The Urban Equilibrium Effects of Electric Vehicle Tax Credits

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Abstract

This paper extends the monocentric city model to incorporate endogenous household automobile fuel choice and dwelling energy consumption. Electric vehicle (EV) tax credits lower direct energy consumption and emissions via commuting, but also cause important urban general equilibrium effects, including sprawl. This creates a substantial emissions rebound effect via larger homes, longer commutes, and greater consumption of the numeraire good, which reduces the cost-effectiveness of EV tax credits. Nevertheless, unless electricity production is heavily tilted towards coal, total household energy consumption and carbon emissions fall substantially.

JEL Codes: R41, R48, R28, R21, R31, R38
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1 Introduction

The last decade has given rise to the electric-powered vehicle (EV). One of the promises of EVs is reduced greenhouse gas emissions: pairing widespread adoption with a greening of the electricity production mix can result in substantial direct emissions reductions. Purchase tax credits have been a popular way for policymakers to incentivize the widespread adoption of EVs, with the recent Inflation Reduction Act offering $7,500 per vehicle. However, by reducing per-mile commuting costs, EVs are likely to cause urban sprawl, with associated increases to commute length, dwelling size, and increases in dwelling energy intensity. Accordingly, it is crucial to evaluate the effectiveness of EV tax credits in urban general equilibrium, rather than in partial equilibrium considering only commuting. Three questions motivate this paper: what are the effects of EV tax credits on the urban form of the city, do EV tax credits reduce emissions despite urban form rebound effects, and if so, are they cost-effective?

These questions are difficult to answer with existing data and modeling approaches for several reasons. First, short-run demand elasticities of new technology types may be lower than long-run elasticities, making it difficult to predict the long run effects of such a policy using early data. Second, general equilibrium effects at the city level are essential to consider. While direct emissions reductions are easily quantifiable holding commuting patterns constant, standard models of urban systems suggest the location, sizes, and types of housing in a city adapt to changes in commuting costs. Thus a change in commuting costs is likely face both a direct rebound effect of longer commutes, and a secondary effect of changing residential energy demand. Finally, there may be interactions with the city's climate, existing tax policies, and existing residential land use regulations, with policies such as minimum lot zoning, height limits, and greenbelts interacting to give larger or smaller effects on emissions relative to a laissez-faire (no regulation) city.

To answer these questions, we build on the classic monocentric city model of Alonso (1964), Mills (1967), Muth (1969), and the urban energy footprint model of Larson et al. (2012) and Larson and Yezer (2015), in two ways. First, we endogenize the automobile fuel choice, with households electing to purchase either an electric or gasoline-powered vehicle with technology-specific fixed and marginal commuting costs. Second, we endogenize residential energy consumption, treating it as part of a household's total housing costs. This model is numerically solved ("simulated") and calibrated to real-world data from a composite medium-sized U.S. city, giving a baseline city with reasonable price, density, and emissions gradients.

Given this calibrated urban model, we then perform a variety of counterfactual experiments and compare model solutions. For example, to implement a change in EV purchase tax credits, we solve the model twice, once under a tax credit of zero and once under a positive tax credit. The difference between model solutions gives the model-generated effects of the tax credit in general equilibrium as housing producers and consumers are able to optimize with respect to the location and intensity of housing production. From the outset, we caution against interpreting these predictions as forecasted effects; after all, this is a calibrated theoretical model and not a forecasting exercise. Nevertheless, our model offers a number of novel and important qualitative findings regarding EV adoption in response to purchase tax credits.

In the short run, in line with current stylized facts, EV adoption among identical households is concentrated near the CBD where trips are short. This occurs in spite of lower per-mile commuting costs due to a variety of factors related to the newness of EVs as a technology.[1] A higher share of EVs reduces direct energy consumption and emissions as a first-order effect. However, as EV technology matures, these same households choose EVs in more suburban locations, and EV tax credits encourage such sprawl. This sprawl induces an energy rebound effect through two channels. First, housing shifts towards single-family construction, increasing energy consumption and emissions due to housing structure composition. Second, the commuting cost savings from EVs is reallocated to other energy and emissions-intensive consumption. This reduces the total energy reduction effect of EV adoption and demonstrates the need to model EV tax credit effects in local general equilibrium.

We also offer findings of differential effects across cities depending on climate, land use regulation, and tax regime. The model predicts cities in moderate climates to sprawl more because home energy needs are lower. Accordingly, effectiveness of EVs in such climates are therefore higher. Cost-effectiveness of EV credits are tied to the CO_2 intensity of the electricity mix. When electricity is produced with dirty (e.g. coal) inputs, it harms the cost-effectiveness of EV subsidies because fuel source substitution from gasoline to electricity reduces CO_2 emissions by less. Land use regulations interact with the effects of EVs; in cities with density-reducing policies, EVs are more important for reducing energy consumption and emissions, but will cause even greater sprawl. Finally, some tax policies interact with the effects of EVs. Among those considered, only taxes that affect differential marginal commuting costs have interactive effects. Of particular note is that carbon tax and EV

[1]Some of these factors include long charging times, limited driving range, limited model variety, and political beliefs.

subsidies are duplicative: a carbon tax incentivizes EV adoption such that additional tax credits are very expensive relative to their marginal effect on EV adoption and CO_2 reductions. When EV tax credits are financed directly by all drivers, a virtuous prisoner's dilemma exists that enhances credit effectiveness.

This research contributes to several important literatures. The first is the extensive literature on how transportation innovations, land use regulations, and interactions between them affect the internal spatial structure of cities. Along this line of inquiry are contributions such as Larson and Zhao (2017) and Delventhal et al. (2022) who examine the effects of widespread telework on the city, Bertaud and Brueckner (2005) who study the effects of building height restrictions, Borck and Brueckner (2018) who examine energy taxation regimes, and Agrawal and Zhao (2023) who investigate the effects of ride-sharing services, to name several. This paper also has implications for the quantitative urban models introduced in the seminal work of Ahlfeldt et al. (2015). This important model relaxes some of the assumptions in the classic Alonso-Mills-Muth model to more accurately model microgeographies present in cities. Endogenizing automobile fuel choice and layering energy demand onto this model would surely be a fruitful endeavor, though as we show, it is not necessary to generate useful and novel predictions.

Another is the burgeoning research on electric vehicles, consumer choice, and commuting behavior. EVs in their current form are relatively new, and researchers have undertaken much work attempting to understand the pace of innovation, who currently purchases EVs, and how to increase availability to a larger share of the population. Egbue and Long (2012), Rezvani et al. (2015), and Archsmith et al. (2022) provide comprehensive overviews of the basic economics of EVs and important barriers to widespread adoption. Our model attempts to synthesize both short-run and long-run factors incentivizing EV purchase, including vehicle costs for both new and used models, maintenance and fuel costs, range limitations, altruistic climate beliefs, charging infrastructure, and policies meant to support adoption.

The remainder of the paper is as follows. In Section 2, we provide some institutional background and stylized facts on energy consumption and policies that seek to reduce emissions in the transportation sector. Section 3 introduces our urban model with endogenous vehicle fuel choice and residential energy demand. Section 4 proceeds through a number of model solutions corresponding to various settings. Section 5 concludes.

2 Stylized facts and policy environment

2.1 Stylized facts

Before moving to the early 21st century policy environment regarding electric vehicles (EVs), it is first useful to review some stylized facts and why EV incentives have become a popular policy tool. In 2021, 28 percent of all energy consumed in the United States was used in the transportation sector (Energy Information Administration, 2022). Despite using around 30 percent of all energy consumed, the transportation sector is responsible for a disproportionate share (35 percent) of CO_2 emissions. Accordingly, reducing emissions from the transportation sector is a way to meaningfully decrease total U.S. and global CO_2 emissions.

Table 1 shows average direct energy consumption and emissions by automobile fuel type. To start, gasoline is less energy efficient, consuming over 4x more energy per mile than electric power (O'Dell, 2022). Then, each unit of energy represents a different quantity of CO_2 emissions. A gallon of gasoline, when burned, produces 19.6 pounds of CO_2, at a rate of 156 pounds per million (mm) British thermal units (BTUs). Emissions from electricity consumption depends on the fuel used to produce the electricity. Coal and natural gas produce 212 and 117 pounds per mmBTU, respectively. So-called "green" energy sources, which from a CO_2 emissions standpoint include nuclear, hydroelectric, biomass, solar, and wind, produce 7 pounds of CO_2 emissions per mmBTU. Overall, electric vehicles reduce emissions through lower energy consumption, and then as long as the electricity source is not coal, through reduced carbon intensity of the fuel consumed.[2] Moving forward, shifts in electricity generation from fossil fuels to renewables will likely cause emissions per mile for EVs to decrease, offering the potential for EVs to substantially reduce direct emissions in the transportation sector.

[2]While these statistics represent national averages, there is both intertemporal and cross-sectional variation in emissions from electricity generation. Borenstein and Bushnell (2022) notes that the social marginal cost of driving an EV relative to a gasoline powered vehicle varies widely across the country due to variation in electricity input type and other factors.

Table 1: Energy consumption and emissions by automobile fuel type

	Gasoline	Electric
Energy consumption per mile	5,020 BTU (24.9 mpg)	1,160 BTU (0.34 mpkWh)
CO_2 emissions per mile		
U.S. average	0.78 pounds	0.11 pounds
Coal		0.25 pounds
Natural gas		0.14 pounds
"Green"		0.01 pounds

Note: Authors' calculations based on U.S. Department of Energy and Environmental Protection Agency statistics.

While EVs show great promise in achieving emissions reductions through widespread adoption, they face many technological, infrastructure, and design limitations. This has, so far, limited their attractiveness to a small segment of the vehicle market, with an EV market share of all light-duty vehicles of 1.4% in 2019 rising to 3.1% in 2021 (Figure 1, panel (a)). Combined, hybrid, electric, and plug in hybrid vehicles surpassed 10% in 2021. For the purposes of this paper, we focus on the plug-in electric vehicle segment (PEV), while recognizing that plug-in hybrids and electric vehicles share many features including charging stations and a reliance on battery technology.

