Self-Driving Cars and the City: Long-Run Effects on Land Use, Welfare, and the Environment

William Larson*
Weihua Zhao

October 13, 2017

Abstract

This paper considers the widespread adoption of electric, shared, autonomous vehicles (AVs). Numerical simulations suggest falling transportation costs and changing center-city land use patterns will reshape the urban form of the city, with several primary consequences. The most likely scenarios suggest substantial household welfare increases, suburbanization, and increased household energy consumption, calling into question claims that autonomous vehicles will save energy.

JEL Codes: R11, R28, C60

Keywords: autonomous vehicle, transportation, energy consumption, land use

---

*The authors are Senior Economist, Federal Housing Finance Agency; and Assistant Professor, University of Louisville. The views expressed in this paper are solely those of the authors and not necessarily those of the Federal Housing Finance Agency or the U.S. Government. Address correspondence to: William Larson (10-250), Federal Housing Finance Agency, Constitution Center, 400 7th St SW, Washington, DC, 20024. Email: larsonwd@gmail.com. The authors declare that they have no relevant or material financial interests that relate to the research described in this paper.

1 Introduction

The city in the 20th century was dominated by the rise of a new technology–the automobile–causing dramatic urban decentralization. However, by the end of the 20th century, the trend reversed, with increasing costs of transportation and the rise of center-city amenities drawing people back into cities (Glaeser, 2011). In 2015, house price gradients in American cities were steeper than at any point since the mid 1970s, reflecting this new state of affairs (Bogin et al., 2016).

In the 21st century, a new technology is under development that has the potential to reshape the city again–the autonomous vehicle (AV). Passengers in these automobiles, freed from the need to attend to driving, are likely to face dramatically lower fixed and marginal costs of commuting. These include greater leisure possibilities, reduced collision risk,[1] greater fuel efficiency through more optimal acceleration and breaking,[2] greater road throughput,[3] and higher automobile utilization rates (i.e. car sharing)[4].

However, unlike other recent transportation innovations such as telework or electric vehicles, which simply reduce marginal transportation costs, AVs also untether commuter parking land use from residential and commercial land use.[5] According to estimates in Meyer, Kain, and Wohl (1965) and Shoup (2005), parking typically occupies between 20% and 40% of all land in center-cities in the U.S., and large amounts in residential districts elsewhere in the city. With widespread adoption of AVs, cities and households may choose to reduce or eliminate most CBD commuter parking, instead having cars return home between morning and evening commutes. Or cars may never park at all during the day, instead joining a fleet of autonomous taxis for the duration of the workday, before transitioning back to commuter vehicles for workers' trips home. It may even be viable to eliminate both CBD *and* residential parking, and instead warehouse vehicles in giant suburban parking lots when not in

---

[1] Blincoe et al. (2002), in a National Highway Traffic Safety Administration (NHTSA) report, estimate the costs of traffic collisions to be $230 billion in 2000. KPMG (2015) estimates that 80% of all traffic collisions could be eliminated through widespread adoption of AVs.

[2] A RAND Corporation (2016) report cites research suggesting AVs can increase fuel economy by 4-10% through more optimal acceleration and deceleration.

[3] AVs are shown in traffic simulations to increase throughput by upwards of 500% (Fernandez and Nunes, 2012), and total vehicle miles travelled (VMT) by 35% (Bierstedt et al., 2014). Shoup (2005) finds that nearly half of all congestion delays are caused by crashes, which AVs would reduce.

[4] Santi et al. (2014) estimates that the New York City taxi fleet could be cut by 40% or more with ride sharing. Were an AV used in a commute to be re-purposed to an autonomous taxi during the workday, both the number of vehicles and the number of parking spaces could be presumably reduced.

[5] The distinction between commuter parking and retail parking is intentional. This paper considers only parking and transportation costs borne by commuters. While commuter trips are only a fraction of all trips made by automobile, travel times for other purposes are likely correlated with commute times.

use. These factors have the potential to reshape the city in important ways, yet the final outcome is uncertain. Because AVs reduce the cost of commuting and decrease the land necessary for parking in the center city, they simultaneously create forces for both increasing and decreasing urban density (Zakharenko, 2016; Rappaport, 2016).[6]

The major question, then, is if we can predict the effects of AVs on the city. While households will unquestionably benefit from AVs, density, energy consumption, land use, and even earnings may change. Responding to this need, research on AVs and their effects is a popular topic. Some, such as Rappaport (2016) predict sprawl as the result of lower marginal transportation costs, while others, such as Zakharenko (2016) predict a smaller, denser city once the reclamation of parking spaces has been completed. But none considers the commuting, housing production, land use, and energy effects within a single endogenous system. In this paper, we develop a rendition of the standard urban model that incorporates autonomous vehicles and endogenous land use for parking.[7] This model is solved numerically using a calibrated simulation model to give predictions of several scenarios. These scenarios consider the reduction in the time cost of commuting, implications of different parking regimes, the possibility of car-share arrangements (e.g. Uber and Lyft), and the marginal effects of other coincident technologies such as widespread adoption of electric cars.

Our model suggests that AVs have the potential to change land use, household welfare, density, and energy consumption in cities. There are several main findings. First, household density decreases and the physical footprint of the city increases due to the partial effect of AVs reducing marginal commuting costs. But, when AVs are paired with CBD parking land reallocation to commercial or residential uses, this result is reversed, and the city becomes denser and smaller in total land area. In this "CBD infill" case, the car autonomously travels back home when not in use, doubling the marginal pecuniary cost of commuting distance, and steepening bid-rent curves. When combined with other technologies, such as electric vehicles or car-sharing technologies, the combined effect is unequivocally urban decentralization. The combined effect of each of these transportation cost reductions, when paired with the reallocation of parking land to other uses, is to significantly flatten the

---

[6] Throughout the paper, we refer to "autonomous vehicles" to mean Level 4 autonomous vehicles, as defined by NHTSA (2013): "Level 4 (full self-driving automation): The vehicle is designed to perform all safety-critical driving functions and monitor roadway conditions for an entire trip. Such a design anticipates that the driver will provide destination or navigation input, but is not expected to be available for control at any time during the trip. This includes both occupied and unoccupied vehicles. By design, safe operation rests solely on the automated vehicle system."

[7] We assume AV technology is implemented everywhere, giving a "closed-city" rendition of the model where there is no net incentive for migration between cities.

bid-rent curve for housing and the land rent gradient.

Second, we find that the best alternative use for CBD land currently used for parking is for commercial uses, rather than parking or residential. The costs of residential displacement in the AV scenarios are almost identical to current benefits from CBD parking, making residential use an unlikely transition. On the other hand, there are large benefits to household earnings when the land previously used for parking goes to export good production. We also find that a suburban parking lot, where there is no parking in either the CBD or the residential district, is not welfare increasing unless it is to house a fleet of autonomous taxis, rather than as a lot for owner-used vehicles.

Finally, in no scenario do AVs reduce energy consumption or carbon emissions. The combined substitution (i.e. rebound) and income effects on other expenditures, instead, cause energy consumption and emissions to increase. While substitution from gasoline to electricity produced under the current U.S. energy mix of 39% coal, 27% natural gas, and 34% "green" has a partial effect of reducing emissions, this is more than offset by the increase in the total amount of energy consumed.

The cumulative effect of AVs, electric cars, and car-sharing technologies is dramatic. Land prices near the center of the city fall, density dramatically decreases, the city area expands, energy consumption and carbon emissions rise, and welfare increases substantially. Overall, this paper suggests that cities in the latter half of the 21st century may face a reversal of late 20th and early 21th century trends, and embark on a second broad period of suburbanization, mimicking the experience of the middle half of the 20th century.

2 Background

The standard urban model (SUM) of Alonso (1964), Mills (1967), and Muth (1969) treats as endogenous housing production, housing consumption, commuting costs, and location choice within an urban environment. Extensions within this framework are numerous, with those particularly relevant to the study of autonomous vehicles including the allocation of roads (Wheaton, 1998), space for parking (Brueckner and Franco, 2017), and energy consumption (Larson, Liu, and Yezer, 2012) within the city. The foundations and extensions of the SUM make it an ideal basis for modeling and predicting the general equilibrium effects of changes to transportation technologies.

While many of these papers provide analytical solutions to the models, this is not always possible. Because of the increasing layers of complexity needed to augment the model in innovative ways, extensions are often simulated to provide numerical solutions (e.g. Muth, 1975, Altmann and DeSalvo, 1981, Bertaud and Brueckner, 2005, and Borck, 2016, to name several). The strategy in this simulation literature is to calibrate the model to a real-world city or an average of cities, and then alter the core parameters in the model to produce counterfactual predictions.

In the classic rendition of the SUM, the city lies on a featureless plane, with no geological or regulatory features that would inhibit development. Firms occupy the Central Business District (CBD), and they exogenously demand identical workers to produce a single exported good, which provide the impetus for households to locate and remain in the city. An agricultural hinterland determines the reservation land rent at the edge of the city. Between the CBD and the hinterland is the residential district, which houses the workers who commute to the CBD, always by car. There is typically no mixing of market-driven land use at a particular location, but there are some exceptions, including Wheaton (2004).

There is substantial research that considers the inter-relation between parking, congestion, roads, and urban spatial structure. The consensus in this literature is that underpriced parking in the CBD leads to traffic congestion (Arnott and Inci, 2006), and parking alternatives beyond street parking are often desirable, such as garage and underground parking lots, which are better options when the price of land is high (Brueckner and Franco, 2017). AVs have two potential channels to reduce the demand for parking, both in the CBD and in the residential district. Due to car-sharing, the utilization rate of an individual car will increase, first, reducing the total number of vehicles in operation, and second, decreasing the amount of time an average car spends parked (Rappaport, 2016; Zakharenko, 2016). This parking effect is predicted to increase city density. The city is putty-putty, meaning that changes to parameters give a new long-run solution to the model, including land use. So, when AVs are introduced, and the model allows land use to change, less land is used for parking.

Housing producers and households receive a reservation profit and level of utility, respectively, at every location inside the city. This iso-utility condition is fundamental to "Muth's (1969) equation," governing the relation between house prices, housing consumption and transportation costs. AVs will undoubtedly reduce the marginal cost of commuting. Muth's equation then predicts a fall in house prices and an increase in housing consumption—in a word, sprawl.

When combining these effects, we see that there is not an unambiguous prediction of AVs on urban form. For instance, while Rappaport (2016) predicts the sprawl effects of AVs, he does not consider the land savings effect. On the other hand, Zakharenko (2016) takes into account both and predicts a shrinking of the city. The major question, it appears, is the extent to which cities are able to reclaim parking and put the land to more productive uses, in addition to the other parameters in the model. A central goal of the model in this section is to provide a framework in which a clear answer to this sprawl vs density question can be addressed.

Finally there are the energy considerations of AVs. While energy consumption may fall due to effects of lower congestion and faster commuting speeds, there are additional reasons for higher energy consumption due to the sprawl effects of larger houses, longer commutes, and pick-up trips where the car is unoccupied. Some of these rival forces are considered by Borck (2016), Larson and Zhao (2017), and others in the context of height limits, greenbelts, and telework.

3 Baseline Model Structure

The purpose of the baseline model is to produce a simulation that mimics a present-day city, while providing a platform on which experimental scenarios can be explored. The first step is to assume functional forms for the behavior of the agents and engineering constraints in the city. Values for parameters in these functions are then taken from the prior economics literature or engineering relationships, and then calibrated with respect to a vector a city attributes. The following model describes a baseline city in which each commuter drives a car to the CBD for work. In later AV scenarios, parameters and functions from this section are modified consistent with engineering estimates or predictions from the literature, and certain behaviors, such as parking location, are freed from current constraints.

3.1 The Central Business District

3.1.1 Land Use

Treatment of the CBD in the model is rather rigid and requires a number of standard assumptions that are necessary to facilitate simulation of the model. Robustness tests are conducted to bound and assess the sensitivity of the model to alternative assumptions and parameters.

