flat tax with a fare reduction and the flat rate subsidy financed by a lump sum deduction. To verify robustness of the model and to conduct exercises in the spirit of comparative statics, we increase various parameters by 10%. This allows us to verify the sensitivity of the results. It also allows us to study the “comparative statics” in a local neighborhood of the equilibrium. Each column in the table represents a change where the change is the post-policy equilibrium value minus the laissez faire equilibrium value. The results can then be compared to the baseline change given in the tables

Table 6
Random Benefits of Taking Uber to Transit.

Scenario	Laissez Faire	Fixed tax/rebate	Fixed tax/reduce transit fare	Fixed Subsidy
Mode Shares: All Trips				
Walking	1.19%	1.31%	1.21%	1.28%
Total public transit (L train)	6.48%	6.40%	6.92%	8.51%
Walking to public transit	4.84%	4.77%	4.85%	1.82%
Taking bus to public transit	0.96%	1.16%	1.51%	0.00%
Taking Uber to public transit	0.68%	0.48%	0.56%	6.69%
Bus to final destination	4.38%	4.30%	4.76%	6.19%
Taking Uber direct	4.05%	3.00%	2.85%	2.86%
Solo driving	80.72%	81.79%	80.99%	77.75%
Carpooling	3.17%	3.19%	3.28%	3.41%
Uber Outcomes: All Trips				
Driving time per trip (minutes)	20.27	21.51	21.30	12.49
Driving distance per trip (miles)	6.75	7.59	7.64	3.57
Average Uber price per trip (pre-tax)	14.00	15.21	15.17	8.87
Car Ownership				
Total car ownership rate	90.47%	90.74%	89.75%	86.52%
Car ownership rate for commuting	79.90%	81.41%	81.09%	80.40%
Car ownership rate for noncommuting trips	10.57%	9.33%	8.66%	6.11%
Driving Characteristics				
Average speed on highways	45.25	45.36	45.54	45.50
Average commuting time to work	29.32	29.36	29.54	29.52
Maximum commuting distance	31.60	31.60	31.70	31.80
Public transit average waiting time (minutes)	5.27	5.45	6.03	6.17
Public transit headway (minutes)	10.00	10.00	10.00	10.00
Downtown driving speed	14.26	14.71	15.20	18.34
Uber speed near transit	25.00	25.00	25.00	19.70
Equilibrium in Ride Hail Market				
Percent of profit that Uber takes	30.00%	24.27%	23.86%	37.98%
Tax Revenue				
Aggregate tax revenue/cost (millions)	0.00	124.84	122.22	1074.49
Welfare				
Utility per household	1279.79	1280.79	1279.05	1266.78

The table shows the model solution for a model when individuals receive random benefits, distributed according to a Pareto distribution, from taking Uber to a rapid transit station. The columns correspond sequentially to the no tax/subsidy case, a fixed tax with a lump sum rebate, a fixed tax with public transit fare reductions, and the fixed subsidy for Uber to transit financed by a lump sum deduction. The rows represent select endogenous variables. Other endogenous variables are omitted from the table.

(e.g. Table 2 Column 5 minus Column 1). We show the change because any change in the parameter value necessitates re-simulating both the laissez faire and the policy-equilibrium.

As can be seen, the results are qualitatively and oftentimes quantitatively similar to the baseline changes. We discuss some key checks briefly. Increasing headway, transit capacity, and the elasticity of transit improvements allow for larger increases in public transit ridership, but other transit system changes such as the number of lines have the opposite effects. When focusing on the time cost parameters, there are two effects. First, an increase in the time cost of transit, for example, raises the laissez faire share of people taking Uber, which allows for a larger number of riders to substitute to transit following a tax. However, the higher time cost also dampens this response. Thus, whether the mode that experiences the higher time cost has a larger or smaller change depends on these two offsetting effects.

Simulations altering floor area ratios, road speeds, and transit availability or capacity are designed to show if the model can capture alternative mechanisms via which Uber and transit are complements. Focusing on the results of the subsidies, the higher the road speed, the more transit capacity, and the greater the transit frequency, the bigger the increase in Uber to transit and L-train usage, implying the products are more complementary. Eliminating bus connections to transit also mitigates the overall increase in public transit usage, again suggesting the extent of transit availability matters for whether Uber is a complement or substitute. These results are consistent with the mechanisms in Hall et al. (2018). Imposing a floor area ratio restriction has minimal effect, however.