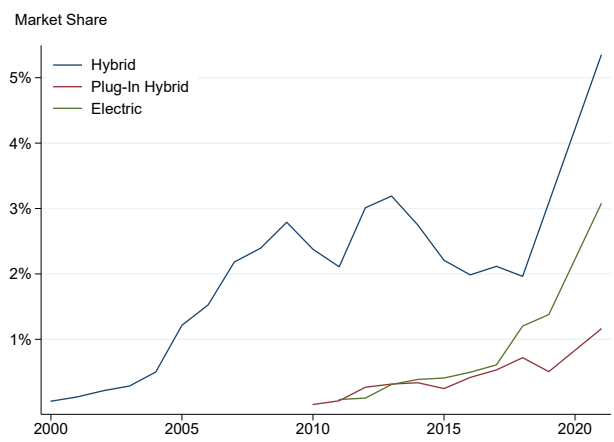
Limitations to battery charging infrastructure and storage technology have prevented EVs from widespread adoption in suburban locations where households tend to drive the most. Using data from `atlasevhub.com`, we downloaded and cleaned individual-level EV registration data from 12 states for the year 2022, and created aggregate totals for ZIP codes. After filtering the data to keep only medium and large cities with little fixed-rail public transportation, we are left with 9 cities [3] To normalized the data, we divided the total EV registrations by the ZCTA-level population for 2019 5-year ACS. To focus on urbanized regions in the selected cities, we drop all ZIP codes with ZCTA centroids further than 25 miles from the CBD. The resulting bin-scatter (see Chetty et al., 2014) of per-capita EV registrations over the 763 ZIP codes in these 9 cities is shown in Figure 1, controlling for the log of household income, the share of households with income greater than $200k, children

[3]The states with data are: CO, CT, ME, MN, NJ, NY, NC, OR, TX, VT, WA, and WI. The final CBSAs surviving data filtering are: Albany-Schenectady-Troy, NY Dallas-Fort Worth-Arlington, TX, Denver-Aurora-Lakewood, CO, Houston-The Woodlands-Sugar Land, TX, Minneapolis-St. Paul-Bloomington, MN-WI, Portland-Vancouver-Hillsboro, OR-WA, Rochester, NY, San Antonio-New Braunfels, TX, and Seattle-Tacoma-Bellevue, WA.

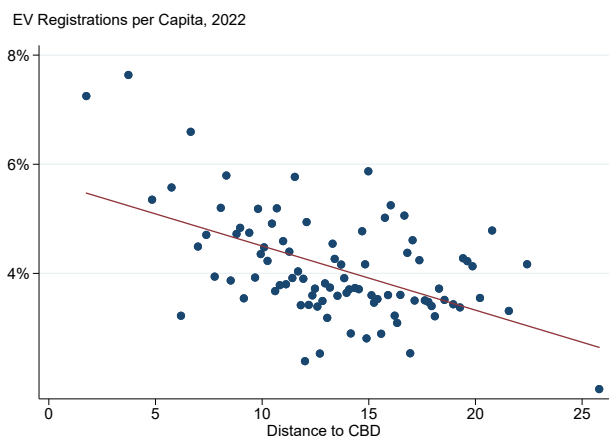
per household, log of population density, the Biden (vs. Trump) presidential vote share in 2020, and CBSA fixed effects. This figure shows a clear downward-sloping EV registration gradient for households in otherwise observationally-identical ZIP codes.[4]

Figure 1: Electric vehicle statistics

(a) Time series



(b) Within-city gradient



Note: Author's calculations using data from the Bureau of Transportation Statistics (panel a) and Atlasevhub.com for ZIP code-level EV registration data (b). Panel (a) is the light-duty market share for new vehicles. Panel (b) is a bin-scatter of ZIP-code electric-only vehicle registrations per-capita in 2022, conditional on various socioeconomic and voting controls.

One survey by the AP-NORC Center for Public Affairs Research (2023) offers some further insights driving the EV market share and where it may be headed, while highlighting some specific obstacles to widespread EV adoption; they could be summarized concisely as costs, infrastructure, and politics.

Despite the 3% market share, 41% of respondents say they are "somewhat likely" to purchase an EV for their next car. Yet, substantial hesitation exists for many respondents. For example, 3/4ths of respondents worry about charging their vehicle, as charging infrastructure is not standard in most locations, and current charging technology is slow compared to filling up a gasoline tank at a gas station. There is low vehicle variety available until recently, with mid-sized sedans being the only type of EV with wide availability. EVs are very expensive, with most manufacturers targeting the luxury segment of the market. Stated willingness to pay for an EV car falls when EV costs rise relative to gasoline vehicles, with 60% saying cost

[4]The unconditional gradient and other conditioning sets give qualitatively similar depictions.

is a major reason they have not purchased one so far and 25% saying it is a minor reason. Climate altruism and virtue signalling may play important roles in EV adoption; 2/3rds of respondents cite climate change as a major or minor reason for purchasing an EV. Finally, there is a large partisan divide, with 54% of Republicans preferring gasoline vehicles, with only 29% of Democrats sharing the same preference. The fact that the current market share is 3% yet nearly half of all of those surveyed are likely to consider an EV purchase sometime soon, make an attractive setting for policymakers to intervene federal, state, and local level to incentivize EV adoption.

2.2 Federal policies

The United States has implemented various policies at the national level to help reduce emissions in the transportation sector.[5] Corporate Average Fuel Economy (CAFE) standards set fleet-wide fuel economy targets in terms of miles driven per gallon of gasoline consumed, and these standards have existed since the Clean Air Act of 1970. The first Federal legislation encouraging the transition of vehicle fuels away from gasoline was the Alternative Motor Fuels Act of 1988. This law introduced manufacturer credits to achieve CAFE standards, making it possible for a manufacturer to specialize in the development of alternative fuel technologies and recoup costs by selling CAFE credits, the sort of behavior we would eventually see from companies like Tesla.[6] The Clean Air Act Amendments of 1990 gave the EPA more power to regulate mobile sources of pollution, such as cars and trucks. This led to the establishment of tighter standards for emissions from cars and trucks.[7] Later, the Energy Policy Act of 1992 established the first Alternative Fuel Vehicle (AFV) program, which included electric vehicles and directed federal purchases towards an increasing share of vehicles powered using alternative fuels throughout the 1990s.[8] However, because electric and hybrid vehicles did not exist in large numbers, this legislation had little effect on electric or hybrid-electric vehicle market penetration.

The Energy Policy Act of 2005 was the first major consumer-focused tax credit, with

[5]There are additional state and local policies aimed at increasing EV usage. With the exception of California's recent gasoline vehicle phaseout, scheduled to occur before 2035, these tend to focus on charging infrastructure.

[6]In 2021, regulatory credits made up over 27% of Tesla's net income, with $1.5 billion selling various regulatory credits versus $5.5 billion net income (https://news.bloombergtax.com/financial-accounting/sec-pushes-tesla-to-reveal-how-regulatory-credits-boost-profits).

[7]https://www.epa.gov/clean-air-act-overview/1990-clean-air-act-amendment-summary-title-ii.

[8]https://afdc.energy.gov/laws/key_legislation#:~:text=Energy%20Policy%20Act%20of%201992,-Back%20to%20Top&text=EPAct%201992%20encourages%20the%20use,to%20acquire%20alternative%20fuel%20vehicles.

Section 1341 directing up to $2,400 towards the purchase of electric or hybrid electric vehicles. However, this credit was capped at 60,000 vehicles per manufacturer, a constraint that hampered the effectiveness of this and similar tax credit policies. This law also saw the introduction of the Alternative Fuel Vehicle Refueling Property Credit, which provided a 30% tax credit up to $1,000 for residential installation of alternative fuel equipment, including charging stations.

The Energy Improvement and Extension Act of 2008 increased the tax credit to $7,500 for the purchase of a new electric vehicle and increased the per-manufacturer phase-out quantity to 200,000 vehicles. Between 2008 and 2022, this tax credit has existed in various forms (with some brief interruptions) at the same amount with the same per-manufacturer caps (Sherlock, 2019). Other policies, however, focused on investments up and down the supply chain and on consumer ease-of-use. For instance, the American Recovery and Investment Act of 2009 included about $10 billion in grants for advanced battery systems and electric vehicle components manufacturing, incentives for charging stations, and the Infrastructure Investment and Jobs Act of 2021 greatly scaled up these sorts of incentives, with $15 billion in direct purchases of EV vehicles by the U.S. government, $7.5 billion in charging stations and other infrastructure and $5 billion for electric school buses.

The Inflation Reduction Act of 2022 made a substantial commitment to EV technology adoption in the United States. Eligible purchasers between 2023 and 2032 receive up to $7,500 for a new EV, and up to $4,000 for a used EV. Beginning in 2024, the EV credit can be applied at point-of-sale, reducing timing frictions in payments. While the $7,500 credit has existed since 2008, the Inflation Reduction Act removed the manufacturer cap, meaning that some cars made by manufacturers who exceeded the 200,000 limit (e.g., General Motors, Toyota, and Tesla) will now be eligible to claim the credit.

Overall, EVs have the potential to substantially reduce energy consumption and emissions in the transportation sector, and the U.S. government has acted to support this transition. But the remarkable fuel efficiency of EVs may have a downside. By lowering marginal commuting costs, EVs may make suburban locations more desirable as battery technology and infrastructure improve, adding to sprawl and shifting consumption towards larger homes that are less efficient to heat and cool than apartments or attached units. This behavior could reduce—or even reverse—the anticipated energy and emissions reduction benefits of EVs. The question which motivates the remainder of the paper is, what are the effects of EVs and EV incentives, such as contained within the Inflation Reduction Act, in an urban equilibrium after households have re-optimized their consumption and commuting patterns?

3 An urban model with endogenous residential energy demand and automobile fuel choice

This section introduces a model that can predict the effect of EV tax credits on the urban form, energy consumption, and carbon emissions decisions of households. The model is in the monocentric city tradition, with new features including endogenous household energy demand and transportation fuel choice. Traditional features of the model are maintained, following Alonso (1964), Mills (1967), Muth (1969), as synthesized by Brueckner (1987). The city lies on a featureless plane with a central business district (CBD) that provides exogenous employment. Identical households seek to live as close as possible to the CBD but are willing to trade off commuting costs for larger homes and more numeraire good consumption. The solution to the household's problem gives the house price at each location in the city. Bid-rent curves are then taken by housing producers to produce optimal quantities of housing at each location in the city.