The first major assumption is to treat the CBD as a single, homogeneous, mass. This assumption is made to avoid modeling the internal spatial structure of the employment center, and allows variables within the CBD to be expressed as averages. However, we maintain the notion of implicit agglomeration externalities that cause clustering of production in the CBD, which is necessary for city formation. We also implicitly assume, but do not explicitly model, downward sloping price and density gradients that reflect differential bid-rent curves for commercial and residential activity.

The second assumption is that the total CBD land area is fixed, as is the fraction of land used for each purpose ("land use shares"). The notion that land use shares are fixed is potentially realistic due to the myriad of land use regulations that mandate parking spaces and the path-dependence of road networks. The CBD area, on the other hand, may be endogenous and determined by the interaction of the bid-rent curves for households versus firms. Instead, we make the assumption that the CBD radius is set to one mile in the baseline simulation, following most of the existing literature. In scenarios, we allow CBD land area to vary in ways meant to reflect endogenous change, though it is mechanically constructed via exogenous parametrization.

In the CBD, land use is divided between parking, export goods production (commercial), and roads, with values of θ indicating land use shares. The CBD extends from radius zero to radius k_{CBD}.

$$1 = \theta_{park} + \theta_{prod} + \theta_{road}, 0 < k < k_{CBD} \tag{1}$$

As a result, the land used for production is

$$L_{q,CBD} = \theta_{prod} \pi k_{CBD}^2 \tag{2}$$

and land used for parking is

$$L_{p,CBD} = \theta_{park} \pi k_{CBD}^2 \tag{3}$$

Land used for parking is not structurally modeled as a function of the number of parking spaces, but rather as a fixed fraction of the land area. Implicit in this representation is the possibility of parking density greater than one which would indicate the presence of garage parking as in Brueckner and Franco (2017). With the introduction of AVs in later sections, workers can choose alternatives to CBD parking such as parking at a different location. In this case, land previously devoted parking can be allocated to either commercial production which will lead to higher wage rate, or residential housing which will cause CBD to shrink.

3.1.2 Export Good Production

Export goods are produced by a single perfectly competitive firm using labor, land, and capital inputs subject to a Cobb-Douglas production function given by $F(N, L, K)$, where N is the number of workers, which is equal to the city population, L is the land input, which depends on the fraction of land in CBD devoted to commercial production along with the total land area of the CBD, and K is the endogenous capital input. With technology parameter B, the production function is the following:

$$F(N, L, K) = BN^{\nu_1} L_{q,CBD}^{\nu_2} K^{1-\nu_1-\nu_2} \tag{4}$$

The firm maximizes profits subject to the land endowment, the price of capital p_K, and the population of the city.

The first order conditions imply that wage rate W is determined by the marginal productivity of labor, which is in turn a function of the parameters and fixed quantities in the model. We set the wage rate in our baseline simulation to our composite-city average, and use the production function to generate endogenous changes in the wage rate.

$$W = p_K \frac{\nu_1}{1 - \nu_1 - \nu_2} \frac{1}{N} \left(\frac{p_k}{\nu_3 B N^{\nu_1} L^{\nu_2}} \right)^{\frac{1}{\nu_3 - 1}} \tag{5}$$

One implication is that, as the land share used by firms rises, a higher wage rate will result, both through a direct effect of land increasing the marginal product of labor and a secondary effect of a higher level of capital which pushes wages higher still.

3.2 The Residential District

3.2.1 Land Use

The residential district occupies land between k_{CBD} and $\bar{k}$.[8] Land use in the residential district is divided between surface parking, roads, housing, and other uses. Road use and other uses within the residential district are constant across k.

$$1 = \theta_{park}(k) + \theta_{hous}(k) + \theta_{road} + \theta_{oth}, k_{CBD} \leq k \leq \bar{k} \tag{6}$$

Because the fractions of land used for roads and other uses (e.g. parks, services, and

---

[8] All characteristics of the city at a particular radius are identical, allowing the city to be expressed in radial terms.

amenities) are fixed in each annulus, land for housing and parking is zero-sum.[9]

To close this portion of the model, land used for parking is determined as follows. Let c be parking land use per car, ϵ the number of commuters per household, and $D(k)$ the density of households at radius k.[10] Under this representation, parking in the residential district is exclusively surface parking and explicitly modeled.

$$\theta_{park}(k) = c\epsilon D(k) \tag{7}$$

The proportion of land used for housing can then be expressed in terms of the density, the only remaining endogenous variable in the land use system.

$$\theta_{hous}(k) = 1 - (\theta_{road} + \theta_{oth} + c\epsilon D(k)) \tag{8}$$

3.2.2 Housing Production

Housing H at distance k from the CBD, is produced by combining structure, S, and land, L, inputs under a constant returns to scale technology according to a CES production function:

$$H(k) = A\left[\alpha_1 S(k)^{\rho} + \alpha_2 L(k)^{\rho}\right]^{1/\rho} \tag{9}$$

Structure inputs are perfectly elastically supplied. Land is supplied from $\theta_{hous}(k)$.[11]

3.2.3 Households

All households are identical and maximize a CES utility function consisting of two goods, rental housing h and a numeraire consumption good y, subject to a budget constraint.

$$U = \left[\beta_1 y^{\eta} + \beta_2 h^{\eta}\right]^{1/\eta} \tag{10}$$

β_1 and β_2 are related to consumption shares between the two arguments, and $1/(1-\eta)$ represents the constant elasticity of substitution between housing and the numeraire good. Household income, w, is divided among a basket of goods and costs that vary based on residential location, and include the numeraire good, $y(k)$, housing purchases, $r(k)h(k)$, and

---

[9] Duranton and Puga (2015) show land used for transport, and the fraction of developed residential land, is roughly constant between 5 and 15 kilometers from the center of Paris.

[10] Parking space size and the number of commuters per household are constant at each radius k.

[11] This model ignores the role of maintenance, rehabilitation and durability of structures in housing production.

total transportation costs given by the product of workers per household, ϵ, and transportation costs per worker, $T(k)$.

$$w = y(k) + r(k)h(k) + \epsilon T(k) \tag{11}$$

The treatment of the transportation cost is one of the key innovations in the model. In the baseline, the function is simple and standard in the literature. This consists of a fixed cost t_f, which includes taxes, insurance, and obsolescence; pecuniary costs $t(k)$, which includes both the constant marginal cost per unit distance m and a variable marginal cost which varies according to traffic congestion; a time-cost, $t_w(k)$; and parking-related costs, $t_p(k)$.

$$T(k) = t_f + t(k) + t_w(k) + t_p(k) \tag{12}$$

where

$$\begin{array}{rcl} t(k) & = & 2(mk + p_g \int_0^k \frac{1}{G(V(M(\kappa)))} d\kappa) \\ t_w(k) & = & 2(\tau w \int_0^k \frac{1}{V(M(\kappa))} d\kappa) \\ t_p(k) & = & p_{parkCBD} + \gamma p_L(k) \end{array}$$

In $t(k)$ and $t_w(k)$, there are two commuting trips each day–to and from work. The first term in the function $t(k)$ is the constant marginal cost of distance multiplied by distance to give mk. The constant marginal cost of distance includes routine maintenance based on miles traveled, including tires, oil changes, and the like. The variable marginal cost of distance includes the price of gasoline, p_g, multiplied by the integral of the inverse of the fuel economy of the vehicle G, a function of the speed of the vehicle V, which in turn is a function of traffic congestion, which includes the argument M, the ratio of commuters to roads.

Engineering relationships govern the use of gasoline while commuting. Using data gathered by West et al. (1999) for an average vehicle in the U.S. fleet, $G(V(k))$ in Equation 12 is estimated by Larson, Liu, and Yezer (2012) based on a 4th degree polynomial.

$$G(V(k)) = .822 + 1.833V(k) - .0486V(k)^2 + .000651V(k)^3 - .00000372V(k)^4 \tag{13}$$

This gives about 14 miles per gallon at 10 miles per hour, up to a maximum of 29 miles per gallon at 50 miles per hour, and then falling to about 25 miles per gallon at 70 miles per hour. Under the assumptions that each worker in the city owns the same vehicle as the average vehicle in the U.S. fleet, this function gives an appropriate representation of commuting fuel use in the simulation.

We use the "Bureau of Public Roads" congestion function used by Muth (1975), where velocity is related to the ratio of cars travelling through the annulus, $\overrightarrow{N}(k) = \int_k^{\bar{k}} \epsilon 2\pi\theta_{hous}(k)kD(\kappa)d\kappa$, to the road area, $R(k)$, of the annulus, or $M(k) = \overrightarrow{N}(k)/R(k)$. The parameters a, b, and c are calibrated congestion parameters.

$$V(k) = \frac{1}{a + bM(k)^c} \tag{14}$$

The term $t_w(k)$ in equation 12 represents the time-cost of commuting. The product τw is the time cost of commuting, which is a fraction, τ, of the wage rate, w, and the integral of the inverse velocity. The parameter τ is assumed to be 0.5 by Bertaud and Brueckner (2005), and we follow this assumption in our baseline city. In the AV scenarios, we reduce this to 0.2 to reflect enhanced leisure activities available while commuting.

The term $t_p(k)$ includes the rental costs of the primary parking space and the CBD parking space. The first term in this expression is the rental price of a CBD parking spot, $p_{parkCBD}$. The second term is the cost of the primary parking spot. We assume this is a surface parking spot (no potential for a floor-area ratio of parking greater than one), and the cost is therefore the area of the spot multiplied by the land price.

3.3 Model Solution

The solution method follows Muth (1975), Arnott and MacKinnon (1977), Altmann and DeSalvo (1981), and McDonald (2009). The system of equations described above can be solved and reduced to a system with two simultaneous nonlinear equations with initial values. After a solution is obtained, the remaining gradients can be found recursively. The two-equation system of equations includes differential commuting costs and the household density at radius k, with known initial values at the CBD. This system is solved numerically using Matlab's ODE45 solver with a differential of 0.01 mile and default convergence tolerance.

$$\begin{bmatrix} dT(k) \\ dN(k) \end{bmatrix} \text{and} \begin{bmatrix} T(k_{CBD}) \\ N(k_{CBD}) \end{bmatrix} \tag{15}$$

After solving this system, it is possible to derive house prices, housing demand, land prices, structure/land ratios, energy consumption (see Appendix), and housing and parking land shares as a function of commuting costs and housing unit density, following Altmann and DeSalvo (1981). Then it is possible to calculate energy consumption using methods found in the Appendix.

There are two conditions that then must be met. First, the land price at the edge of the city must be equal to the agricultural land rent $p_L(\bar{k}) = p_L^a$, and second, the number of workers in the city must be equal to the number of jobs available $\epsilon N = E$. If either of these equilibrium conditions is not met, the simulation is re-initialized and simulated again until subsequent iterations achieve an equilibrium solution.

4 Baseline City Calibration

Parameters are calibrated following the literature and with respect to characteristics of a selected group of cities. These parameter values are shown in Table 1. Cities are selected based on three filters which are set to capture cities that have low regulation, few topographic interruptions, and are of moderate size. The regulation filter is based on the Wharton Residential Land Use Regulatory Index (WRLURI; Gyourko, Saiz, and Summers, 2008), and includes cities with an index value of less than zero. The topography filter includes cities with over 90% of nearby area topographically available for development. Saiz (2010). Finally, the city size filter includes cities with between 300,000 and 700,000 housing units in the principal cities. The principal cities of Charlotte, Indianapolis, Kansas City, and San Antonio pass these criteria, and our simulation is calibrated to a simple average of values in these cities.[12]

Once calibrated, the housing and utility parameters are close to those found in Altmann and DeSalvo (1981). Altmann and DeSalvo (1981) employs elasticities of substitution between structure and land inputs in the housing production function, and housing and the numeraire consumption good, of 0.75 in both equations. Land shares to housing and roads are similar to Muth (1975), as well as the speed parameters in the congestion function. Fixed and marginal commuting costs are from the American Automobile Association. The time cost of commuting for drivers is from Bertaud and Brueckner (2005), and set to 50% of the wage. The reservation agricultural rental price per acre per year is \$500, which corresponds to \$10,000 per acre at a 5% capitalization rate. Parking space per car is set to 300 square feet of land area, and the annual parking fee per car in CBD is set to \$1,200.