Finally, the last column in each of these tables, shows the results of a simple partial equilibrium analysis where we rely

entirely on the direct shifts of the transportation cost curves. To conduct this analysis, we hold fixed housing consumption and location choice, so the partial equilibrium analysis can be viewed as a short-run rather than long-run effect. As can be seen, eliminating the general equilibrium effects generally amplifies the mode choice effects, suggesting our transportation cost curve figures would have even starker shifts in a partial equilibrium economy. Utility is always higher under the partial equilibrium scenario.

Uber to Transit. In the laissez faire situation, no one takes Uber to transit. This might be viewed as implausible because we know it happens at least some. However, we do not view this as a problem, as it means it will be even harder for us to find that policies change the share of people making this choice. Nonetheless, a way forward would be to assume that Uber trips to transit stations (perhaps for leisure purposes) have an idiosyncratic benefit much like the one we modeled for Uber trips downtown.³⁵ As a robustness exercise, we add such an idiosyncratic benefit, which might capture the effect of the weather or time-of-day on the relative cost of taking Uber rather than a bus or walking to transit stations.

Table 6 shows the results. As can be seen, random benefits of Uber to transit move us away from the corner solution. Taxing Uber with a lump-sum rebate, reduces the prevalence of the trips, lowering overall transit ridership on the L-train. In this way, Uber can become a complement to transit. Intuitively, raising the price of Uber lowers Uber usage to transit, which also lowers usage of public rapid transit. This result confirms some of the mechanisms discussed in Hall et al. (2018), which notes that idiosyncratic fac-

³⁵ We did not model this directly in our baseline because we do not have data to calibrate the distributional parameter on the idiosyncratic term.

tors can make Uber and transit complements because individuals no longer worry about needing to walk from transit in the rain or at an unsafe time of day. Critically, in the absence of these benefits, this mechanism did not exist and we found in the analogous column of Table 2, that the L-train and Uber were substitutes. In other words, there are offsetting forces that depend on the relative magnitudes of these idiosyncratic factors. The results of the Uber subsidy are similar to those in the text, although the magnitudes of the responses change.

Subsidy Manipulation. It is possible that individuals may ride Uber to a transit station, obtaining the subsidy, and then not riding rapid transit. As with any policy program, manipulating behavior for unintended purposes is possible. In practice, the way these subsidies are designed generally does not require the person to actually take transit. Of course, the *spirit* of the subsidy would be violated, if individuals who know about the subsidy deliberately distorted their arrival or drop-off location to benefit from it. This would be analogous to tax avoidance and would be bad from a welfare perspective. In practice, this means that some of our shift to transit may be an overestimate.

External Validity. We have calibrated the model to the city of Chicago, but would like to discuss the generality of the results. Hall et al. (2018) indicates that the effect of Uber is more likely to be stronger (in absolute value) in larger cities with higher incomes. In Tables A10.1–A11.2 we consider changes in the income level of the city, and as expected, higher incomes amplify the transit responses. Given this, marginally lower incomes likely mute the magnitudes of our cross-price elasticities.

In addition, smaller cities are likely to have less public transit coverage (both in terms of geography and frequency). This effect cuts both ways: Uber becomes more valuable because it can fill these larger holes (stronger complement in these cities), but alternatively, Uber is relatively more appealing than transit for individuals without a car (stronger substitute). As noted above, although the sign of the changes is similar to the baseline, our results altering the length of transit lines, number of transit lines, transit capacity, bus waiting times, and headway of transit find the transit responses could be amplified or diminished depending on how the extent of transit is altered.

Combining these exercises, income is likely positively associated with the elasticities in absolute value, but city size could be positively or negatively correlated with the elasticities.

Another issue of generality is whether the city has a dominant CBD like Chicago or is polycentric like the Bay Area. The way we model local leisure trips is not dependent on city structure, as we assume these trips are to/from an unspecified origin/endpoint. The assumption is that there is a reasonable belief that a bus could service the local trip. If so, the city form is unlikely to affect these trips much except via endogenous car ownership.