The present model extends the "urban energy footprint model" approach of Larson et al. (2012), Larson and Yezer (2015), Larson and Zhao (2017), Proque et al. (2020), and Larson and Zhao (2020). These previous papers model household energy demand in a block-recursive structure, layering energy consumption parameters onto optimized transportation costs and housing demand. The present model is the first to treat as endogenous demand for energy consumed while commuting and in dwellings. We also introduce different vehicle fuel technologies. While prior models assume all households commute via gasoline-powered vehicles, the model in this paper allows households to choose endogenously whether to commute via an electric or gasoline powered vehicle. In this decision, our paper is perhaps most closely related to Agrawal and Zhao (2023), which introduces commuting choice via driving or ride-sharing taxi, and layers this choice onto the monocentric city model.

Combined, these two extensions to the monocentric city model allow household and housing producer optimization to reflect the full cost of energy and vehicle fuel choice in determining bid-rent curves, the urban form, and carbon emissions of the city. In later sections, this model will be used to assess the effects of a stylized electric vehicle tax credit resembling that which was recently signed into law in the Inflation Reduction Act.

3.1 Model

The city lies on a featureless plane under the classic radial assumption such that the city is circular but can be expressed in terms of distance to the central business district (CBD),

k. Labor demand is exogenously provided by the CBD is such that E identical workers are needed with wage W per year.

Housing production: Housing H is produced by combining structure S and land inputs L under a constant returns to scale technology according to a CES production function with an elasticity of substitution of $1/(1-\rho)$.

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

Structure inputs are perfectly elastically supplied, but aggregate land input is fixed at each radius as the fraction of land available for residential development, θ.[9]

Households: Households are identical, providing ϵ units of labor and and generating utility by consuming two goods, rental housing h and a numeraire consumption good y under a CES utility function.

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

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.

Households maximize utility subject to the budget constraint, below, where $y(k)$ is numeraire good expenditure, $r(k)h(k)$ is housing expenditures, $\epsilon T(k)$ is household transportation expenditures, and $p_e e^d(k)$ is residential energy expenditure. In equilibrium, utility is equal at all locations, allowing for the solution to be expressed in terms of distance to the CBD.

$$\epsilon W = y(k) + r(k)h(k) + \epsilon T(k) + p_e e^d(k) \tag{3}$$

The number of households living in the city is the integral of the density of households per unit of land, multiplied by the area of the annulus at radius k, calculated between the exogenous CBD radius k_{CBD} and the endogenous edge of the city $\bar{k}$.

$$N = \int_{k_{CBD}}^{\bar{k}} 2\pi\theta k D(k) dk \tag{4}$$

[9]This model ignores the role of maintenance, rehabilitation and durability of structures in housing production. Land rent is assumed to be earned by absentee landowners, who live outside the city and do not remit any funds into the city; see also Bertaud and Brueckner (2005).

Transportation costs: The representative household commutes to the CBD under a complex commuting cost formula that includes a probabilistic choice of using an electric versus gasoline powered vehicle. The EV share, along with other commuting cost parameters, gives an average commuting cost at each annulus. The average annual commuting cost $T(k)$ for workers living at distance k includes fixed costs of owning and operating a vehicle m_0 (e.g. insurance, licensing), variable costs linearly related to distance traveled m_1 (e.g. vehicle depreciation), and two costs that vary non-linearly with respect to distance traveled, fuel and time costs. The cost parameters m_0, m_1, and p, and the fuel economy function G are each indexed by fuel technology $F \in \{E, G\}$, indicating an electric or gasoline-powered vehicle, respectively.

Households residing at location k with fuel technology F have the pecuniary cost function:

$$T_F(k) = m_{0F} + m_{1F}k + p_F \int_0^k \frac{1}{G_F(V(M(\kappa)))} d\kappa + \tau W \int_0^k \frac{1}{V(M(\kappa))} d\kappa \tag{5}$$

The expressions for fuel and time costs have a number of nested functions and parameters that deserve discussion. $G_G(V(k))$ represents miles per gallon (mpg) as a function of the vehicle speed and p_G represents the gasoline price per gallon. $G_F(V(k))$ represents miles per kilowatt hour (kWh) for electric cars and p_E represents the electricity price per kilowatt per hour. These cost factors encompass many of the calculations present in Borenstein and Bushnell (2022) and Rapson and Muehlegger (2021), who highlight the cost differential between gasoline and electricity and note that this affects EV uptake.

The introduction of time costs of commuting has presented challenges in the literature, as it is desirable to avoid full treatment of the labor/leisure optimization for tractability. Bertaud and Brueckner (2005), Brueckner and Selod (2006), and others assume leisure is fixed and time spent commuting reduces the effective wage on a one-for-one basis. This assumption implicitly sets $\tau = 1$ and places it on the left-hand side of the budget constraint as a subtraction from wages as opposed to an expenditure. We adopt a similar treatment, except we allow $\tau < 1$, in line with the literature on the time-cost of commuting. This assigns a leisure benefit to commuting equal to $1 - \tau$ that is additive with respect to numeraire consumption. For simplicity, we assume this time-cost of commuting does not affect the number of workers in the city.

Both fuel and time costs are related to the velocity of the automobile at various locations in the city, which is in turn related to the ratio of traffic volume to roads. Following the "Bureau of Public Roads" specification that is common in this type of model, velocity is

expressed as $V(k) = 1/(a+bM(k)^c)$ where $M(k) = \overrightarrow{N}(k)/R(k)$, and a, b, and c are congestion parameters, and $\overrightarrow{N}(k)/R(k)$ is the ratio of traffic passing through annulus k to roads. It is assumed that fraction of land area allocated to roads is exogenous and uniform, therefore $R(k) = \bar{R}$ is a constant fraction of land area in each annulus. The traffic volume at radius k, $\overrightarrow{N}(k)$, is calculated as the sum of the workers living at or beyond radius k, $\overrightarrow{N}(k) = \epsilon 2\pi\theta \int_k^{\bar{k}} kD(\kappa)d\kappa$, where $\bar{k}$ is the endogenous edge of the city.

In addition to direct pecuniary costs, electric vehicles also have a money-additive benefit (or cost, if positive) drawn from a normal distribution, $\ell_E(k) = \mathcal{N}(z_1 k, z_2^2)$. This variable has two components, a fixed distance cost that increases at a rate of z_1 with k, and a normally distributed random cost with standard deviation z_2. This money-additive factor is a stand-in for low vehicle variety, idiosyncratic preferences (modeled outside the utility function), charging infrastructure, local incentives such as free charging and parking to EVs, lack of a thick used car market making EVs unaffordable to low income households, and range anxiety from the necessity of trips of increasing length. Practically, the distance cost cost in the model reconciles the negative slope of the EV adoption gradient in 2021 with the data showing the marginal cost of distance for EVs is less than gasoline vehicles. If ℓ were zero, any reasonable urban model would show an upward sloping EV gradient, as the vehicle fuel type with lower per-mile cost would be chosen in suburban locations. The parameter z_1 rotates the gradient to fit the data. Then, the probabilistic factor prevents corner solutions where the optimal vehicle choice completely switches at some radius. Note that draw with standard deviation z_2 can be positive or negative. After defining ℓ, the electric vehicle share is then calculated as

$$\lambda(k) = 1 - \Phi((T_E(k) - T_G(k) + z_1 k)/z_2) \tag{6}$$

where Φ is the cumulative standard normal density function. For a simple numerical illustration of the necessity of non-pecuniary EV costs in fitting the data, see the appendix.

We propose that z_1 is likely to converge to 0 over time. As EVs become a more mature technology, vehicle variety will increase and charging infrastructure will promulgate. Local incentives such as free charging and parking are likely to go away. The used-car market will become thicker, making it affordable for low-income households to purchase EVs. Increases to battery and charger technology are sure to improve to the point where range anxiety becomes minimal. As this mean component of $\ell(k)$ falls towards 0, the EV gradient will rotate and eventually become upward-sloping, a fact that has been documented in California between 2018 and 2022 by Huang and Kahn (2023).

Finally, average commuting costs in an annulus, $T(k)$, are calculated as the weighted average of EV costs net of the average money-additive benefit for those who choose EVs, $\bar{\ell}(k)$, and gasoline vehicle costs. This average money-additive benefit includes the fixed distance cost and the average of draws where EVs are the lower-cost fuel choice.[10]

$$T(k) = \lambda(k)(T_E(k) + \bar{\ell}(k)) + (1 - \lambda(k))T_G(k) \tag{7}$$

This average commuting cost is used by the representative household in establishing its bid-rent curve.

Energy consumption: Energy consumption $e(k)$ is generated in three ways in the model: direct consumption of electricity and gasoline, and indirect consumption via all other non-direct energy costs (e.g. numeraire consumption, housing rents, and vehicle costs). In all cases, energy consumption calculations include energy loss in production and transmission.

$$e(k) = e^d(k) + e^c(k) + e^n(k) \tag{8}$$

First, electricity in dwellings, $e^d(k)$ is paid for directly out of the budget constraint. A fraction of energy is lost in the production and transmission, giving a scaling inefficiency factor E_e. Gross dwelling energy demand is expressed as a function of variables constant within-city such as energy prices p_e, wages, the number of heating (HDD) and cooling degree days (CDD), and variables endogenously determined at each radius k, including housing consumption per household and the structure type $s(h(k))$ which is a function of the unit-average interior square feet at k,[11]

$$e^d(k) = E_e \exp(g'\Gamma) \tag{9}$$

where $g = [h(k), s(h(k)), W, p_e, cdd, hdd]$.

Second, energy is consumed when commuting $e^c(k)$, with expenditure accounted for within the transportation cost function for technology type V. The fuel-specific inefficiency

[10] The variable $\bar{\ell}(k) = t_1 k - t_2 k\varphi(\Phi^{-1}(\lambda(k)))/\lambda(k)$, where φ and Φ are the standard normal probability and cumulative density functions, respectively, and the total quantity is the integral under the density function for $\ell(k) = \mathcal{N}(z_1 k, z_2^2)$ over the range $[-\infty, \Phi^{-1}(\lambda(k))]$.