The resulting baseline city is remarkably similar to the four-city composite. The major

---

[12] Suburbs are not included in the tabulation because the simulation is focused on areas nearest to the center of cities where gradients are closest to being monotonic.

difference is the city we simulate is slightly denser and geographically smaller.[13] Gradients within the city are shown in Figures 1 and 2, including downward sloping land price, house price, FAR, and density gradients, and upward sloping housing consumption, lot size, total transportation cost, and energy use gradients.

5 Autonomous Vehicle Scenario Design and Results

With a model calibrated to a current, real-world composite city, it is now possible to design counterfactual scenarios. Each of these scenarios serves a different purpose. Some are designed to measure the pure, unadulterated, marginal effect of a parameter change, while others are designed to present more elaborate scenarios. The primary goal, however, is to consider different dimensions over which the widespread adoption of autonomous vehicles may affect the urban form of the city. Because these cities are completely re-simulated with each parameter change, they are effectively long-run changes with free factor mobility, where the elasticities of supply of non-land inputs are infinity. Throughout these exercises, we assume vehicle technologies are implemented everywhere at the same time. This gives households no incentive to migrate between cities, fixing population and allowing earnings and utility to potentially change within the city.[14]

5.1 Scenario 2: Autonomous Vehicles with No CBD Land Use Changes

The first scenario we consider takes the baseline city and alters a single parameter, the time-cost of commuting (τ). In the baseline model, this is set to 50% of the wage rate. Autonomous vehicles are widely expected to reduce the time-cost of commuting by freeing the driver from the need to attend to the driving of the vehicle. Instead, this time and attention is put to other uses, such as leisure, allowing the time spent commuting to create a higher level of pseudo-leisure benefit. To reflect this change, we set $\tau = 0.2$ and simulate the city. In effect, this takes a current city and assumes all households now commute via autonomous vehicle while keeping major decisions regarding parking location the same.

---

[13] This is a well-known characteristic of cities simulated with a single income group (Muth, 1975), and previous research has shown this characteristic—and small perturbations in other simulation parameters—to have negligible effects on differences between baseline and counterfactual cities (Larson and Zhao, 2017).

[14] This is commonly referred to as a “closed-city” model. This framework does not necessarily require the city to be closed to migration—only that the population does not change on a net basis.

The effects of this change are predicted by the broad literature on transportation costs in the standard urban model. A reduction in the marginal cost of distance will flatten the house price, land price, and density gradients, and increase housing consumption, energy consumption, and carbon emissions (see Coulson and Engle, 1987, Mieszkowski and Mills, 1993, Brueckner, Mills, and Kremer 2001, and Larson and Zhao, 2017, for instance). Outcome variables from this city are shown in Figures 1, 2, and 3, and Table 3, and are consistent with the literature.

Residential land prices at the edge of the CBD fall 44%, house prices fall by 4%, and housing consumption increases by 6%. In the city as a whole, the city footprint expands by 33% and the fraction in multifamily units drops from 31% to 11%. Housing expenditures rise by 2%, numeraire expenditures fall by 2%, and commuting expenditures actually rise by 2%, as the savings from a reduction in the time-cost of commuting are more than offset by the general equilibrium effects of decentralization. Household energy consumption and carbon emissions increase by 2%. Overall household utility increases by 4%.

5.2 Scenario 3: Residential CBD Infill

The next scenarios consider alternative uses for land that is used for CBD commuter parking in Scenarios 1 and 2. Implicit in these scenarios is the assumption that the household rents two parking spaces, one in the CBD and one at the residence. But this need not be the case when the commuter vehicle is autonomous. Rather, the household can presumably rent one or two parking spaces, and the car can travel autonomously between parking and pickup locations.

In general, and for the remainder of this paper, we conceptualize land used for commuter parking at all locations as endogenous. The most general form of a day's worth of commuter travel for a vehicle is shown in Figure 4, which includes only a suburban parking location and requires travel between three nodes during the day for a total of six trips. These nodes include a CBD parking space, the residential unit, and a parking space that is further from the CBD parking space than the residence. Not all trips must include passengers—some are made empty between a parking spot and pick-up location.

Choice of combinations of parking spots at home and/or in the CBD may eliminate some of these trips, but at the cost of the rental price of land for parking. When parking is not at the departure location, a vehicle must travel to pick up the commuter with the full pecuniary transportation costs of fuel and depreciation.

This general representation of transportation costs (including parking) is then as follows, where households at radius k choose the location of their primary parking spot, $k_p(k)$, and whether to rent a CBD parking spot, $\lambda(k) \in \{0, 1\}$.

$$T(k, k_p, \lambda(k)) = t_f + t_w(k) + t(k) + t_p(k, k_{park}, \lambda(k)) \tag{16}$$

where

$$\begin{array}{lcl} t(k) & = & 2(mk + p_g \int_0^k \frac{1}{G(V(M(\kappa)))} d\kappa) \\ t_w(k) & = & 2(\tau w \int_0^k \frac{1}{V(M(\kappa))} d\kappa) \\ t_p(k, k_{park}, \lambda(k)) & = & \lambda(k) p_{parkCBD} + \gamma p_L(k_p(k)) + 2|t(k_p(k)) - t(k)| + (1 - \lambda(k)) t(k_p(k)) \end{array}$$

The values for t_f, $t_w(k)$, and $t(k)$ are identical to Equation 12. The term $t_p(k, k_{park}, \lambda(k))$ includes the rental cost of the primary parking space, the CBD parking space if it is rented, and pick-up costs where the car is empty but travelling between the parking spot and the location of the eventual commuter. The first term in this expression is the rental price of a CBD parking spot, which is the land price at the CBD, $p_L(k_{CBD})$, multiplied by the land area required for the spot, which is the space required for parking divided by the floor-area ratio of garage parking. The second term is the cost of the primary parking spot—where the car resides overnight when not in use—which is the area of the spot multiplied by the land price. The third term is refers to segments one and six in Figure 4, and the fourth term refers to segments three and four. In the baseline scenario, $k_p(k) = k$, and $\lambda(k) = 1$, indicating a parking spot at the residence, and the rental of an additional CBD parking spot.

Due to complexities in the simulation, we are forced to assume various corner solutions in order to bound the estimated endogenous effects, which are likely to lie somewhere in the middle of simulated scenarios. We are able to rule out certain bundles, narrowing down the potential solution set. In particular, we can easily rule out $k_p(k) < k$, because land prices are higher nearer to the CBD, and deviation of k_p from k requires pick-up transportation costs. This condition ensures that if there is a single parking spot, it is no closer to the CBD than the residence. Additionally, if there is more than one spot, one is at the CBD and the other is no closer to the CBD than the residence.

For Scenario 2, we assume each household rents a single parking spot at its residence. This eliminates CBD land use for parking, allowing it to be repurposed. We term this repurposing of land to other uses as “parking infill”, and for Scenario 2, we assume that agents in the residential district are able to outbid the agents that would exist in the CBD, and the CBD shrinks by an amount equal to the prior land use for parking.[15]

The results of this scenario are shown in Figures 1, 2, and 3, and Table 3. The first thing to note from the figures is the bid-rent curves are steeper than the baseline simulation, despite the fall in transportation costs per unit distance. This is due to travel costs spent to pick up the commuter in the CBD for the trip home, reflected in segments 3 and 4 in Figure 4. So, while transportation costs per unit distance fall, these are multiplied by two. Offsetting these additional costs is the savings from not having to rent a CBD parking spot, and the reduction in average commute times due to a smaller CBD. Thus, bid-rent curves are steeper, but there is a positive level shift as well. This city is substantially different than the one simulated in Scenario 2, indicating that the effects of AVs on the form of the city hinge on decisions related to CBD land use.

Land and house prices at the CBD are higher than in Scenarios 1 and 2. The fraction of households housed in 5+ unit structures doubles from 14% in the baseline simulation to 27%. Density is higher and the CBD is smaller, resulting in a smaller city footprint. Energy consumption rises 2% but carbon emissions rise 4%, reflecting a change in energy mix from electricity in the home to gasoline on the road, which emits more carbon per BTU generated. Utility is higher, indicating that replacing CBD parking with housing may be slightly beneficial, but not substantially so, despite differences in the form of the city.

5.3 Scenario 4: Commercial CBD Infill

In Scenario 4, rather than households outbidding firms for land previously used for parking, instead, thes firm occupying the CBD are able to outbid households for the entirety of this land area. Because the output production function is Cobb-Douglass, there is an increase in household wages based on two effects. The first is a direct effect of increased land input on wages. The second is an indirect effect of increased capital input on wages, with the increase in capital input due to the effect of land on the productivity of capital.[16]

The key effects of this scenario are shown in Figures 1, 2, and 3, and Table 3, along

---

[15] Scenario 2 is similar to Zakharenko (2016), who assumes CBD land used for parking is eliminated and replaced by households. This paper predicts CBDs will shrink by more than the residential district will expand, with the net result being a shrinking physical footprint of the city. However, this paper does not consider the possibility that housing consumption may rise, which would increase the footprint. The endogenous tension between higher and lower city density is a main strength of the modeling approach in our present paper.

[16] There are three first-order conditions. We hold labor, N, land, L, and the rental price of capital r_K constant, and solve for the market wage rate. Recall we hold N constant because we assume all areas have autonomous vehicles and the reservation wage and utility change at the same rate everywhere (the open-city interpretation of the closed-city assumption).

with the baseline simulation and prior two scenarios. This city is similar in many respects to Scenario 3, including the location of parking and therefore the pick-up costs associated with no CBD parking. The two primary differences are the size of the CBD, which is larger in Scenario 4, and average earnings, which increase due to the higher marginal product of labor. Both of these are level-shifts, however, making it simple to evaluate the overall effects once the CBD variables are calculated: if the increase in transportation costs from the larger CBD are smaller than the increase in earnings, then the city is better off with commercial infill.

In Scenario 4, earnings rise by 4%, but commuting expenditures fall by only 5% rather than 7% in Scenario 2. The net effect, however, is an increase in housing consumption of 8% versus 4%, numeraire good consumption of 2% versus -2%, energy consumption of 6% versus 2%, carbon emissions of 7% versus 4%, and utility of 8% versus 4%. The utility increase, in particular, is striking. Half of the increase in utility from AVs is due to transportation cost reductions, as shown in Scenario 2, but another 4% utility gain is possible by repurposing land previously used for parking in the CBD to other productive uses. Based on this finding, for the remainder of the scenarios where CBD commute parking is eliminated, we assume firms outbid households for this land.

5.4 Scenario 5: Electric Cars

A coincident technology to autonomous navigation is the electric powertrain. The remaining scenarios we consider involve the universal adoption of electric vehicles and interactions with autonomous vehicle technology.

The urban economics of the widespread adoption of electric cars without automation is much like that of a reduction in gasoline prices in that it reduces transportation costs. Alone, this effect would not be germane to the study of AVs, but there is an important interaction between the location of the optimal parking spot and marginal transportation costs. In $t_p(k, k_{park}, \lambda(k))$, pick-up costs are directly related to $t(k)$ vis-a-vis $k_{park}(k)$, so a reduction in $t(k)$ will increase the relative desirability of parking locations further from the residential location, and decrease the relative desirability of a CBD parking spot.[17] Scenario 5 begins a series of scenarios whose purpose is to evaluate interactions between electric cars and autonomous vehicles. The first evaluates electric cars with human drivers and second layers AVs onto the electric car simulation.

---

[17] Differential slopes of bid-rent curves for housing versus parking are arguably within the scope of the present paper, but we have not explicitly performed such an examination in the present draft.

In Scenario 5, we take the baseline simulation and alter one equation: the fuel economy function, $G(V(k))$, which in the baseline, is a function of the velocity. For gasoline powertrains, this function is concave, with extremely low and high speeds resulting in low miles per gallon and peak fuel economy around 45 miles per hour. Electric powertrains do not have gears and recharge batteries during braking, giving this type of vehicle a nearly flat relation between velocity and fuel economy. In this scenario, we set $G = 96$, which is the average of the Nissan Leaf and Chevy Volt (Cosby, Errington, and Ober, 2016). There are no AVs in this scenario, so the time cost of commuting is unchanged at $\tau = 0.5$.