Commuting trips to downtown and leisure trips to downtown depend on city form. Leisure trips to downtown could most easily be modified by splitting them into multiple types of trips to each city subcenter, as long as it is accessible by rapid transit. If public transit lines easily connect each of the city centers, as in the Bay Area, where Bay Area Rapid Transit (BART) allows access to any of the three centers (San Francisco, Oakland, San Jose), then the mechanisms underlying our commuting trips still persist even if the magnitudes are qualitatively affected. Because the radial lines are not so dense in the Bay area as in Chicago, the complementary channel may be most affected, as discussed in relation to the extent of public transit above. If a city center cannot be accessed by public transit, that would dampen the last mile complementarity because transit does not allow for easy travel to a core center. Commuting trips would be more challenging to modify as, the polycentric nature of cities would require endogenizing a cutoff that determines which sub-city individuals commute to. But absent having addi-

tional endogenous variables, we believe the qualitative mechanisms would persist, but again not necessarily magnitude. Future research might study such spatial configurations.

Of course, having a polycentric urban area also means that having a single tax/subsidy within the urban area would require state-level policy making. If policies remain decentralized to the cities, then decentralized taxes or subsidies could distort leisure destinations within the urban area, making it more important to endogenize the number of leisure trips to each city subcenter. In the current model, making the share of trip types endogenous is less of a concern because of the ability to have a single uniform policy and because the distances traveled for leisure purposes is endogenous for our downtown leisure trips.

6. Welfare calculations

We now turn to the welfare implications. The approach for the welfare analysis follows Sullivan (1985) and Borck and Brueckner (2018). Note, we are not calculating excess burden in this welfare analysis. There are several components in our aggregate welfare analysis. First, imposing taxes leads to welfare losses for landowners. The welfare losses 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. We then calculate the decline in land rents accounting for the endogenous border of the city radius, which partitions land into residential and agricultural areas.

Second, the imposition of the tax and expenditures on transit results in behavioral responses, but the income effect also changes household's utility. In particular, because households can move within the city, changes in income have implications for housing demand that depend on the income elasticity. Moreover, the *laissez faire* equilibrium is not first-best due to the presence of congestion externalities. As a result, any distorted quantity (e.g., congestion) that is affected by income effects will have a different change in utility relative to the case of no income effects. The welfare change experienced by households is measured based on the compensating variation (CV) associated with the adoption of the policy. The CV is calculated as the change in income required to achieve the same utility as before the policy is imposed. To compute the compensating variation in earnings, the model is re-simulated holding households' utility level constant—but now in an open-city model framework. The direction of the compensating variation can be inferred from the change in the utility level.

Thirdly, assuming each Uber driver is a self-employed (resident) entrepreneur, then her profit is a part of the city's welfare change. The net profit for each Uber driver is the difference between the total revenue from Uber rides net of Uber's commission and the driver's operating cost. The operating cost includes the variable cost of operating a car and gasoline cost. In our analysis, the firm's profit (Uber's) does not enter into the welfare analysis of the city, as we assume it is owned by non-residents.³⁶

We aggregate these individual components into the total change in welfare and then present the change as a percent of aggregate urban income in Table 7.

Focusing on the \$0.67 trip tax with a lumpsum rebate, the welfare effect of taxing Uber is negative, although smaller in absolute value than the revenue raised. This negative effect is the net of two counteracting forces: the fact that a tax on Uber distorts the optimal mode choice, but at the same time improves congestion on roadways. The first of these effects dominates because the tax affects many trips (leisure) that are not subject to congestion exter-

³⁶ Alternatively, we could assume it makes zero profit: the commission just covers costs of the platform.

Table 7
Aggregate Welfare Analysis (Percent of Income)

	Policy 1	Policy 2	Policy 3	Policy 4
Panel A: Tax Policies				
	no rebate	lump sum rebate	improve transit	reduce transit fare
Trip tax (67 cents per trip)	-0.09%	-0.06%	-0.05%	-0.13%
Sales (9.75%)	-0.08%	0.06%	-0.12%	-0.26%
Mile tax (20 cents per mile)	-0.11%	0.03%	-0.11%	-0.27%
Panel B: Subsidy Policies				
	\$3 off Uber to transit externally financed	\$3 off Uber to transit lump sum deduction	50% Uber to transit lump sum deduction	Free public transit lump sum deduction
Subsidy	0.01%	-0.46%	-0.36%	-1.15%
Panel C: Congestion tolls				
	no rebate	lump sum rebate	improve transit	reduce transit fare
Optimal toll	-1.14%	1.06%	-1.28%	-1.49%
Fixed toll	-0.01%	0.02%	-0.06%	-0.12%