[11] We assume $s(h(k))$ follows an ordered logit functional form, with cutoffs calibrated to give urban area averages, and interior square feet transformed into its natural log. Heating and cooling degree days are calculated as the annual sum of negative and positive daily differences in average temperature from 65 degrees.

factor is E_V, which is the same as E_e in the case of electric vehicles.

$$e^c(k) = E_V \epsilon \int_0^k \frac{1}{G_F(V(M(\kappa)))} d\kappa \tag{10}$$

Finally, numeraire energy is calculated as all energy implicitly consumed elsewhere in the exhaustion of the household budget. This includes consumption of the numeraire good and also elements of commuting and housing consumption that are not direct energy consumption, net of the full time-cost of commuting. The energy factor E_N is the average energy embodied in \$1 of consumption.[12] Note that the wage reduction due to time spent commuting is fully incorporated in the reduction in expenditures by $\int_0^k \frac{1}{V(M(\kappa))} d\kappa$.

$$e^n(k) = E_N \left(\epsilon W \left(1 - \int_0^k \frac{1}{V(M(\kappa))} d\kappa \right) - p_V e^c(k)/E_V - p_e e(k)/E_e \right) \tag{11}$$

Carbon dioxide emissions: Carbon dioxide (CO_2) gas emissions are calculated based on energy consumption in the three energy categories, each multiplied by a CO_2 emissions coefficient reported by the U.S. Energy Information Administration. The combustion of one gallon of gasoline results in 19.6 pounds of CO_2, or 156 pounds of CO_2 per million BTUs.[13] 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 26% of all electricity generated, with an average of about 212 pounds per million BTUs over each of the types of coal consumed. Natural gas produced 32% 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 42% of all energy production, resulting in an average of 7 pounds of CO_2 per million BTUs. The weighted average of the U.S. electricity production basket from these three main categories is 96 pounds of CO_2 per million BTUs. All dwelling and electric vehicle energy is assumed to be produced using this basket.

[12] Different types of energy consumption embody 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 model in this paper does not consider these nor other local environment or climate-related externalities, with the exception of calculations of carbon emissions and a social cost of carbon calculation.

[13] See `https://www.epa.gov/greenvehicles/tailpipe-greenhouse-gas-emissions-typical-passenger-vehicle#:~:text=Every%20gallon%20of%20gasoline%20burned%20creates%20about%208%2C887%20grams%20of%20CO2.`

3.2 Model Solution

The model is solved numerically as a system of non-linear partial difference equations with initial values. The initial values are known at the CBD edge, and from this annulus, variables are solved radiating outwards using spatial recursion. After the model solution has been calculated, closing conditions are checked to ensure the city is in equilibrium; if out of equilibrium, initial conditions are altered and the model is re-solved until equilibrium is achieved. The city is discretized into annuli with a width of $d = 0.01$ mile, or 52.8 feet.

The model is initialized with a guess of the house price at k_{CBD}. Using the first order condition in the housing producer's problem and taking the structure price as given, the land price is known. This gives the optimal floor-area ratio (FAR) and the structure type for the annulus. With the house price and commuting costs known at k_{CBD}, the household chooses an optimal level of housing consumption. Dividing the FAR by the optimal housing consumption gives land consumption per household, also known as household density.

With the initial values at k_{CBD} known, the rest of the model is solved recursively using spatial difference equations. These difference equations ensure the spatial isoutility condition holds: households are just as well off at radius k as they were at radius $k - d$. The key solutions are commuting costs at each k and the population living within radius k. These are each solved using spatial recursion such that values at k are based on values at $k - d$.

$$\begin{bmatrix} T(k) \\ N(k) \end{bmatrix} = \begin{bmatrix} T(k-d) + d\left(T_G(k) + \lambda(k)(T_E(k) - T_G(k)(k))\right) \\ N(k-d) + 2\pi\theta d D(T(k)) \end{bmatrix} \tag{12}$$

With these known, the rest of the variables in the system can be solved for radius k. There are two equilibrium conditions that then must be met. First, the labor market clears such that the edge of the city $\bar{k}$ is the solution to $N(\bar{k}) = E/\epsilon$. Second, the land price at the edge of the city must be equal to the agricultural land rent $p_L(\bar{k}) = p_L^a$. If either of these equilibrium conditions is not met, the simulation is re-initialized with a higher or lower house price at k_{CBD} and solved again until subsequent iterations achieve an equilibrium solution.

3.3 Calibration

Parameters

While many parameters in the model are found in the literature (e.g. utility and housing production parameters), some must be calibrated with respect to real-world cities to achieve a reasonable model solution. Parameters used are found in Table 2 and throughout the text.

For additional details about parameter values, see the appendix. This appendix includes estimation of transportation cost parameters, residential energy demand parameters, and description of all others required of the model. The energy demand parameters are updates to those found in Larson et al. (2012) but the transportation cost parameters are new and based on `cars.com` listings data in 2022.

The primary model parameters in the model are found below in Table 2. Of most consequence are those in the housing production and utility functions. The elasticity of substitution parameters for both production and utility functions are set equal to 0.75 following the literature (Muth, 1975; Altmann and DeSalvo, 1981; Albouy, 2016). The CES share parameters are calibrated to give reasonable land value and housing expenditure shares, respectively. Land use and commuting parameters are either found in the literature or calibrated to give a reasonable model solution. The various price parameters are taken from the literature (Small and Verhoef, 2007; Davis et al., 2021) or calibrated. Where applicable, one-time costs are converted to annual flow costs using a 5% cost of capital.

Many of the other required parameters in the model consider EV versus gasoline vehicle ownership. Prior research that requires vehicle cost information has used data from the American Automobile Association (AAA) and engineering studies (see West et al., 1999; Larson et al., 2012). Electric vehicles are rather new, however, so research on these parameters is much less settled. Complicating factors are that EVs are undergoing rapid innovation and often include premium features to make them attractive to the luxury segment of the market. Accordingly, it is not trivial to hold quality constant when considering electric versus gasoline vehicles. Our strategy is to combine information from AAA, Tesla, and `cars.com` vehicle listings data to arrive at a parameter set for both gasoline and electric vehicles that are identical in all respects except for the vehicle fuel technology. For a description of the model, data, and estimates that generate these vehicle cost parameters, see the appendix.

Table 2: Primary model parameters

Parameter	Value	Description	Source
City income and size			
W	55,000	Annual earnings	ACS (2012-2017)
N	875,000	Households	ACS (2012-2017)
ϵ	1.14	Workers per household	ACS (2012-2017)
Housing production			
$1/(1-\rho)$	0.75	Elasticity of substitution	Muth (1975), AD (1981)
α_1	1	Numeraire parameter	
α_2	0.19	Land parameter	Davis et al. (2021)
A	0.23	Technology parameter	Calibrated
Household utility			
$1/(1-\eta)$	0.75	Elasticity of substitution	Albouy et al. (2016)
β_1	1	Numeraire parameter	Numeraire
β_2	0.265	Housing parameter	Calibrated
Land use			
θ	0.4	Fraction of land used for housing	Muth (1975) uses 31.8%
ψ	0.2	Fraction of land used for roads	Muth (1975) uses 19.7%
k_{CBD}	1	Radius of the CBD	Assumed
p_L^a	4,000	Reservation ag. land rent per acre	Davis et al. (2021)
Transportation			
v_{low}	5	Minimum commuting speed	Calibrated
v_{high}	50	Maximum commuting speed	Calibrated
c	1.75	Parameter in speed function	Calibrated
τ	0.6	Commuting time cost fraction of income	Small and Verhoef (2007)
m_{0G}	7,494	Annual fixed costs, gasoline vehicle	AAA, `cars.com` (see appendix)
m_{1G}	57	Annual per mile costs, gasoline vehicle	AAA, `cars.com` (see appendix)
p_G	4	Gasoline cost per gallon	Assumed
m_{0E}	8,709	Annual fixed costs, EV	AAA, `cars.com` (see appendix)
m_{1E}	59	Annual per mile costs, EV	AAA, `cars.com` (see appendix)
p_E	0.13	Electricity cost per kWh	Assumed
z_1	90	Annual per mile EV distance cost	Calibrated
z_2	450	Standard deviation of EV cost draw	Calibrated

From this table, we can see the myriad costs that go into the purchase, upkeep, and use of EVs versus gasoline-powered vehicles. The key takeaway from this table is that EVs have higher fixed costs but lower marginal costs. Differences in fixed costs include a higher rate of obsolescence for EVs and charger costs. Maintenance costs for EVs are lower, but per-mile depreciation is higher. In the model, fixed annual costs sum to the parameter m_0 in equation

5, and fixed per-mile cost sum to the parameter m_1. Annual non-pecuniary costs are entirely calibrated to fit the empirical gradient in figure 1.

Calibration target

The standard method of forming a calibration target is to construct a composite city made up of an average of several similar cities. For the purposes of this model, cities are selected if the following conditions are met: 1) a 2018 Wharton Land Use Regulatory Index (Gyourko et al., 2021) less than 0.5, indicating a relatively market-based home construction regime; 2) a share of unavailable land near the city center of less than 10% according to Saiz (2010); 3) a share of workers commuting via automobile greater than 90% according to the 2015 5-year ACS; and 4) a number of households between 800,000 and 1,000,000 in the 2015 5-year ACS. A total of five cities pass these criteria: Charlotte, NC, Columbus, OH, Indianapolis, IN, Kansas City, MO, and San Antonio, TX.[14]

The calibrated model has a stylized pre-Inflation Reduction Act (IRA) subsidy. Prior to the IRA, vehicles were eligible for tax credits until a lifetime manufacturer cap was hit. Our EV market penetration target corresponds to 2019 where most of the large manufacturers (e.g. Nissan and Tesla) had passed their eligibility limit. The remaining manufacturers' total market share totaled about 1/3 in 2019, so we set the baseline credit equal to this fraction. The EV tax credit considered is \$7,500. This value is multiplied by a 5% cost of capital to arrive at a flow-subsidy of \$375 per year. The subsidy in the calibration is 1/3 of this amount, or \$125. The actual EV market share in 2019 was about 1.4% to which we calibrate the market share at the edge of the city.

In all solutions, unless otherwise noted, EV tax credits are paid for in a manner external to the model. The easiest way to interpret this is as a local land acreage tax, with land prices inclusive of this tax. This tax does not affect any agents in the model, assuming the tax is less than the agricultural land rent which is easily maintained.

Calibration fit

Table 3 shows key characteristics of the individual cities, the 5-city composite, and calibrated model solution. Overall, the model solution is quite close to composite city averages. While the number of households, workers, income, and city edge land price are all assumed, the solved interior square feet, land area, and commute times all match the targets well. The

[14] "Cities" are defined as counties in the CBSA identified as "principal cities" by the Census Bureau.

departure in the model from the calibration target is dwelling energy per household, which is lower than the average reported by the U.S. Energy Information Administration, largely because housing units in areas subject to steep urban price gradients cities are smaller than those elsewhere in the country. The modeled city radius and area are also smaller, a well-known artifact of an urban spatial model with a single income group (Altmann and DeSalvo, 1981).