Effects of this scenario are shown in Figure 5 and Table 4. Urban form and energy consumption effects are predictable in terms of direction of the effect in ways similar to Scenario 1, so instead, we focus on energy consumption, emissions, and utility. In this present-day, electric car scenario, commuting energy consumption falls by 50%, but dwelling and numeraire energy consumption increase. The net effect is only a -1% change in energy consumption due to these "rebound" effects. However, because gasoline is more carbon-intensive than electricity, emissions change by -3%. Overall, utility increases by 1% due to the $455 per year fall in fuel costs.

5.5 Scenario 6: Electric Cars and Autonomous Vehicles

Scenario 6 takes Scenario 5 and layers on the reduction in the time-cost of commuting and CBD commercial infill from Scenario 4. This city, when compared to those in Scenarios 4 and 5, reveals the partial interaction effects of electric cars with AVs. Because a reduction in transportation costs mitigates some of the costs associated with pick-up trips, it is expected that the introduction of electric vehicles will enhance the effects of AVs.

Results from this city are shown in Figure 5 and Table 4. Universal adoption of electric AVs increases the city area by 12.1%, versus 12.6% in the electric, non-AV scenario presented in Scenario 5. Other variables related to density behave similarly, including structure type, house and land price gradients, and commute times. These results combine to suggest the partial effect of AVs is to increase the density of the city, as with the results in cities with gasoline.

The utility increase from the baseline gasoline city to the gasoline CBD infill scenario (Scenario 4) is 8%, while the same comparison with electric cars gives a utility change of 10% (11% - 1%). Thus, the marginal benefit of AVs is larger for a city with electric vehicles than for a city with gasoline vehicles. This indicates that, indeed, electric vehicles interact in positive ways with the introduction of AVs.

5.6 Scenario 7: Suburban Parking Lot

The final two scenarios we consider are highly speculative because of the radical nature of our assumptions regarding parking land use in the residential zone. In both of these cities, there is no commuter parking anywhere in the city. On the border between the residential and the agricultural districts is a ring of parking where all the cars in the city are warehoused when not in use. The rental price of parking in this suburban lot is equal to the agricultural land rent.

All six trips in Figure 4 are active in Scenario 7. We undertake this simulation for three main reasons: 1) to consider the potential optimality of such an outcome, 2) to explore extreme anti-parking policies, and 3) to act as a bridge to Scenario 8 to allow the calculation of partial effects.

Table 5 and Figure 6 present the characteristics of a city with electric vehicles and where all commuter parking has been removed from the city. The house price gradient in this scenario is extremely flat because pecuniary transportation costs are identical everywhere in the city. The vehicle travels from the edge of the city to the CBD and back twice each day, regardless of the residential location. The slope of the gradient is due exclusively to the time-cost of commuting. Because marginal transportation costs are so low, the city area nearly doubles from the baseline city. Utility is much lower (7% less) than in Scenario 6, though still 4% higher than the baseline. Energy consumption in this city is 15% higher than Scenario 6.

It is clear that this type of policy harms welfare and increases energy consumption relative to scenarios where CBD parking is eliminated but residential parking remains. Therefore, this type of parking regime would not likely be the result of optimizing behavior. However, there may be other reasons to remove parking from the city that are not considered in our simulation. For instance, physical proximity of households to schools, retail, and work may make the city much more able to sustain a walking or biking transportation network. Amenity or agglomeration externalities may also induce localities to remove parking, and this is not considered in the simulation model. These factors may provide an impetus for anti-parking policies at an administrative level.

5.7 Scenario 8: Autonomous Car Sharing

One of the main drawbacks of eliminating CBD parking is the return trip to the primary parking spot during the day, then the trip back to the CBD to pick up the commuter for the trip home. This problem is exacerbated the further the parking spot is from the CBD, and taken to an extreme in Scenario 7. Real-time car sharing obviates the need for mid-day return trips to the primary parking space, eliminating these costs. Car sharing also results in economies of scale in vehicle ownership and higher vehicle utilization, which reduce the cost of commuting by reducing the fixed costs borne by the household.[18]

The final city we simulate considers the trifecta of emergent vehicle technologies: autonomous, electric, shared vehicles. Shared vehicles already exist, in a sense, with companies like Lyft and Uber. These companies have pioneered a technology where a person with a computer or smart-phone can request a vehicle to pick them up from a destination and drive them to another. While these vehicles currently have human drivers, the technology would presumably work in a nearly identical fashion as a fleet of autonomous vehicles owned by a firm.

There is currently some nascent discussions of this type of future city, and it is important to consider the economics of the widespread adoption of this particular basket of technologies. For instance, a recent article in *Mother Jones* (Thompson, 2016) posits what cities and parking will look like in the future if parking were removed from the city. One statement in particular by Thompson draws attention, "A city run on shared autonomous cars would likely have a dramatically lower environmental footprint." This statement is based on a line of research by Greenblatt and Saxena (2015) which argues that AVs will result in an up to 90% decrease in emissions per mile due to commuting. However, by omitting economic behavior from these simulations, they may be severely biasing their results.

We implement autonomous car sharing by making several main assumptions. These assumptions are made based on economic theory and assumptions of how technologies will evolve. The first major assumption we make is to assume that all autonomous vehicles will be warehoused in the same suburban parking lot as in Scenario 7, at a cost per unit of land area equal to the agricultural land rent. The second assumption is that the vehicles are either idling or in use when not warehoused. When not used for commuting trips, vehicles are implicitly transporting non-workers—for instance, school children or shoppers. The car may also be used for courier services such as food, goods, or postal delivery.

The third assumption is that the autonomous vehicles in the city are owned by perfectly competitive firms that practice cost minimization. The price charged to consumers is a

---

[18] This scenario highlights one of the main benefits of AV technology when combined with car-sharing, identified by Carlo Ratti, the Director of the MIT Senseable City Lab (Wired Magazine, 2016)–a reduction in the number of cars needed to transport the population of a city, holding the number and distance of trips constant.

combination of distance and time costs. We assume the cost per mile is 30.1 cents plus an additional 3.1 cents per minute, with calculations found in the footnote below.[19] These rates are an order of magnitude lower than current taxi rates ($2.16 per mile and 58 cents per minute) or Uber rates ($1.08 per mile and 17 cents per minute) in Washington, DC in 2017. However, current rates are based on vehicles that are rarely electric, and include substantial, implicit labor costs.

We present results from this simulation in Table 5 and Figure 6. The land price gradient is still very flat compared to the baseline scenario, but is steeper than Scenario 7. This reflects the low pecuniary cost of distance due to the economies in scale generated by car sharing. The land rental price per acre at the edge of the CBD falls by 42% relative to the baseline scenario, indicating remarkable fall in demand for center-city real estate. Accordingly, the fraction of multifamily housing units falls by 2/3 (down from 30% to 10%), and the city area expands by 45%. The average lot size increases by 30% and the average housing unit increases by nearly 300 square feet.

Utility is 18.5% higher than the baseline in this scenario, and 9.7% higher than the best non-car sharing city, Scenario 6. Unlike Scenario 7, a suburban warehouse for autonomous vehicles is potentially a viable market outcome with the widespread adoption of car sharing.

Of course there are many possibilities we do not consider in this particular simulation. For instance, it may be possible for the city to reduce the number of cars to the point where street parking is adequate to park all vehicles when not in use, and no suburban lot is needed. Or in the presence of a suburban lot, street parking is no longer necessary, more lanes are available for traffic flow, and speeds increase at a given radius. Or it is possible for other ownership structures such as household-owned cars that can enter a “car sharing mode” when not in use, or a municipal network that is subsidized or taxed for policy reasons. Our simulation here is but one possibility.

---

[19] The per-mile cost includes per-mile maintenance and tire costs (6.3 cents), electricity costs (3.86 cents), and capitalized fixed costs of about 20 cents per mile ($30,000 vehicle divided by 150,000 miles). The time cost is calibrated to arrive at a 20% return on equity. We assume the car is in use 16 hours per day, is in service 300 days in service per year, and makes 2 trips per hour, for a total of 9,600 trips per year. At an average of 5 miles per trip (including both commuting and non-commuting), this gives 48,000 miles per year, meaning a car will be in service for 3 years. A 20% return on equity (assuming no depreciation net of maintenance) gives the company $6,000 per car per year. If the car is in use for 40 minutes per hour, this results in 3,200 hours of use per year. Dividing $6,000 by 3,200 gives $1.875 per hour, or 3.125 cents per minute.

6 Conclusion

As we have shown, autonomous vehicles (AVs) differ from other reductions in transportation costs in the ways they might reshape the city. By reducing the demand for parking spaces in areas where land is scarce and expensive, AVs will affect future land use decisions. Coincident technologies, such as car-sharing and electric cars, may amplify or reverse these effects.

The models and simulations presented in this paper indicate that these technologies, when combined, are likely to decrease density, decrease center-city housing and land prices, increase energy consumption and carbon emissions, and dramatically improve household welfare. We believe these results are robust to factors that we are unable to consider in the present research. For instance, AVs, because they are governed by computers, are likely to have reaction times that are superior to humans. This will decrease the headway distance between vehicles for a given speed and reduce collisions, thus reducing both fixed and marginal costs of owning a vehicle. In addition, by completely removing the human-vehicle physical operating interface (steering wheel, breaking, gas pedal), weight and volume are reduced, allowing cars to shrink in size, become more fuel efficient, and provide further amenities. Our simulation model does not consider any of these effects, each of which reduces transportation costs further than our simulations would indicate, suggesting our results are a lower bound.

While we do not compute all of the myriad ways AVs may increase transit efficiency, one potentially counterintuitive result is clear: in nearly every simulation considered, autonomous vehicles *increase* overall energy consumption. Parking and energy cost savings are spent on numeraire and housing goods, and these other goods and services embody as much or more energy than what was saved. These substitution effects (often called "rebound effects" in the energy literature) and income effects call into question engineering approaches to estimating energy consumption changes due to AV introduction. Clearly, the full millieu of decisions by agents in the economy needs to be considered, especially regarding demand-side changes to transportation technologies.

Overall, the combination of AVs, electric powertrains, and car-sharing technology has the potential to cause substantial rotations in house price, land price, and density gradients that are in many ways similar to those experienced in the 20th century. In the same way that the introduction of the freeway into the city gave rise to the suburb at a cost to many center-cities, similar dynamics may take place in the middle of the 21st century as AVs become ubiquitous.

References

Albright, J., Bell, A., Schneider, J., and Nyce, C. (2015). Automobile insurance in the era of autonomous vehicles. Technical report, KPMG.

Alonso, W. (1964). *Location and land use: toward a general theory of land rent*. Harvard University Press.

Altmann, J. L. and DeSalvo, J. S. (1981). Tests and extensions of the Mills-Muth simulation model of urban residential land use. *Journal of Regional Science*, 21(1):1–21.

Arnott, R. J. and MacKinnon, J. G. (1977). The effects of the property tax: A general equilibrium simulation. *Journal of Urban Economics*, 4(4):389–407.

Bertaud, A. and Brueckner, J. K. (2005). Analyzing building-height restrictions: predicted impacts and welfare costs. *Regional Science and Urban Economics*, 35(2):109 – 125.

Bierstedt, J., Gooze, A., Gray, C., Peterman, J., Raykin, L., and Walters, J. (2014). Effects of next-generation vehicles on travel demand and highway capacity. *FP Think Working Group*.

Blincoe, L., Seay, A., Zaloshnja, E., Miller, T., Romano, E., Luchter, S., and Spicer, R. (2002). The economic impact of motor vehicle crashes, 2000. Technical report, National Highway Traffic Safety Administration.

Bogin, A. N., Doerner, W. M., and Larson, W. D. (2016). Local house price dynamics: New indices and stylized facts. Technical report.

Borck, R. (2016). Will skyscrapers save the planet? building height limits and urban greenhouse gas emissions. *Regional Science and Urban Economics*, 58:13 – 25.