This table shows the welfare effects of each policy. The welfare calculations account for aggregate (residential plus agricultural) land rent, the welfare of households as measured based on compensating variation, Uber driver profits net of Uber’s commission. Uber’s profits are not in the welfare calculation as we assume Uber’s profits accrue to shareholders/owners primarily outside of the city of Chicago. We normalize the welfare numbers to be a percent of aggregate income in Chicago.

nalities. Interestingly, the welfare decline resulting from using the revenue to subsidize public transit is larger in absolute value than the lump sum return. In part, this is likely a result of how this added subsidy reduces car ownership, while only having a relatively small increase in transit usage. The effects are qualitatively similar for other tax policies, except that the sales tax and mile tax may have positive welfare effects under the lump sum rebate. In part, this is due to the magnitude of these taxes, which raise more revenue than the \$0.67 trip tax. As a result, the lump sum rebates are larger in these scenarios, and thus the income effects have larger effects on initially distorted quantities. To verify this, we resimulate the flat per-trip tax with lump-sum rebates at different values, and can show that welfare is increasing in the tax rate, suggesting that from an optimally perspective, the choice of the tax rate is important. The laissez faire equilibrium is not optimal, nor is the 0.67 tax, but there do exist tax policies that improve welfare.

With respect to the subsidy policies, given they are effective at increasing transit ridership, they reduce congestion in the city. But, at the same time when they are financed via income reductions, those income losses have adverse effects. Although effective at improving transit ridership, the welfare effects are negative, likely because they are inefficiently targeted. In particular, the subsidies reduce rush-hour transportation for commuting trips, but at the same time, the city spends money on subsidies for leisure trips that occur at off-peak hours. For these latter trips, the subsidies have no externality-reducing effect, but reduce income. If the subsidies were only targeted to Uber trips to transit stations for commuting purposes, then the welfare effects would likely be more positive. Moreover, when the subsidies are externally financed, they improve a welfare, just like a “free lunch”.

The welfare effects of the optimal toll with a lump sum rebate are also positive. However, the welfare effects of the congestion toll may sometimes come with some negative effects. Although the marginal damage is internalized and speed increases, the average commuting time to work increases. This is partially a result of the congestion toll increasing urban sprawl because individuals further away have less viable options to substitute toward. Nonetheless, the large lump sum return from the congestion toll combined with the increases in speed, raises welfare. This is not the case when the toll is externally rebated or when revenue is then used to improve transit or reduce fares. With respect to the latter two, this suggests that these policies are excessive relative to the already levied optimal toll, which internalizes the marginal damage of congestion. This result might no longer hold if we accounted for additional environmental externalities, which could be added, in the welfare calculation.

7. Conclusion

Technological changes create important new challenges and opportunities for cities and their public finances. Ride-hailing apps represent one of the most important technological changes of the last decade for urban transportation, but the effect of government policies on these companies remains uncertain. We provide evidence that some of the existing policies targeting ride-hailing apps are ineffective at meeting their stated goals of reducing congestion externalities and increasing public transit usage. Instead, subsidies for ride-hailing apps or congestion tolls are more effective of meeting these two goals. Our results suggest that taking Uber directly to the final destination is a substitute for rapid transit. At the same time, Uber being a substitute to rapid transit does not mean it is also a substitute for buses, as lower Uber prices can endogenously lower car ownership decisions, possibly raising bus transportation for trips where rapid transit does not go. But, Uber and rapid transit can be complements if cities adopt appropriate policies to encourage Uber to be a “last-mile” service provider. In other words, the cross-price elasticities are not immutable, and can be chosen by the policies set by cities.

While we have made much progress studying the taxation of ride-hailing apps, much more research is needed. While our robustness exercises provide some evidence, future research might consider how results differ depending on the size of the city. Given sufficient density is critical for public transit system, the mechanisms we identify may be even more applicable in smaller cities where buses or other modes of transit do not readily cover suburban parts of the urban area. Finally, our model does not feature any regulatory policies (Mangrum et al., 2020) on taxis or ridehail applications, but such policies could have their own effects on the cross-price elasticities of demand, and thus merit further study.

Our model represents a comprehensive model of transit choice in urban areas. As evidenced by the wide array of policies we can consider, the model is flexible enough to study other policy interventions on completely unrelated topics, making the modeling contributions in our paper important—in their own right—for the study of transportation choices in cities.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Online appendix

Supplementary data associated with this article can be found, in the online version, at <https://doi.org/10.1016/j.jpube.2023.104862>.

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