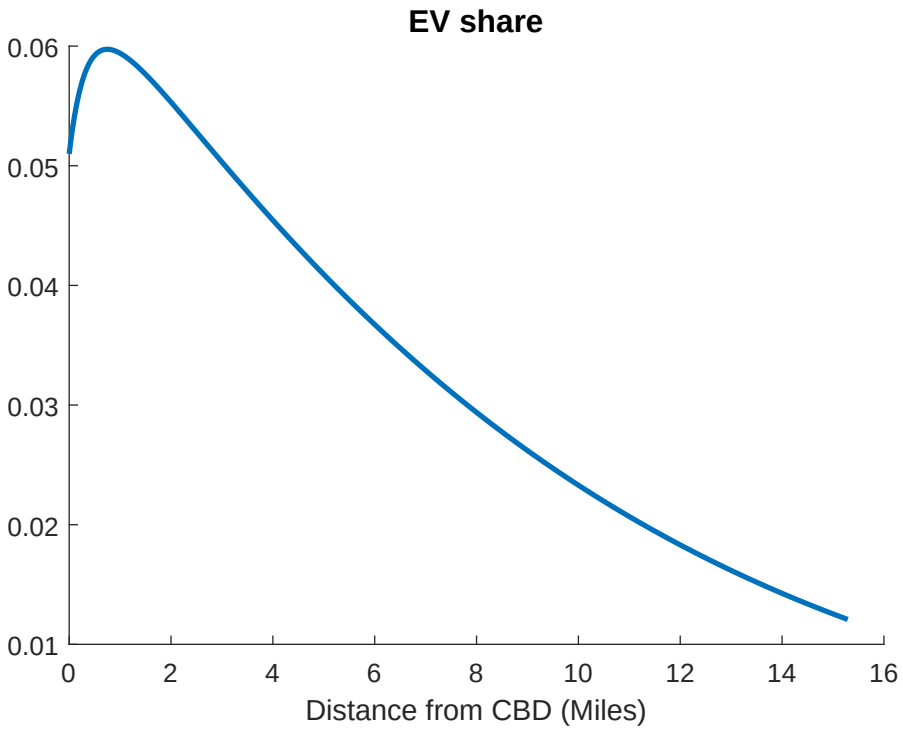
Table 3: Baseline Model Calibration

City	**Charlotte**	**Columbus**	**Indianapolis**	**Kansas City**	**San Antonio**	**Composite**	**Calibrated**
CBSA Code	**16740**	**18140**	**26900**	**28140**	**41700**	**Average**	**Solution**
Population	2,364,927	1,972,375	1,950,674	2,055,675	2,286,702	2,126,071	2,126,071
Number of households[a]	973,522	834,170	831,014	880,710	857,732	875,430	875,267
Households/Workers ratio[a]	1.13	1.14	1.11	1.13	1.20	1.14	1.14
Median Income[a]	$53,246	$56,766	$54,274	$58,212	$53,558	$55,211	$55,211
Interior Square Feet[a]	1,951	1,623	1,596	1,377	1,691	1,647	1,636
Lot Size (acre, single family)[b]	0.46	0.34	0.35	0.30	0.31	0.35	0.26
City edge land price (acre, single family)[a]	$22,300	$29,800	$26,100	$29,600	$25,800	$26,720	$26,720
Detached housing structure[a]	73%	64%	71%	71%	73%	70%	72%
Attached housing structure[a]	5%	7%	6%	6%	2%	5%	6%
2-4 unit housing structure[a]	4%	10%	6%	6%	5%	6%	6%
5+ unit housing structure[a]	17%	19%	17%	16%	20%	18%	16%
Area (sq. miles)[a]	741	511	706	678	597	647	835
Radius (assuming circle)	15.4	12.7	15.0	14.7	13.8	14.3	16.3
Time to work[a]	26.0	23.4	24.7	23.0	25.5	24.5	26.2
Commuting via Automobile[a]	91%	91%	92%	92%	91%	91%	100%
Wharton Land Use Regulatory Index[c]	(0.27)	0.06	0.18	0.13	0.22	0.06	-
Unavailable Land[d]	5%	2%	1%	6%	3%	4%	0%
Electric vechicle share[f]						1.4%	3.0%
Dwelling energy per household (mmBTUs)[e]	-	-	-	-	-	75.8	57.1

Sources: a: American Community Survey (2012-2017); b: Davis et al. (2021) c: Gyourko et al. (2021) d: Saiz (2010); e: Residential Energy Consumption Survey (2015), f: Bureau of Transportation Statistics (2023).

The calibrated EV adoption gradient is shown in Figure 2. The EV share gradient in this baseline calibration matches closely the empirical gradient in Figure 1, giving EV shares of about 5% near the CBD, down to about 1.5% at the edge of the city. The upward sloping portion between 0 and 1 miles is due to the marginal fuel cost of gasoline rising more slowly than the EV distance cost (equation 7) over this window.

Figure 2: Electric vehicle adoption in calibrated city



While our calibrated model has a $125 per year tax credit, consistent with the pre-Inflation Reduction Act level, our so-called "baseline" model to which other parameterizations are compared has no EV tax credit. Figures 3, 4, and 5 show solutions under different parameterizations as a function of distance to the CBD. The baseline model with no EV tax credit is the solid blue line; two other model solutions that will be discussed in the next section are shown in the yellow and purple lines.

In these figures, gradients are sloped as predicted by the textbook monocentric city model: commuting times rise with distance to the CBD, causing housing and land prices to decrease with distance. This causes lot sizes and the share of single-family housing to rise as we approach the edge of the city. Travel speed increases with distance because there is more land dedicated to roads and fewer drivers. Dwelling and commuting energy

demand rises with distance to the CBD as home sizes increase and become less efficient structure types, and commutes lengthen. Numeraire good energy demand falls with distance because the relative price of numeraire and housing goods increase with distance, causing numeraire consumption to decline and housing consumption to increase. Overall, in the baseline calibration, energy demand increases with distance to the CBD. However, as we will soon explore, EV cost changes and tax credits can result in substantial changes to the footprint of the city, automobile fuel choice, and changes in demand for all types of energy

4 Scenario Design and Results

This section uses the calibrated model to perform various counterfactual experiments by altering parameters. Solutions under alternative parameterizations are compared to each other to generate estimated urban equilibrium effects.

The key parameter of interest is the tax credit for EVs. The EV credit considered is a flow-subsidy of \$375 per year, corresponding to 5% of a \$7,500 lump-sum credit. This subsidy is implemented by reducing m_{0E} in the model. Across a battery of alternative parameterizations, we examine the effect of the subsidy alone, and then interacted with climate parameters indicating dwelling heating and cooling requirements, the fuel input mix used to generate electricity, and land use regulations such as height limits and greenbelts. We also consider Pigouvian carbon and congestion taxes, and income versus land value tax funding of the EV credits. These counterfactuals are designed to provide a range of findings concerning the effects of EV tax credits in various settings.

We also assess interactions of EV tax credits with *technological maturity*. Recall the non-pecuniary CBD distance cost of EVs, z_1, that is a stand-in for factors such as suitability of infrastructure, deviation of available EV types from optimal vehicle types, range limitations or anxiety, political beliefs and preferences, and deviation of available EV quality from optimal vehicle quality. We posit this fixed cost of distance will decline over time as EVs become a more mature technology. Accordingly, we also perform counterfactual experiments with z_1 at different values to represent the effects of EV technology maturity on the city, and how this interacts with EV tax credits.

4.1 Effects of EV tax credits

Our first solution takes the full EV distance cost under the current-city calibration, and solves the model with no EV tax credit. We compare this to the solution under the full EV

tax credit to estimate the counterfactual general equilibrium effects of EV tax credits. The next two scenarios offer a comparison of EV tax credits under a counterfactual environment with all other parameters identical except the EV distance cost is 25% of the original calibration, representing EVs as a moderately mature technology. Finally, we eliminate the entire distance cost and assess the effects of the tax credit. Together, these six model solutions generate estimates of effects of EV tax credits over a range of technological maturities as though they existed in a medium-sized U.S. city in 2019.

Results from these six model solutions are found in Table 4. In response to the tax credit, the fixed cost of EVs falls, decreasing their cost relative to gasoline vehicles in all locations. In the model with no EV tax credit and early 2020s technology (100% distance costs) EV adoption is 1.6%. When changing only the tax credit parameter, adoption rises to 9.1%. In this case, there is little urban form effect. The average household has a slightly steeper bid-rent curve and chooses to locate near the CBD where EVs are more cost effective. Commuting energy falls by 4.7%, leading total energy consumption and carbon emissions fall by 0.3% and 0.6%, respectively. Carbon emissions fall by more than energy consumption because gasoline is more carbon-intensive than electricity for the same number of BTUs. Despite almost no urban form effect, there is a substantial short-run rebound effect, as the savings from more efficient EVs are redistributed to purchases of non-energy goods. Consumption of indirect energy rises by 0.1%, or about 300 thousand BTUs per household. This is in comparison to the 1.5 million BTUs per household saved using additional EVs. Dividing one by the other gives the goods substitution rebound effect of about 20%. To summarize, EV tax credits are spent on EVs, but general equilibrium effects offset some of the energy and carbon emission benefits.

We can also perform a rudimentary cost-benefit analysis of the tax credit, assuming the only benefits are directly from the household sector, and the only costs are the credits themselves.[15] Current U.S. EPA estimates of the social cost of carbon (SCC) range between $120 and $340 per ton, depending on the discount rate used (U.S. Environmental Protection Agency, 2022). Under a SCC of $190, the per-household cost of tax credit is $34 per year, and the benefit is $27 per year. Thus, even using these extremely narrowly-defined benefits, EV tax credts are within the range of cost effectiveness. The break-even SCC using only these narrow costs and benefits is $239 per ton.

[15]Other costs and benefits would be considered in a more real-world holistic approach, including changes to individual utility, production factors, and other local externalities such as the production of particulate matter and volatile organic compounds. Prior research has examined Pigouvian carbon taxes in urban systems, including Borck and Brueckner (2018).