Brueckner, J. K. and Franco, S. F. (2017). Parking and urban form. *Journal of Economic Geography*, 17(1):95–127.

Brueckner, J. K., Mills, E., and Kremer, M. (2001). Urban sprawl: Lessons from urban economics [with comments]. *Brookings-Wharton Papers on Urban Affairs*, pages pp. 65–97.

Coulson, N. and Engle, R. F. (1987). Transportation costs and the rent gradient. *Journal of Urban Economics*, 21(3):287 – 297.

Duranton, G. and Puga, D. (2015). Urban land use. In Gilles Duranton, J. V. H. and Strange, W. C., editors, *Handbook of Regional and Urban Economics*, volume 5 of *Handbook of Regional and Urban Economics*, pages 467 – 560. Elsevier.

Fernandes, P. and Nunes, U. (2012). Platooning with ivc-enabled autonomous vehicles: Strategies to mitigate communication delays, improve safety and traffic flow. *IEEE Transactions on Intelligent Transportation Systems*, 13(1):91–106.

Glaeser, E. (2011). *Triumph of the city: How our greatest invention makes us richer, smarter, greener, healthier, and happier.* Penguin.

Greenblatt, J. B. and Saxena, S. (2015). Autonomous taxis could greatly reduce greenhouse-gas emissions of us light-duty vehicles. *Nature Climate Change*, 5(9):860–863.

Gyourko, J., Saiz, A., and Summers, A. (2008). A new measure of the local regulatory environment for housing markets: The Wharton Residential Land Use Regulatory Index. *Urban Studies*, 45(3):693–729.

Larson, W., Liu, F., and Yezer, A. (2012). Energy footprint of the city: Effects of urban land use and transportation policies. *Journal of Urban Economics*, 72(2-3):147–159.

Larson, W. and Zhao, W. (2017). Telework: Urban form, energy consumption, and greenhouse gas implications. *Economic Inquiry*, page forthcoming.

Lubell, S. (2016). Here's how self-driving cars will transform your city. Technical report, WIRED Magazine.

McDonald, J. F. (2009). Calibration of a monocentric city model with mixed land use and congestion. *Regional Science and Urban Economics*, 39(1):90 – 96.

Meyer, J., Kain, J., and Wohl, M. (1965). *The urban transportation problem.* Harvard University Press.

Mieszkowski, P. and Mills, E. S. (1993). The causes of metropolitan suburbanization. *The Journal of Economic Perspectives*, 7(3):135–147.

Mills, E. S. (1967). An aggregative model of resource allocation in a metropolitan area. *The American Economic Review*, 57(2):197 –210.

Muth, R. (1969). *Cities and housing: the spatial pattern of urban residential land use.* University of Chicago Press.

Muth, R. F. (1975). Numerical solution of urban residential land-use models. *Journal of Urban Economics*, 2(4):307 – 332.

National Highway Traffic Safety Administration. *Preliminary statement of policy concerning automated vehicles.*

Rappaport, J. (2016). Productivity, congested commuting, and metro size. Technical report.

Saiz, A. (2010). The geographic determinants of housing supply. *The Quarterly Journal of Economics*, 125(3):1253–1296.

Santi, P., Resta, G., Szell, M., Sobolevsky, S., Strogatz, S. H., and Ratti, C. (2014). Quantifying the benefits of vehicle pooling with shareability networks. *Proceedings of the National Academy of Sciences*, 111(37):13290–13294.

Shoup, D. (2005). *The High Cost of Free Parking.* Planners Press, American Planning Association.

Thompson, C. (2016). No parking here. Technical report, Mother Jones.

U.S. Energy Information Administration (2011). Energy consumption, expenditures, and emissions indicators estimates, selected years, 1949-2011. *Annual Energy Review 2011*, page 15.

Wheaton, W. C. (1998). Land use and density in cities with congestion. *Journal of Urban Economics*, 43(2):258 – 272.

Wheaton, W. C. (2004). Commuting, congestion, and employment dispersal in cities with mixed land use. *Journal of Urban Economics*, 55(3):417 – 438.

Zakharenko, R. (2016). Self-driving cars will change cities. *Regional Science and Urban Economics*, 61:26–37.

Figure 1: Baseline City, Autonomous Vehicle, and Parking at Home Simulations, Urban Form

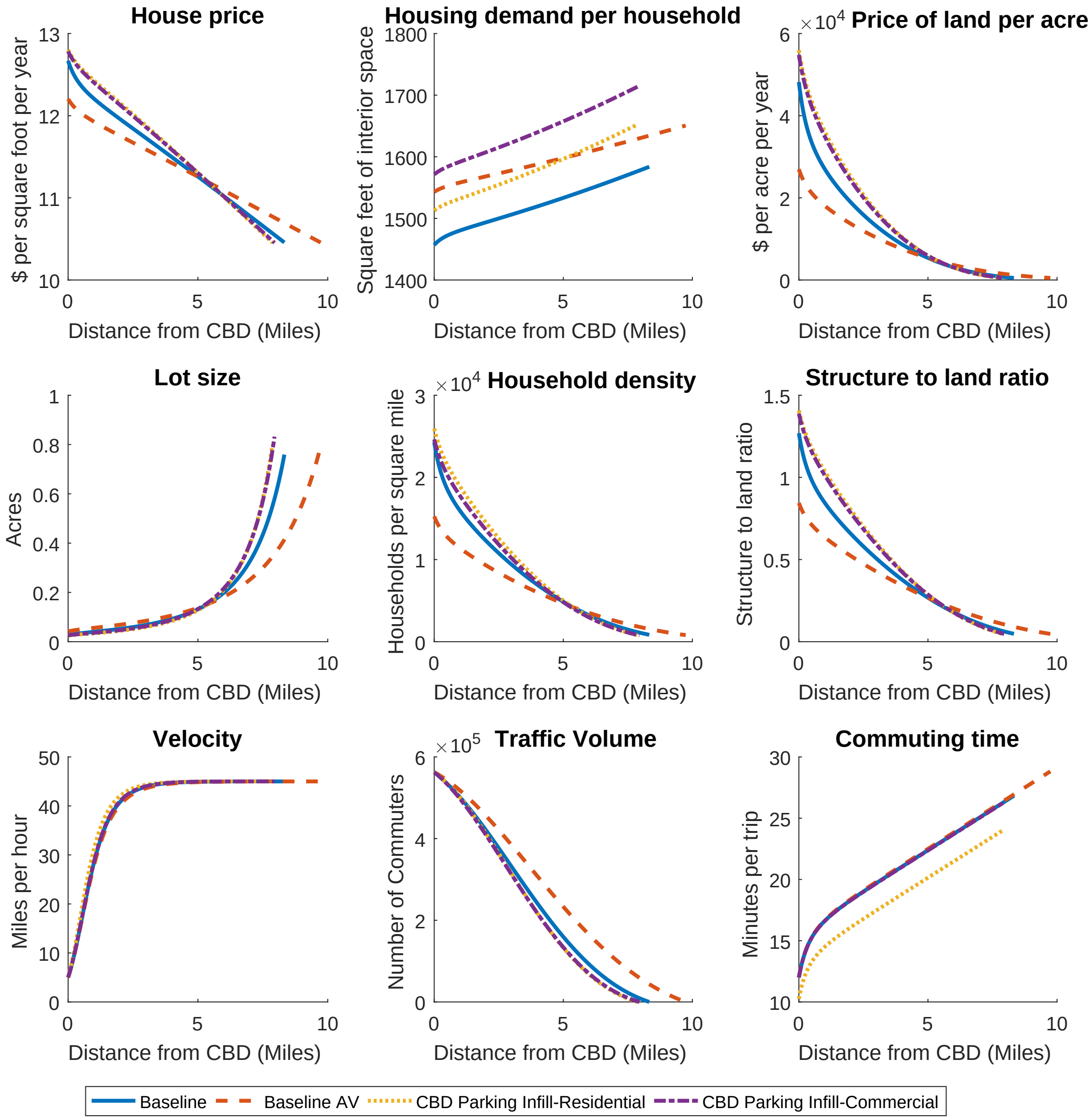

Figure 2: Baseline City, Autonomous Vehicle, and Parking at Home Simulations, Commuting Costs

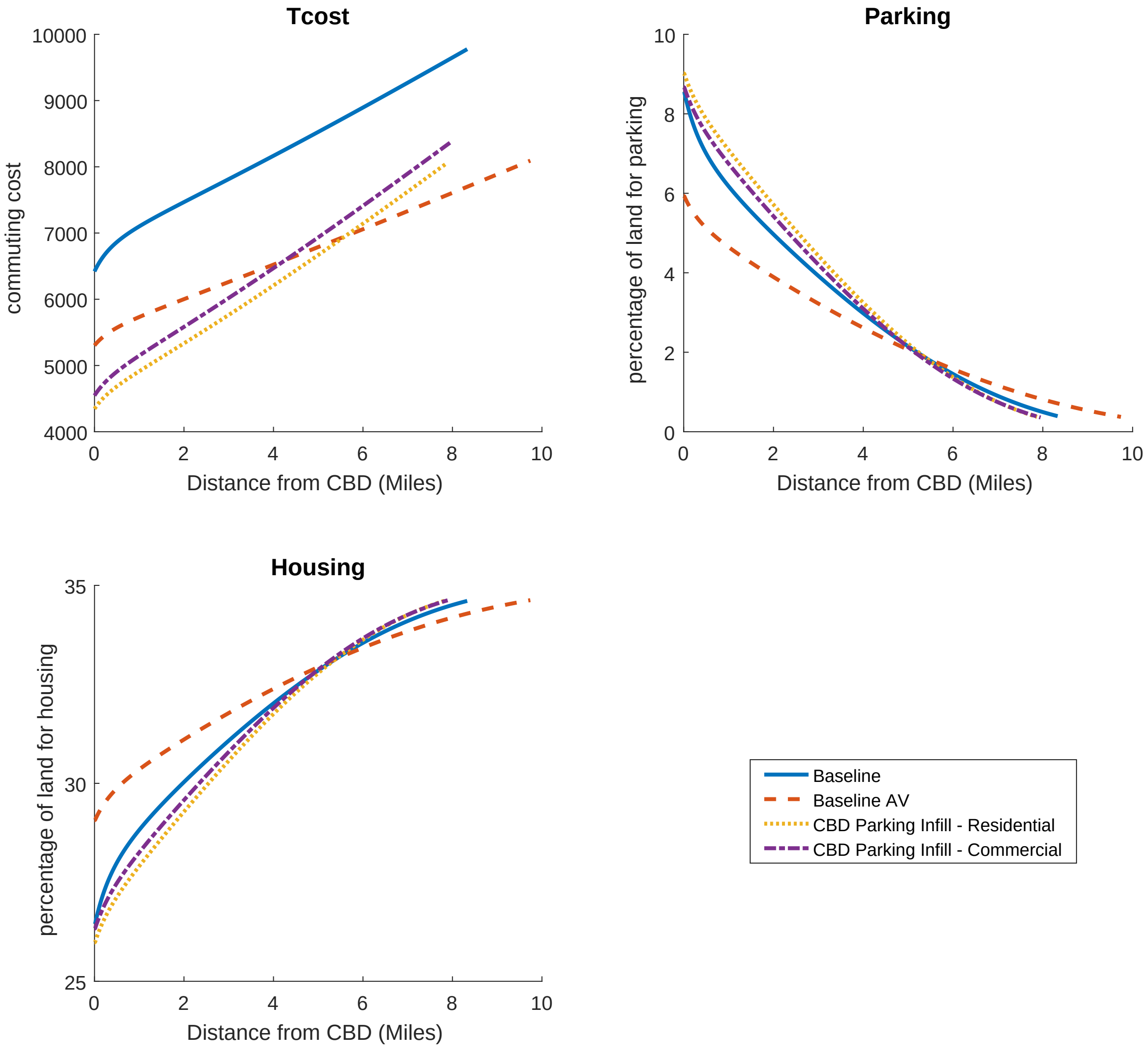

Figure 3: Baseline City, Autonomous Vehicle, and Parking at Home Simulations, Energy Consumption