Next, we consider tax credits assuming EV distance costs are 25% of the baseline value of z_1, corresponding to technology projected to exist in the late 2020s.[16] Despite this technology projected to exist in the future, our counterfactual city is from 2019, with the model solution reflecting a city that is in all respects a 2019 city except it has late 2020s-era EV technology. Under this reduction in distance costs, households with EVs have flatter bid-rent curves causing substantial sprawl. This low distance cost city, with and without tax credits, is depicted along with the baseline calibration solution in Figures 3, 4, and 5. Even with no tax credits in force, the EV gradient rotates (Figure 4), EVs have a 23.7% market share, and the city area expands by 0.7%. With the EV tax credit, the market share rises to 53.2% and the city area expands 5.2%. Unit size rises (Figure 5) with the sprawl resulting from the tax credits, introducing housing electricity demand as another rebound channel. Overall, the effect of the distance cost reduction is to amplify the effects of the EV tax credit.

However, due to the higher base level of EV adoption, the EV tax credit is less cost-effective. The cost of EV credits is \$200 per household and the benefits are \$108 per household. This gives a break-even SCC of \$352, which is at the high end of the current EPA range. One thing that is useful to consider is the benefit of the distance cost reduction of \$102 per household. Presumably this innovation would not take place in absence of the tax credit. If we also incorporate the distance cost reduction into the cost-benefit calculation, the benefits of the tax credit nearly double, to \$210.

Finally, we consider a city with no EV distance cost, corresponding to fully mature EV technology. Even with no EV tax credits, the EV market share is almost 42%. Comparing this value to the city with full distance cost and no tax credits with an EV share of 1.6%, we can see the major role of distance costs in EV adoption. Under the tax credit, the market share rises a further 28 percentage points to 70%. This increase is lower than the increase under a 25% distance cost, implying diminishing returns. Due to the high base number of EVs, the EV tax credit is no longer within the range of cost-effectiveness, with a break-even SCC of \$520 per ton. While urban energy consumption is at its minimum among these six solutions considered, the credit is expensive relative to its benefit.

Overall, this model and these alternative scenarios imply a cost-effective policy strategy. While EV technology is immature, EV tax credits are cost effective because they take gasoline cars off the road with no sprawl rebound effect, and almost all of the EV market share is due

[16]For instance, solid-state batteries are projected to have a range of 500 miles or more and charge in 10 minutes, rather than early 2020s lithium-ion technology which has ranges of about 250 miles and takes 4+ hours using an L2 charger, and 20-60 minutes with a rarer and more expensive DCFC charger (`https://www.reuters.com/technology/solid-state-ev-giants-chase-holy-grail-batteries-2024-01-16/`).

to the credit. As EV technology matures, presumably due to the existence of the tax credit in earlier periods, the tax credit crowds out increasing private consumption, and the city begins to sprawl. At this level of innovation, it may be prudent to phase out the tax credit, because once EVs reach full technological maturity, they become very expensive relative to their benefit.

Table 4: Effects of EV tax credits

EV Purchase Tax Credit	No	Yes	No	Yes	No	Yes
EV Distance Cost	100%	100%	25%	25%	0%	0%
Simulation Output						
Fraction of Electric Vehicles	1.6%	9.2%	23.7%	53.2%	41.6%	70.2%
Urban form	Level	%Δ	%Δ	%Δ	%Δ	%Δ
Unit size (sqft)	1,636	0.0%	0.0%	0.8%	0.8%	1.9%
Lot size (acres, single-family)	0.253	-0.1%	0.8%	3.6%	4.9%	8.6%
House price per sqft	$9.25	0.1%	-0.2%	-1.4%	-1.6%	-3.0%
Land price per acre	$10,775	0.3%	-1.2%	-7.3%	-8.5%	-15.0%
City area	834	-0.2%	0.7%	5.2%	6.2%	11.9%
City radius (assuming circle)	16.29	-0.1%	0.4%	2.6%	3.1%	5.8%
FAR (residential, at CBD)	0.35	0.2%	0.3%	-4.0%	-2.9%	-9.5%
Density (hh per sq. mi.)	1054	0.2%	-0.7%	-5.0%	-5.9%	-10.6%
Time to work (minutes)	0.7	-2.6%	4.8%	50.4%	53.6%	117.8%
Energy consumption per household (million BTUs)						
Total	465.95	-0.3%	-1.1%	-2.2%	-1.7%	-2.6%
Housing Electricity	188.44	0.0%	0.0%	0.7%	0.8%	1.9%
Commuting Energy	36.33	-4.9%	-17.3%	-37.0%	-29.8%	-47.9%
Gasoline	36.18	-7.0%	-26.3%	-56.7%	-46.6%	-75.0%
Electricity (Δ)	0.14	0.61	3.08	6.95	5.89	9.61
Indirect Energy	241.18	0.1%	-0.7%	-0.7%	100.6%	0.6%
CO_2 emissions per household (tons)						
Total	23.34	-0.6%	-2.3%	-4.7%	-3.8%	-6.0%
Housing Electricity	9.00	0.0%	0.0%	0.7%	0.8%	1.9%
Commuting Energy	2.83	-5.7%	-20.8%	-44.6%	-36.3%	-58.4%
Indirect Energy	11.52	0.1%	0.5%	0.8%	0.6%	0.8%
CO_2 cost-benefit	Level	Level	Level	Level	Level	Level
Cost of EV credits per hh. ($190/ton)	$0	$34	$0	$200	$0	$263
Benefit of EV credit per hh. ($190/ton)	$0	$27	$0	$108	$0	$96
Break-Even Social Cost of Carbon (per ton)		$239		$352		$520
Benefit of EV distance cost reduction ($190/ton)	$0	$0	$102	$102	$169	$169

Notes: This table presents solutions to the model described in Section 3. The EV credit $7,500 EV credit, giving a flow-subsidy of $375 per year at a 5% cost of capital.

Figure 3: Urban form solutions

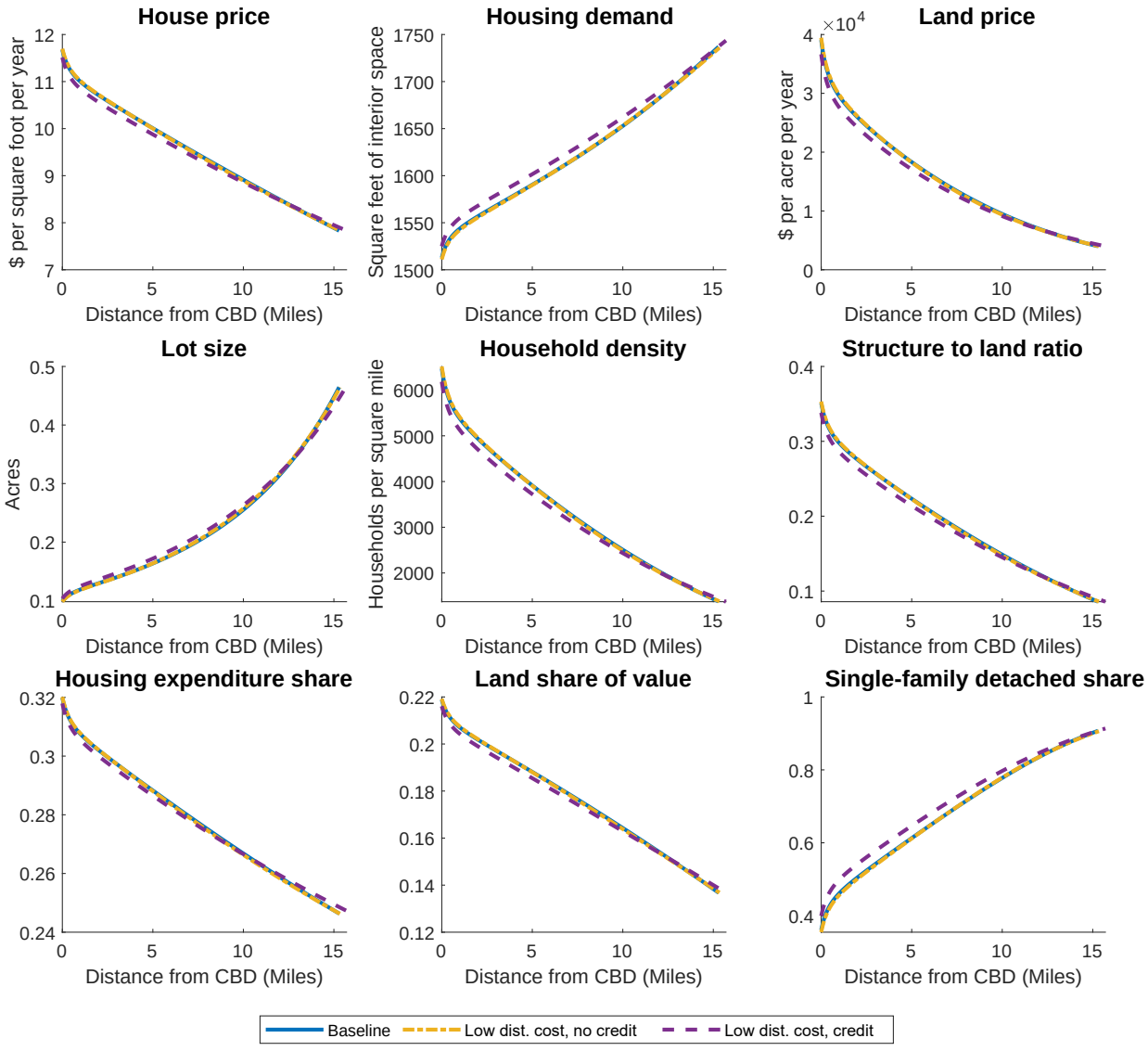


Figure 4: Commuting solutions

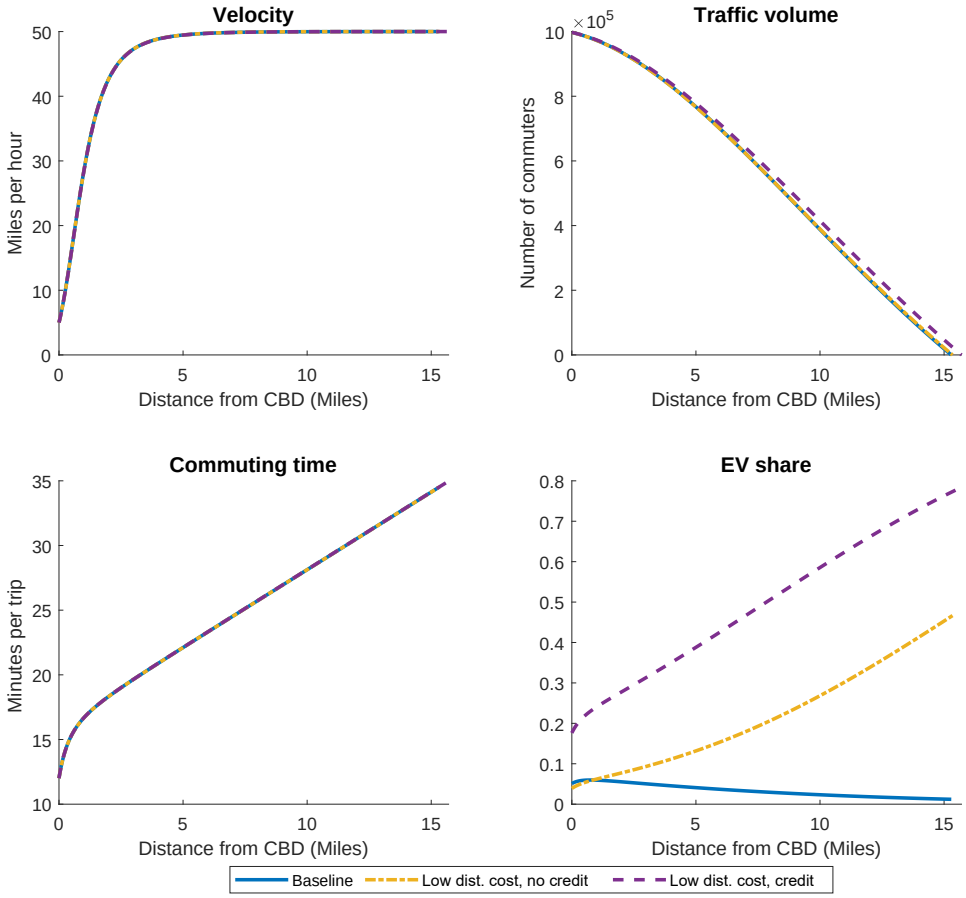
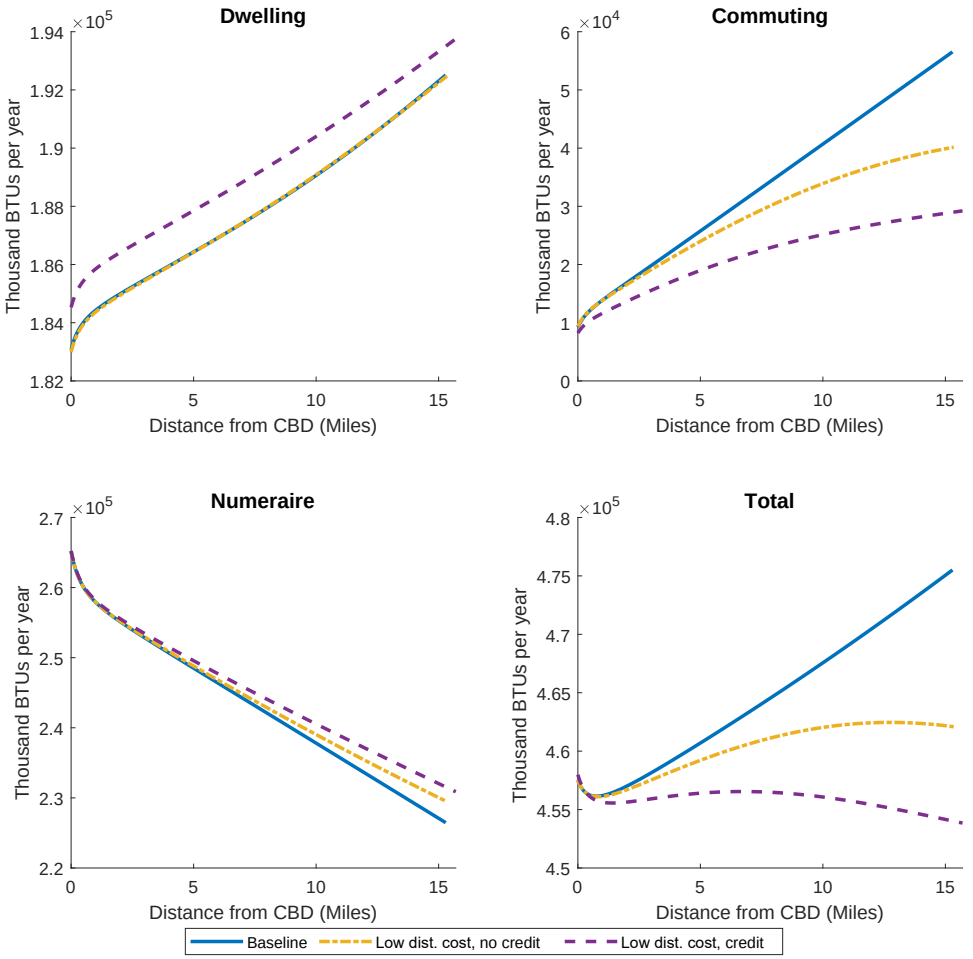


Figure 5: Energy consumption solutions



4.2 Effects in different climates

Because dwelling energy consumption is endogenous, and different local climates vary in their heating and cooling requirements, expected temperatures will have an effect on the urban form and energy consumption of the city even ignoring EVs. This is one application of the model that is not the focus of our research, but a novel result nonetheless. When an EV tax credit is introduced, there are additional interactions with the local climate. For simplicity of exposition, all scenarios from this point forward assume solutions under low EV distance costs (25% of the baseline calibration), with other results available upon request.

The local climate in the baseline scenario is the sample median of 1404 cooling degree days (CDD) and 3824 heating degree days (HDD) per year. This is similar to International Energy

Climate Code (IECC) zone 4A, which stretches from Kansas through the mid-Atlantic. Other climate zones considered are 3C, which includes coastal California, 1A/2A which includes the Gulf coast, and 6A/6B which includes Montana, Wyoming, and extends east through northern Michigan (see appendix for a U.S. map of climate zones). These are called "Mixed", "Maritime", "Hot", and "Cold" climates for the purposes of this section.

Table 5 shows solutions to the model under different climate scenarios.[17] In the mixed climate solution with no tax credit, the city area is 840 square miles and time-to-work is 26.2 minutes.[18] When the climate is more moderate such as in the marine climate, the city is larger at 855 square miles, and when the climate is more extreme, such as the cold climate, the city is smaller at 834 square miles. This occurs because the marginal cost of interior space rises with extreme heat and cold, providing an incentive for households to locate in smaller, denser units. All else equal, the difference between the optimal area of a city in Minnesota versus California is about 2.4% smaller, entirely due to heating and cooling requirements.[19] Energy consumption and carbon emissions also are different, with cold climates consuming more energy and producing more emissions consuming housing, but less on commuting and indirect expenditures. Overall, otherwise identical households in cold climates consume 9% more energy and have 9% higher emissions before even considering EV tax credits.

Climate interacts with the EV tax credits to alter their effects. Because EVs reduce energy consumption due to sprawl, and sprawl is greater in moderate climates, EVs reduce energy consumption and carbon emissions more. We can see from the breakdown of changes to housing, commuting, and indirect energy that EV credits have the same effects in percentage terms in each climate. But because the energy mix is more housing-tilted in harsher climates, the energy consumption reductions are lower. Comparing marine to cold climates, energy consumption and carbon emissions fall by 1.2% versus 1.0% and 2.7% versus 2.4%. EV tax credits are therefore less cost-effective, with a break-even social cost of carbon of $342 per ton in the marine climate versus $356 per ton in the cold climate.

[17] Note that we do not consider effectiveness or efficiency of EVs in hot versus cold climates. Engineering studies suggest extreme temperatures degrade battery performance.

[18] Other urban form variables behave similarly to these two, so they are omitted from presentation for ease of exposition.

[19] It should be noted that the model here does not include urban "heat island" effects of density. See, for example, Borck (2016).

Table 5: EV tax credit effects in different climates

	Marine Climate		Hot Climate		Mixed Climate		Cold Climate	
EV Purchase Tax Credit	No	Yes	No	Yes	No	Yes	No	Yes
EV Distance Cost	25%	25%	25%	25%	25%	25%	25%	25%
Climate								
IECC zone	3C		1A/2A		4A		6A/7A	
Cooling degree days	498		927		1404		7038	
Heating degree days	2114		3690		3824		610	
Simulation Output	Level	Level	Level	Level	Level	Level	Level	Level
Fraction of Electric Vehicles	24.0%	53.6%	23.8%	53.4%	23.7%	53.2%	23.6%	53.1%
Break-even SCC (per ton)		$ 342		$ 347		$ 352		$ 356
Urban form	Level	%Δ	Level	%Δ	Level	%Δ	Level	%Δ
City area	855	4.4%	846	4.3%	840	4.5%	834	4.3%
Time to work	26.3	1.3%	26.3	1.2%	26.2	1.3%	26.2	1.2%
Energy consumption per household (million BTUs)								
Total	433.61	-1.2%	452.17	-1.1%	460.68	-1.1%	474.81	-1.0%
Housing Electricity	159.53	0.7%	179.29	0.7%	188.35	0.8%	203.39	0.8%
Commuting Energy	30.19	-23.9%	30.10	-23.9%	30.04	-23.8%	29.98	-23.8%
Indirect Energy	243.89	0.3%	242.78	0.3%	242.29	0.3%	241.44	0.3%
CO_2 emissions per household (tons)								
Total	21.51	-2.7%	22.40	-2.6%	22.80	-2.5%	23.48	-2.4%
Housing Electricity	7.62	0.7%	8.56	0.7%	8.99	0.8%	9.71	0.8%
Commuting Energy	2.25	-30.3%	2.24	-30.2%	2.24	-30.1%	2.24	-30.1%
Indirect Energy	11.65	0.3%	11.59	0.3%	11.57	0.3%	11.53	0.3%

Notes: This table presents solutions to the model described in Section 3. The EV credit is a $7,500 EV credit, giving a flow-subsidy of $375 per year at a 5% cost of capital. Climate zones are described in the appendix, but the Marine zone roughly corresponds to coastal California, Mixed corresponds to roughly Missouri, Cold corresponds to Montana and the Dakotas, and Hot corresponds to the Gulf south.