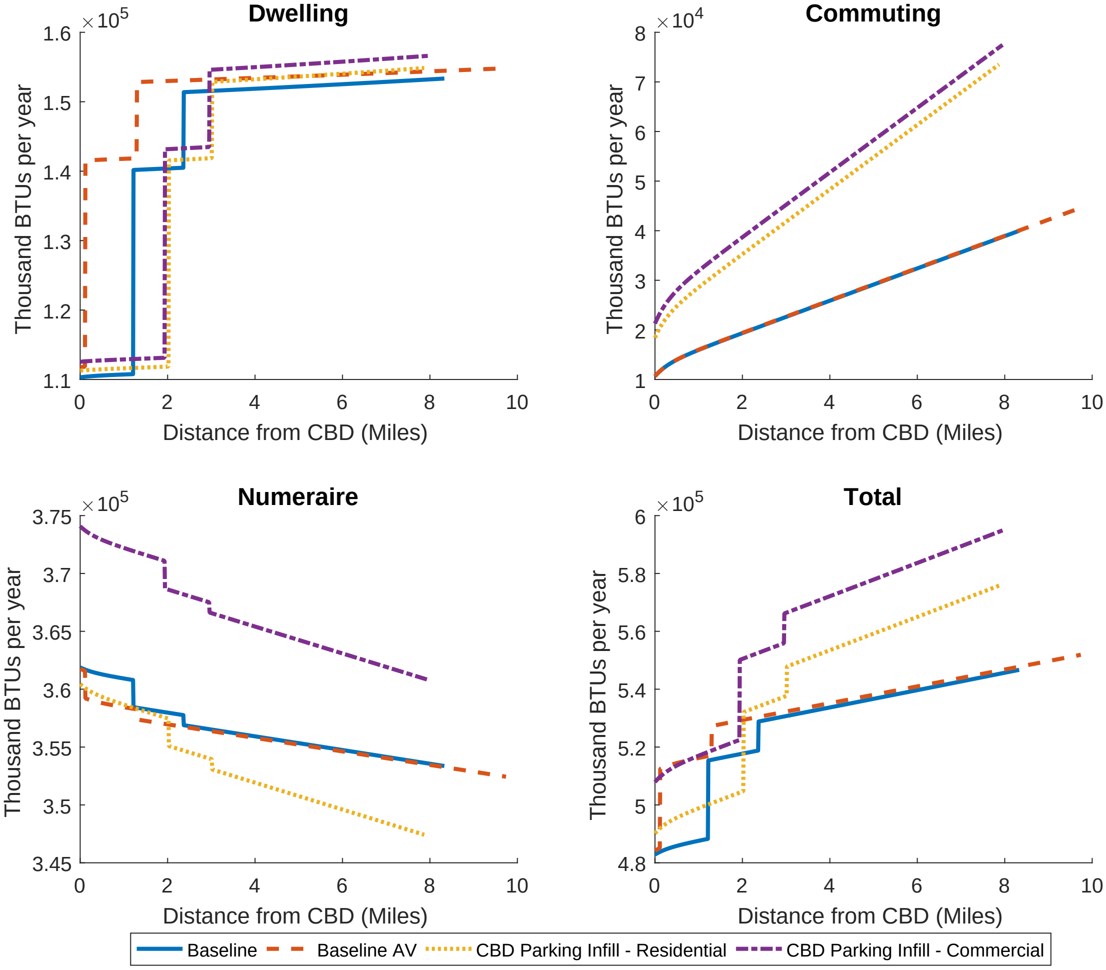

Figure 4: Autonomous Vehicle Travel Route

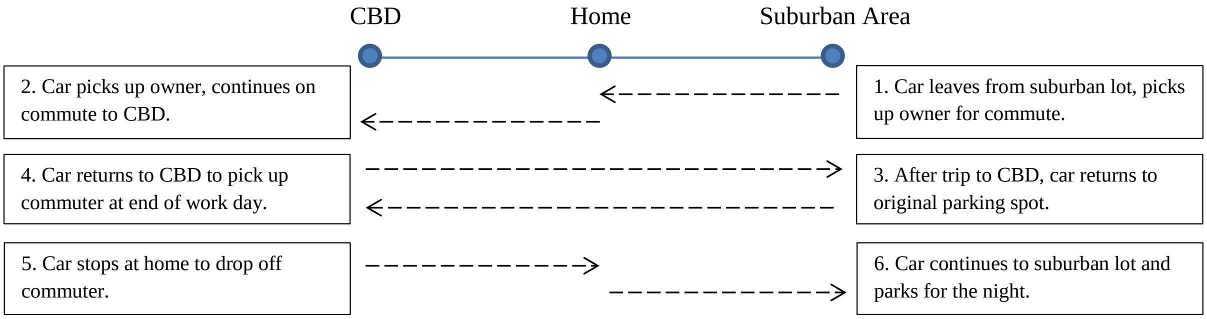

Figure 5: Electric Car Scenarios

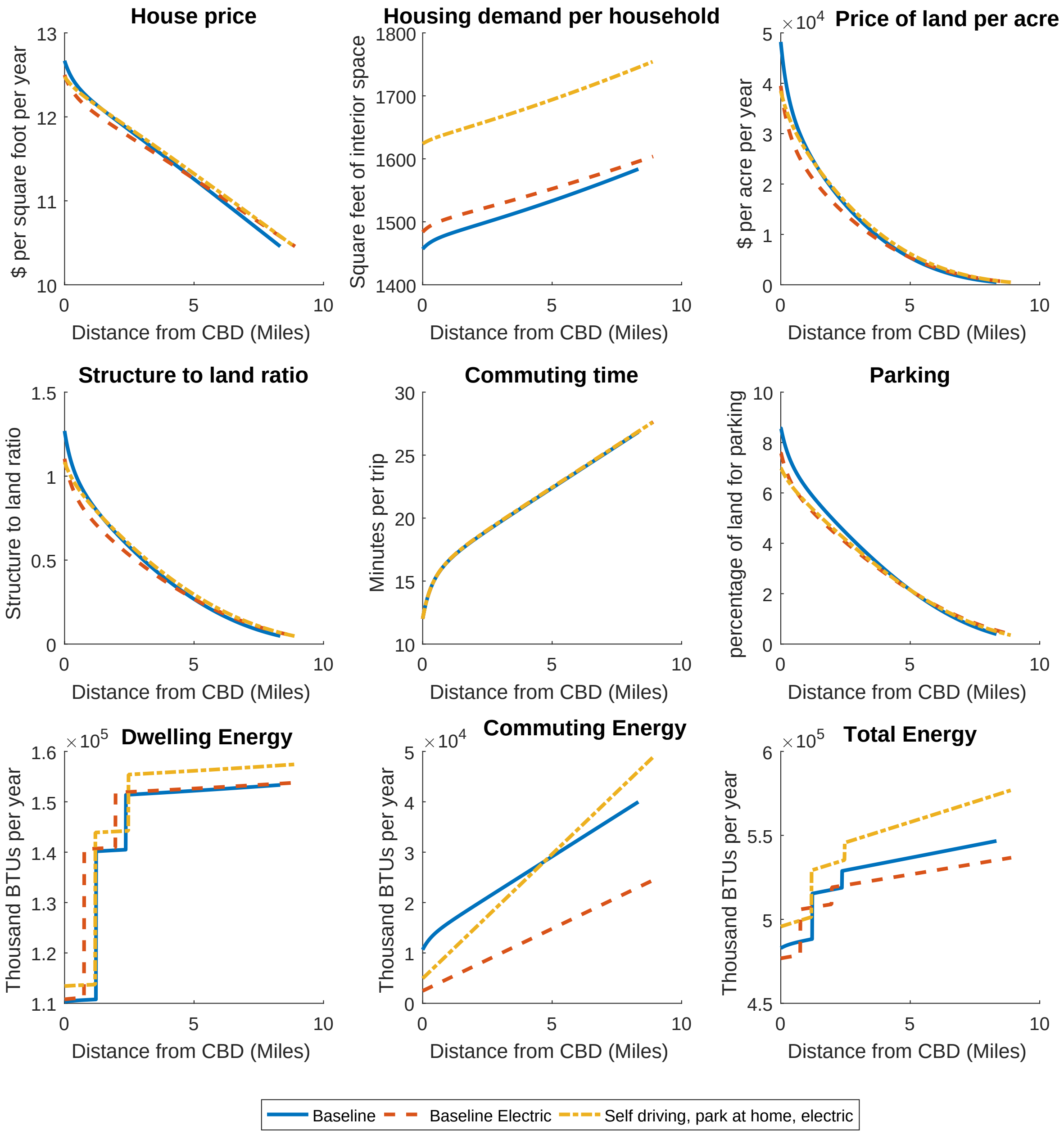

Figure 6: Suburban Parking Scenarios

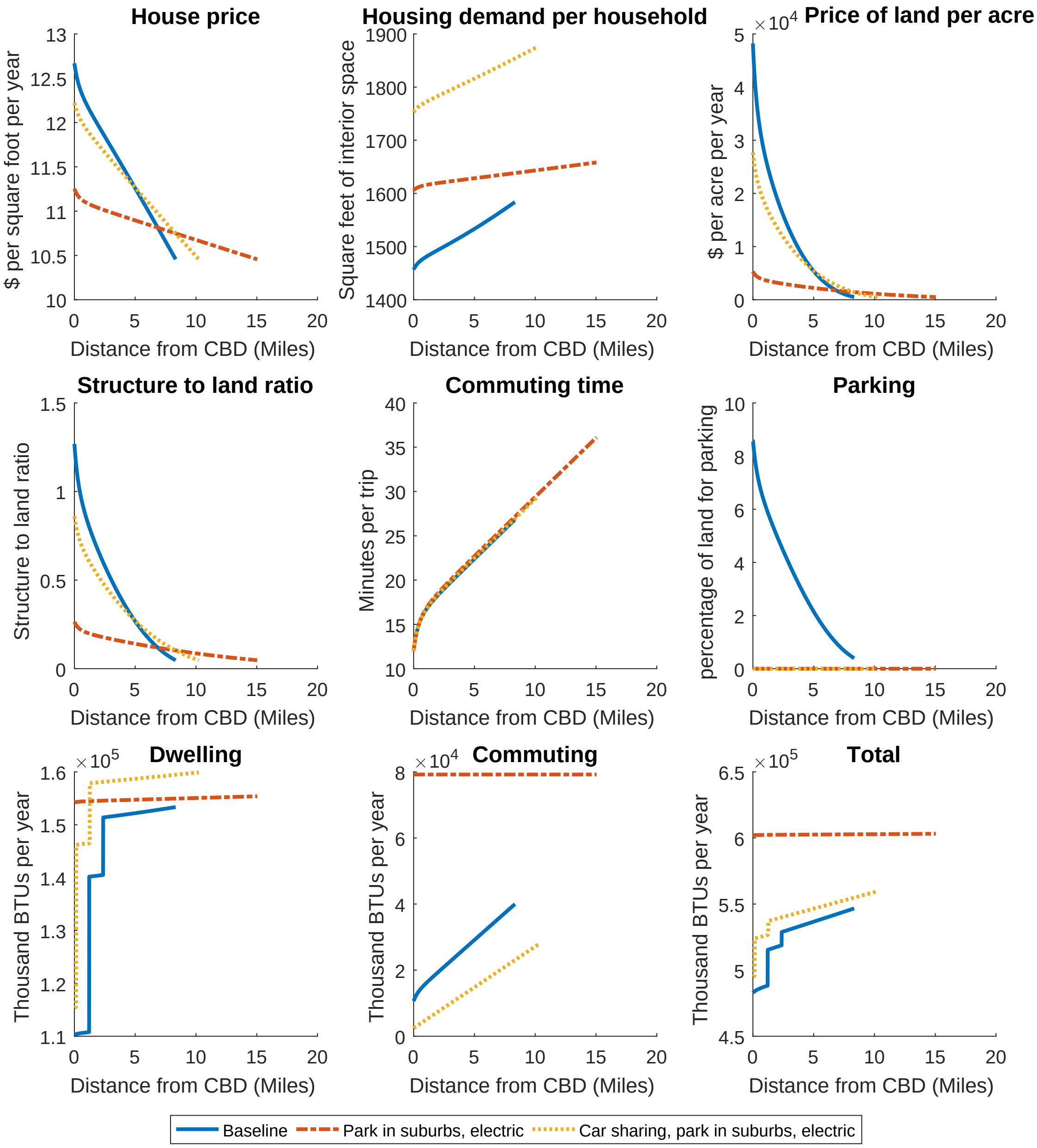

Table 1: Baseline Simulation Parameters

Parameter	Value	Description	Source
Central Business District			
k_CBD	1	Radius of the CBD (miles)	Assumed
θ_{park}	0.25	fraction of CBD land used for parking	Shoup (2005)
θ_{prod}	0.55	fraction of CBD land used for commercial production	Assumed
θ_{road}	0.2	fraction of CBD land used for roads	Muth (1975)
ν_1	0.7	Labor share parameter in CBD production function	Assumed
ν_2	0.1	Land share parameter in CBD production function	Assumed
$park_{CBD}$	$1,200	Annual parking fee in CBD	Various online sources
N	450000	Households	American Community Survey
W	49867	Earnings per household per year	American Community Survey
Residential District			
θ_{road}	0.2	fraction of residential land devoted to roads	Muth (1975)
θ_{oth}	0.45	fraction of residential land devoted to other use	Muth (1975)
$1/(1-\rho)$	0.75	Elasticity of substitution in the housing production function	Altmann and DeSalvo (1981)
α_1	1	Structure share parameter in housing production function	Muth (1975), Altmann and DeSalvo (1981)
α_2	0.03	Land share parameter in housing production function	Muth (1975), Altmann and DeSalvo (1981)
A	0.105	Housing production technology parameter	Calibrated
$1/(1-\eta)$	0.75	Elasticity of substitution in the utility function	Altmann and DeSalvo (1981)
β_1	1	Numeraire share parameter in utility function	Numeraire
β_2	0.2863	Housing share parameter in utility function	Calibrated
τ	0.5	Time-cost of commuting (fraction of wage)	Bertaud and Brueckner (2005)
s	300	parking area per car (sq. ft)	Authors' measurement
p_L^a	500	Reservation agricultural price per acre of land	Bertaud and Brueckner (2005)
p_g	3.5	Gasoline price per gallon	Energy Information Administration
t_f	2123	Fixed cost of commuting	American Automobile Association
m	0.222	Dollars per mile of depreciation	American Automobile Association
G(V(k)): constant	0.822	coefficient in gasoline-speed equation	Estimated by Larson, Liu, and Yezer (2012)
G(V(k)): $\beta_{V(k)}$	1.833	coefficient in gasoline-speed equation	Estimated by Larson, Liu, and Yezer (2012)
G(V(k)): $\beta_{V(k)^2}$	-0.048	coefficient in gasoline-speed equation	Estimated by Larson, Liu, and Yezer (2012)
G(V(k)): $\beta_{V(k)^3}$	0.000651	coefficient in gasoline-speed equation	Estimated by Larson, Liu, and Yezer (2012)
G(V(k)): $\beta_{V(k)^4}$	-3.7E-06	coefficient in gasoline-speed equation	Estimated by Larson, Liu, and Yezer (2012)

Baseline Simulation Parameters, Continued

Parameter	Value	Description	Source
v_{low}	5	Minimum commuting speed	Assumed
v_{high}	45	Maximum commuting speed	Assumed
c	1.75	Parameter in speed function	Calibrated
E_g	150.6	Energy per gallon of gasoline (125 x 1/0.83 efficiency)	Energy Information Administration
q_0	0.8	5+ unit building	Calibrated
q_1	0.7	2-4 unit building	Calibrated
q_2	0.6	sf. attached	Calibrated
E_e	0.303	Production and transmission efficiency for electricity	Energy Information Administration
E_N	7470	BTUs per dollar of GDP	Energy Information Administration

Table 2: Simulation Calibration

City CBSA Code	Charlotte 16740	Indianapolis 26900	Kansas City 28140	San Antonio 41700	Average	Simulation Baseline
Lot Size (acre) – Occupied Units[1]	0.36	0.31	0.25	0.20	0.28	0.16
Unit (square feet) – Occupied Units[1]	1694	1668	1655	1382	1599	1516
Area (sq. miles)[2]	444	409	515	505	468	273
Radius (assuming circle)[2]	11.9	11.4	12.8	12.7	12.2	9.3
Wharton Regulatory Index (WRLURI, 2008)	-0.53	-0.74	-0.79	-0.21	-0.57	-
Unavailable Land (Saiz, 2010)	5%	1%	6%	3%	4%	0%
Median Income[2]	50,702	46,970	49,001	43,586	47,565	48,216
Total Occupied Units[2]	412,445	410,594	360,109	547,627	432,694	450,000
Time to work[2]	25.1	23.8	22.3	24.6	23.9	20.5
Fraction housed in 1 unit structures[2]	71%	71%	70%	54%	66%	69%
Fraction housed in 2-4 unit structures[2]	12%	12%	15%	14%	13%	17%
Fraction housed in 5+ unit structures[2]	16%	17%	15%	32%	20%	14%
Energy consumed in dwelling, per capita (mmBTUs)[3]	-	-	-	-	49.8	43.8
CBD Parking Cost per Month	120	110	70	100	100	100

[1] Source for actual values: AHS (2011)

[2] Source for actual values: ACS (2010)

[3] Source for actual values: RECS (2009) households with 100% electricity consumption

Table 3: Baseline Simulation and Autonomous Vehicle Scenarios

City Simulation	[1]	[2]		[3]		[4]	
Assumptions							
Autonomous Vehicles	No	Yes		Yes		Yes	
Day Parking	CBD	CBD		Home		Home	
Night Parking	Home	Home		Home		Home	
Vehicle Fuel	Gasoline	Gasoline		Gasoline		Gasoline	
CBD Parking Infill	-	-		Residential		Commercial	
Measure	Level	vs [1]		vs [1]		vs [1]	
		Δ	%Δ	Δ	%Δ	Δ	%Δ
Urban Form							
Total Occupied Units	450,000	-	0.0%	-	0.0%	-	0.0%
Lot Size (Acres, Detached Avg)	0.163	0.022	13.4%	0.001	0.6%	0.008	4.9%
Unit Size (CBD)	1,457	86	5.9%	56	3.8%	115	7.9%
Unit Size (Residential Avg)	1,516	77	5.1%	56	3.7%	116	7.7%
Land Price per Acre (CBD)	$48,216	-$21,237	-44.0%	$7,757	16.1%	$6,611	13.7%
House Price per Sq. Ft. (CBD)	12.67	-0.46	-3.7%	0.13	1.1%	0.11	0.9%
Residential Struct./Land ratio (CBD)	1.27	-0.42	-33.5%	0.14	11.0%	0.12	9.4%
Residential Density (hh per sq. mile)	1,665	-412	-24.7%	231	13.9%	146	8.8%
Time to work (Residential Avg	20.5	1.2	5.9%	-2.5	-12.3%	-0.3	-1.7%
Fraction housed in 1 unit structures	69.2%	20.0%	28.8%	-13.6%	-19.6%	-12.9%	-18.6%
Fraction housed in 2-4 unit structures	17.2%	-7.0%	-40.8%	0.2%	1.3%	0.5%	2.7%
Fraction housed in 5+ unit structures	13.6%	-12.9%	-94.9%	13.3%	97.8%	12.4%	91.1%
Land Use							
City Radius (assuming circle)	9.33	1.41	15.1%	-0.59	-6.4%	-0.38	-4.1%
City Area (sq. miles)	273.47	88.90	32.5%	-33.71	-12.3%	-21.82	-8.0%
Area (Commercial)	1.73	0.00	0.0%	0.00	0.0%	0.79	45.5%
Area (Residential)	88.56	31.11	35.1%	-11.46	-12.9%	-7.64	-8.6%
Area (CBD Parking)	0.79	0.00	0.0%	-0.79	-100.0%	-0.79	-100.0%
Area (Residential Parking)	6.05	0.00	0.0%	0.00	0.0%	0.00	0.0%
Income/Expenditure Accounting							
Income per household	49,868	0	0.0%	0	0.0%	1,904	3.8%
Numeraire Expenditure	26,941	-671	-2.5%	-555	-2.1%	546	2.0%
Time Cost of Commuting	2,657	-1,531	-57.6%	-1,714	-64.5%	-1,572	-59.2%
Housing Services Expenditure	17,526	539	3.1%	910	5.2%	1,602	9.1%
Energy Expenditure	1,540	82	5.3%	-45	-2.9%	-24	-1.6%
Non-Energy Expenditure	15,987	456	2.9%	955	6.0%	1,626	10.2%
Commuting Expenditure	5,401	132	2.4%	-354	-6.6%	-244	-4.5%
Gasoline/Electric Expenditure	576	62	10.8%	462	80.3%	540	93.8%
Parking Expenditure	1,518	-42	-2.8%	-1,368	-90.1%	-1,371	-90.3%
Non-Gasoline, non-parking Expenditure	3,307	112	3.4%	551	16.7%	587	17.8%
Energy Consumption per Household (million BTUs)							
Total	525.9	9.3	1.8%	12.5	2.4%	31.3	6.0%
Commuting	24.8	2.7	10.8%	19.9	80.3%	23.2	93.8%
Dwelling	144.4	7.7	5.3%	-4.2	-2.9%	-2.3	-1.6%
Numeraire	356.7	-1.1	-0.3%	-3.1	-0.9%	10.4	2.9%
Carbon Emissions per Household (million BTUs)							
Total	30.9	0.6	1.9%	1.1	3.7%	2.3	7.4%
Commuting	1.9	0.2	10.8%	1.6	80.3%	1.8	93.8%
Dwelling	8.3	0.4	5.3%	-0.2	-2.9%	-0.1	-1.6%
Numeraire	20.6	-0.1	-0.3%	-0.2	-0.9%	0.6	2.9%
Welfare Accounting							
Utility	4757	200	4.2%	205	4.3%	394	8.3%

Table 4: Electric Car Scenarios

City Simulation	[1]	[5]		[6]	
Assumptions					
Autonomous Vehicles	No	No		Yes	
Day Parking	CBD	CBD		Home	
Night Parking	Home	Home		Home	
Vehicle Fuel	Gasoline	Electric		Electric	
CBD Parking Infill	-	-		Commercial	
Measure	Level	vs [1]		vs [1]	
		Δ	%Δ	Δ	%Δ
Urban Form					
Total Occupied Units	450,000	-	0.0%	-	0.0%
Lot Size (Acres, Detached Avg)	0.163	0.008	4.6%	0.018	11.3%
Unit Size (CBD)	1,457	27	1.9%	167	11.5%
Unit Size (Residential Avg)	1,516	25	1.7%	164	10.8%
Land Price per Acre (CBD)	$48,216	-$8,734	-18.1%	-$9,721	-20.2%
House Price per Sq. Ft. (CBD)	12.67	-0.17	-1.3%	-0.19	-1.5%
Residential Struct./Land ratio (CBD)	1.27	-0.17	-13.0%	-0.18	-14.6%
Residential Density (hh per sq. mile)	1,665	-188	-11.3%	-182	-10.9%
Time to work (Residential Avg	20.5	0.5	2.3%	0.4	2.1%
Fraction housed in 1 unit structures	69.2%	8.9%	12.9%	1.4%	2.0%
Fraction housed in 2-4 unit structures	17.2%	-2.2%	-12.6%	0.5%	3.2%
Fraction housed in 5+ unit structures	13.6%	-6.7%	-49.3%	-2.0%	-14.3%
Land Use					
City Radius (assuming circle)	9.33	0.57	6.1%	0.55	5.9%
City Area (sq. miles)	273.47	34.44	12.6%	33.19	12.1%
Area (Commercial)	1.73	0.00	0.0%	0.79	45.5%
Area (Residential)	88.56	12.05	13.6%	11.62	13.1%
Area (CBD Parking)	0.79	0.00	0.0%	-0.79	-100.0%
Area (Residential Parking)	6.05	0.00	0.0%	0.00	0.0%
Income/Expenditure Accounting					
Income per household	49,868	0	0.0%	1,904	3.8%
Numeraire Expenditure	26,941	300	1.1%	1,058	3.9%
Time Cost of Commuting	2,657	62	2.3%	-1,530	-57.6%
Housing Services Expenditure	17,526	131	0.7%	1,868	10.7%
Energy Expenditure	1,540	37	2.4%	49	3.2%
Non-Energy Expenditure	15,987	94	0.6%	1,818	11.4%
Commuting Expenditure	5,401	-432	-8.0%	-1,022	-18.9%
Gasoline/Electric Expenditure	576	-455	-79.0%	-337	-58.5%
Parking Expenditure	1,518	-20	-1.3%	-1,412	-93.0%
Non-Gasoline, non-parking Expenditure	3,307	44	1.3%	727	22.0%
Energy Consumption per Household (million BTUs)					
Total	525.9	-5.8	-1.1%	20.7	3.9%
Commuting	24.8	-12.4	-50.1%	-0.3	-1.2%
Dwelling	144.4	3.5	2.4%	4.6	3.2%
Numeraire	356.7	3.1	0.9%	16.4	4.6%
Carbon Emissions per Household (million BTUs)					
Total	30.9	-0.9	-2.8%	0.7	2.2%
Commuting	1.9	-1.2	-63.3%	-0.5	-27.4%
Dwelling	8.3	0.2	2.4%	0.3	3.2%
Numeraire	20.6	0.2	0.9%	0.9	4.6%
Welfare Accounting					
Utility	4757	60	1.3%	512	10.8%

Table 5: Suburban Lot and Car Sharing Scenarios

City Simulation	[1]	[7]		[8]	
Assumptions					
Autonomous Vehicles	No	Yes		Yes	
Day Parking	CBD	Suburb		Sharing	
Night Parking	Home	Suburb		Suburb	
Vehicle Fuel	Gasoline	Electric		Electric	
CBD Parking Infill	-	Commercial		Commercial	
Measure	Level	vs [1]		vs [1]	
		Δ	%Δ	Δ	%Δ
Urban Form					
Total Occupied Units	450,000	-	0.0%	-	0.0%
Lot Size (Acres, Detached Avg)	0.163	0.239	146.7%	0.050	30.7%
Unit Size (CBD)	1,457	145	10.0%	296	20.3%
Unit Size (Residential Avg)	1,516	118	7.8%	296	19.5%
Land Price per Acre (CBD)	$48,216	-$42,910	-89.0%	-$20,516	-42.6%
House Price per Sq. Ft. (CBD)	12.67	-1.42	-11.2%	-0.45	-3.5%
Residential Struct./Land ratio (CBD)	1.27	-1.00	-79.1%	-0.41	-32.2%
Residential Density (hh per sq. mile)	1,665	-1,106	-66.5%	-522	-31.3%
Time to work (Residential Avg	20.5	6.4	31.4%	1.4	6.7%
Fraction housed in 1 unit structures	69.2%	30.8%	44.5%	20.0%	28.9%
Fraction housed in 2-4 unit structures	17.2%	-17.2%	-100.0%	-7.3%	-42.5%
Fraction housed in 5+ unit structures	13.6%	-13.6%	-100.0%	-12.7%	-92.9%
Land Use					
City Radius (assuming circle)	9.33	6.72	72.0%	1.91	20.5%
City Area (sq. miles)	273.47	535.81	195.9%	123.43	45.1%
Area (Commercial)	1.73	0.79	45.5%	0.79	45.5%
Area (Residential)	88.56	193.59	218.6%	49.25	55.6%
Area (CBD Parking)	0.79	-0.79	-100.0%	-0.79	-100.0%
Area (Residential Parking)	6.05	-6.05	-100.0%	-6.05	-100.0%
Income/Expenditure Accounting					
Income per household	49,868	1,904	3.8%	1,904	3.8%
Numeraire Expenditure	26,941	-646	-2.4%	2,688	10.0%
Time Cost of Commuting	2,657	-1,158	-43.6%	-1,615	-60.8%
Housing Services Expenditure	17,526	54	0.3%	2,998	17.1%
Energy Expenditure	1,540	111	7.2%	135	8.8%
Non-Energy Expenditure	15,987	-57	-0.4%	2,863	17.9%
Commuting Expenditure	5,401	2,496	46.2%	-3,781	-70.0%
Gasoline/Electric Expenditure	576	198	34.4%	-441	-76.5%
Parking Expenditure	1,518	-1,514	-99.7%	-1,514	-99.7%
Non-Gasoline, non-parking Expenditure	3,307	3,811	115.3%	-1,827	-55.3%
Energy Consumption per Household (million BTUs)					
Total	525.9	76.8	14.6%	18.2	3.5%
Commuting	24.8	54.5	219.7%	-10.9	-44.1%
Dwelling	144.4	10.4	7.2%	12.6	8.8%
Numeraire	356.7	11.9	3.3%	16.5	4.6%
Carbon Emissions per Household (million BTUs)					
Total	30.9	3.9	12.7%	0.5	1.7%
Commuting	1.9	2.6	135.1%	-1.1	-58.9%
Dwelling	8.3	0.6	7.2%	0.7	8.8%
Numeraire	20.6	0.7	3.3%	1.0	4.6%
Welfare Accounting					
Utility	4757	213	4.5%	879	18.5%

7 Appendix

This section presents the exact method of computing energy demand as found in Larson and Zhao (2017). Because it is essential to understanding the mechanics of the simulation model, we include both the text and citation here rather than the citation alone:

Total energy consumption, $E(k)$, can be categorized into three main types: electricity in dwellings, $E^D(k)$, gasoline while commuting, $E^C(k)$, and numeraire, which embodies all other forms of consumption, $E^N(k)$. All energy is measured in terms of British thermal units (BTUs) and includes energy consumed in production and transmission.[20]

$$E(k) = E^C(k) + E^D(k) + E^N(k) \tag{17}$$

Total energy consumption in the city is the integral of this function over the city area. Teleworkers have $E^C(k) = 0$ for the days they telework, as represented by the $1 - \delta(k)$ term.

$$E = \int_{k_{CBD}}^{\bar{k}} D(k)\left[(1-\delta(k))E^C(k) + E^D(k) + E^N(k)\right] dk \tag{18}$$

Engineering relationships govern the use of gasoline while commuting. Using data gathered by West et al. (1999) for an average vehicle in the U.S. fleet, $G(V(k))$ in Equation 12 is estimated by Larson, Liu, and Yezer (2012) using a 4th degree polynomial.

$$G(V(k)) = .822 + 1.833V(k) - .0486V(k)^2 + .000651V(k)^3 - .00000372V(k)^4 \tag{19}$$

This gives about 14 miles per gallon at 10 miles per hour, up to a maximum of 29 miles per gallon at 50 miles per hour, falling to about 25 miles per gallon at 70 miles per hour. Under the assumptions that each worker in the city owns the same vehicle as the average vehicle in the U.S. fleet, this function gives an appropriate representation of commuting fuel use in the simulation.

Energy used in commuting by a household living in annulus k who commutes to the CBD is thus given by

$$E^C(k) = E_g \int_0^k \frac{1}{G(V(M(\kappa)))} d\kappa \tag{20}$$

where E_g is the energy embodied in a gallon of gasoline in BTUs, described as follows. The base energy content of a gallon of 100% petroleum-based gasoline is 125,000 BTUs. According to the Federal Register (2000) published by the Energy Information Administration, 1 gallon of gasoline requires an additional 25,602 BTUs to be expended in the process of production and distribution. Thus, $E_g = 150,602$ BTUs of total energy are embodied in final consumption. E_g is multiplied by the amount of fuel consumed in gallons to arrive at

---

[20] Different types of energy consumption may carry with them different types of externalities, and these are not considered. For instance, fossil fuels burned miles away from a city in a power plant may produce less particulate matter and volatile organic compounds that harm households versus those burned within the city in the form of gasoline. The simulation model in this paper does not consider these nor other local environment or climate-related externalities.

the value for commuting energy consumption.

Dwelling energy consumption is determined by three major factors: the income of the household, the square feet of interior space, and structure type. Larson, Liu, and Yezer (2012) also estimate residential energy demand parameters using the 2005 Residential Energy Consumption Survey (RECS). They find the partial elasticity of household energy consumption with respect to interior space is 0.23 and the estimated income elasticity is 0.07. Compared with the energy consumption in single-family detached units, single-family attached dwellings consume 7% less energy and multi-family units consume 31% less energy. In the simulation, the structure type, s, is determined by the structure to land ratio, q, defined as the ratio of housing square footage over lot size, denoted $q = H/L$. The critical value of q for each structure type are calibrated. The structure type is single-family detached if $q \in [0, 0.6]$, single-family attached if $q \in (0.6, 0.7]$, 2-4 unit multifamily if $q \in (0.7, 0.8]$ and 5+ unit multifamily when q is above 0.8.

For simplicity, it is assumed all energy consumed in the dwelling is electricity.[21] Each kilowatt hour of electricity consists of 3,412 BTUs of energy. As with gasoline, there is also energy embodied in production and distribution. The total energy consumed in the production, distribution and final dwelling energy use can be calculated by dividing final dwelling energy use by electricity efficiency parameter 0.303, giving E_e, which is the product of the efficiency parameter for fossil fuel electricity production 0.328 and efficiency parameter for electricity transmission 0.924 (Federal Register, 2000). This gives the function for dwelling electricity as

$$E^D(k) = E_e \exp\left[\gamma_1 + \gamma_2 \ln w + \gamma_3 \ln p_e + \gamma_4 \ln h(k) + s(q(k))'\Gamma\right] \tag{21}$$

The energy embodied in \$1 of numeraire consumption is estimated to be $E_N = 7,470$ BTUs, which is the average energy intensity of the U.S. economy (Energy Information Administration, 2011). Energy intensity is used for this measure because it implicitly includes all energy in the raw materials, intermediate input production, final production, and transportation of the goods and services. Numeraire energy at annulus k is set equal to earnings net of expenditures on gasoline and electricity multiplied by the inverse energy intensity parameter.[22]

$$E^N(k) = E_N\left(w - p_g E^C(k)/E_g - p_e E^D(k)/E_e\right) \tag{22}$$

Greenhouse gas emissions are calculated based on energy consumption in the three categories, each multiplied by a carbon dioxide (CO_2) emissions coefficient reported by the Energy Information Administration.[23] The combustion of one gallon of gasoline results in

---

[21] Electricity-only consumption is associated with lower per-household energy use compared to homes with natural gas, wood, or oil, according to the RECS. Therefore, estimates in this paper serve as the lower bound of energy consumed in the home.

[22] Expenditures for non-gasoline commuting costs and non-energy dwelling costs are assumed to have the same energy content as the numeraire good for purposes of computing energy consumption.

[23] CO_2 is the only greenhouse gas considered. Other greenhouse gases include methane (CH_4), hydrofluorocarbons, and nitrous oxide (N_2O). These are omitted because together, they account for less than 5% of all greenhouse gas emissions from gasoline consumption and electricity generation.

19.6 pounds of CO_2, or 157 pounds of CO_2 per million BTUs. Electricity is produced using a number of methods in the United States, and carbon emissions from electricity consumption is therefore averaged over each of the major sources. In 2014, coal produced 39% of all electricity generated, with an average of about 215 pounds per million BTUs over each of the types of coal consumed. Natural gas produced 27% of all electricity, at 117 pounds of CO_2 emissions per million BTUs. The remaining sources include nuclear, hydroelectric, biomass, solar, and wind, which together make up 34% of all energy production. These sources are assumed to result in zero net emissions in the production of electricity. The weighted average of the U.S. electricity production basket from these three main categories is 103 pounds of CO_2 per million BTUs. Both numeraire and dwelling energy is assumed to be produced using this basket. Because gasoline and the other sources of energy have different emissions coefficients, CO_2 emissions can change when energy consumption does not if the share of energy source is changing.