4.3 Emissions under alternative electricity generation inputs

Because energy is consumed from different sources, including electricity and gasoline, it also makes sense that electricity production input choice matters when considering carbon emis-

sions. Electricity production input type is not internal to the model, so we can exogenously change the electricity input mix with no effect on the city except emissions.[20]

Table 6 shows CO_2 emissions under alternative electricity generation input sources. The mixed electricity input mix is used in other sections of the paper, and corresponds to 26% coal, 32% natural gas, and 42% "green", which consists of hydro, wind, nuclear, solar, and biomass. Coal embodies 212 pounds of CO_2 per million BTUs, natural gas 117 pounds, and green an average of 7 pounds. The "clean" energy mix considered is 68% green and 32% natural gas, and the "dirty" energy mix is 68% coal and 32% natural gas.

The input mix has major effects on carbon emissions generated by households in the model. The mixed level under no tax credit is about 25 tons of CO_2 per year, which includes 9.0 tons from housing electricity, 2.2 tons from commuting, and 11.6 tons indirectly from non-energy consumption. This is cut in half with a clean electricity mix and nearly doubles with a dirty energy mix. Because EVs shift the energy mix from gasoline towards electricity, EV tax credits have effects on emissions that vary depending on the electricity input mix. When electricity is cleaner, emissions per household fall 6.5% versus 0.7% for the dirty mix. But in terms of raw emissions reductions, the figures are much closer, at 0.73 tons of CO_2 per household under clean energy generation and 0.30 tons per household under dirty energy generation. Still, EV tax credits are far more effective if electricity generation is cleaner.

EV tax credits have varying cost-benefit values based on the electricity production mix. With clean electricity, the break-even social cost of carbon is \$273 per ton, versus \$352 for mixed electricity or \$655 for dirty electricity. One clear implication of this model is that in economies powered mostly by coal, EV tax credits do not generate enough emissions reductions to justify their implementation; despite the vehicle CO_2 reductions because coal is less bad than gasoline, the rebound effect of residential electricity consumption is substantial. This result highlights the need to consider energy demand and carbon emissions in an urban equilibrium when evaluating the effects of tax credits. Without this general equilibrium result, the commuting emissions effect of -21% under dirty electricity generation would appear to be a substantial reduction. Alternatively, movements towards home-based solar and a greening of the electricity input mix make EV tax credits increasingly cost-effective.

[20] A richer model would treat as endogenous the electricity price and the input mix.

Table 6: Emissions under alternative electricity production input mixes

	Clean Electricity		Mixed Electricity		Dirty Electricity	
EV Purchase Tax Credit	No	Yes	No	Yes	No	Yes
EV Distance Cost	25%	25%	25%	25%	25%	25%
Simulation Output	Baseline	%Δ	Baseline	%Δ	Baseline	%Δ
CO_2 emissions per household						
Total	11.24	-6.5%	22.80	-2.5%	41.49	-0.7%
Housing Electricity	3.97	0.8%	8.99	0.8%	17.10	0.8%
Commuting Energy	2.15	-36.2%	2.24	-30.1%	2.39	-21.3%
Indirect Energy	5.11	0.3%	11.57	0.3%	22.00	0.3%
Break-even SCC (per ton)		$273		$352		$655

Notes: This table presents solutions to the model described in Section 3. The EV credit is a $7,500 EV credit, giving a flow-subsidy of $375 per year at a 5% cost of capital. Each experiment shows alternative electricity generation mixes: clean is 68% green, 32% natural gas; mixed is 26% coal, 32% natural gas, and 42% green; and dirty is 68% coal and 32% natural gas.

4.4 Interactions with land use regulation

The next setting we consider involves a city with land use regulations. Land use regulations come in many flavors and seek to alter the urban form of the city. Because EVs alter the urban form in laissez faire, there are likely to be important interactions between EV tax credits, urban form, and energy consumption in cities with land use regulation.

The model does not contain any restrictions to residential land use *a priori*, outside of fixed allocations to residential land use at each radius outside of the CBD, and the model's parameters are calibrated using a set of cities with low levels of development interruptions either through natural features or regulation. To consider the effects of regulation on model solutions, we make two changes. First, we consider a "greenbelt" which alters the model closing condition from the reservation agricultural land rent to a fixed maximum city radius of 12 miles, which we set as the laissez faire baseline value. Then, for the height limit scenario we set a maximum FAR of 0.5, which corresponds roughly to single-family zoning throughout the city.

Model solutions are shown in Table 7. A tax credit under a greenbelt induces a smaller

increase in EV adoption in terms of absolute number (27 percentage points). This is because the purpose of greenbelts is to limit commuting distance, and EV adoption is positively linked to commuting distance. However, because greenbelts have a lower base, and then prevent most of the sprawl rebound effect from occurring, the energy reduction is on par with the laissez faire city. However, because of a higher numeraire consumption rebound, the total CO_2 reduction is smaller under a greenbelt, with a reduction of 2.3% versus 2.5%.

Height limits cause sprawl and so do EVs; the city with both is the largest among the various settings considered, with a city area pre-subsidy of 881 square miles that becomes larger post-credit. Overall, the city has a higher EV market both with and without tax credits of 25.4% and 55.0%, respectively. The reduction in energy consumption and CO_2 emissions is similar to laissez faire at -1.1% and -2.6%, respectively. Overall, land use regulations that lower density cause greater adoption of EVs, and EVs are slightly more important for energy and emissions reductions in such cities.

In terms of cost effectiveness, both greenbelts and height limits offer slightly better cost-benefit cutoffs for EV tax credits than laissez faire cities. Accordingly, high land use regulation cities such as Portland, Oregon, or Washington, DC, may offer higher benefit-cost ratios than more market-driven cities such as Houston, Texas.

Table 7: Interactions with land use regulation

	Laissez Faire		Greenbelt		Height Limit	
EV Purchase Tax Credit	No	Yes	No	Yes	No	Yes
EV Distance Cost	25%	25%	25%	25%	25%	25%
Simulation Output	Level	Level	Level	Level	Level	Level
Fraction of Electric Vehicles	23.7%	53.2%	17.4%	44.6%	25.4%	55.0%
Break-even SCC (per ton)		$352		$336		$350
Urban form	Level	%Δ	Level	%Δ	Level	%Δ
City area	840	4.5%	452	0.0%	881	3.2%
Time to work	26.2	1.3%	23.7	0.2%	27.0	0.7%
Energy consumption per household (million BTUs)						
Total	460.68	-1.1%	432.80	-1.1%	459.92	-1.1%
Housing Electricity	188.35	0.8%	158.16	0.1%	187.66	0.9%
Commuting Energy	30.04	-23.8%	26.60	-22.7%	31.12	-24.7%
Indirect Energy	242.29	0.3%	248.04	0.4%	241.14	0.4%
CO_2 emissions per household (tons)						
Total	22.80	-2.5%	21.42	-2.3%	22.79	-2.6%
Housing Electricity	8.99	0.8%	7.55	0.1%	8.96	0.9%
Commuting Energy	2.24	-30.1%	2.02	-27.3%	2.31	-31.1%
Indirect Energy	11.57	0.3%	11.84	0.4%	11.51	0.4%

Notes: This table presents solutions to the model described in Section 3. The EV credit is a $7,500 EV credit, giving a flow-subsidy of $375 per year at a 5% cost of capital.

4.5 Interactions with tax regimes

The primary goal of EV tax credits is to reduce carbon emissions. However, there are alternative taxation regimes which may affect incentives for EV adoption and overall emissions. Additionally, there are other ways of funding the EV tax credit. This section considers several additional tax regimes. While there are many more considered, the goal here is to illustrate how model solutions are sensitive to the fiscal policy milieu in which the EV credit exists.

The first policy considered is an EV tax credit funded through a fee on every driver in the city that scales based on EV credit usage. This is in contrast current funding which is external to the model. Another taxation regime which may interact with an EV tax credit is a carbon tax, a Pigouvian tax levied on consumption based on the harm created by its associated CO_2 emissions. This policy has clear interactions with EV adoption because it affects marginal transportation cost differential. The final taxation regime considered, which may intuitively appear to be a second-best carbon tax, is a Pigouvian congestion tax (toll), which charges drivers based on the marginal congestion introduced to all other travelers on the commuting route Borck and Brueckner (2018). While this policy combats inefficient sprawl, it has no clear interaction with EVs because congestion is introduced equally by both EVs and gasoline-powered vehicles.

Driver tax

The driver tax is interesting to consider because it assesses a user-fee for every driver to pay for the total number of EV credits used. In effect, it turns the EV subsidy into a cross-subsidy between gasoline and electric vehicle owners.

This cross-subsidy creates a prisoner's dilemma for EV credits: households receive a large private benefit under the credit but impose a funding cost on the rest of the tax base when they buy an EV. So, from a direct funding perspective, there are incentives to take the credit even though in many cases it would be cheaper for the city not to have credits at all.

When putting a value on the CO_2 avoided through the EV credit, it appears the prisoner's dilemma may have a positive outcome. The value of CO_2 reductions amount to about \$128 per driver at a cost of \$199, compared to the external funding of the credit, which has a similar cost but a substantially lower benefit of \$108. Accordingly, driver-financed EV tax credits are more cost-effective than one financed in a manner external to urban households.

Carbon tax

The optimal carbon tax is simple to calculate using publicly available social cost of carbon. We use the middle range of the most recent estimate from the U.S. Environmental Protection Agency of \$190 per ton (US EPA, 2022). This gives a carbon tax of \$2.232 per gallon of gasoline, \$0.102 per kWh of electricity, and \$0.038 per dollar of other consumption. The carbon tax is cycled back to households in the form of a lump-sum cash grant, regardless of expenditure basket.

Alone, without the full EV tax credit, a carbon tax results in substantial CO_2 reductions for all households. The carbon tax changes relative prices, causing substitution away from CO_2-intensive goods and services, including housing and commuting. This causes a net increase in energy embodied by numeraire good consumption relative to the baseline no-credit case, of 8.0%, but a fall in commuting energy of 24.0%. Overall, without the EV tax credit, the carbon tax reduces energy demand by 21.0% and emissions by 22.0%. When EV credits are layered onto the carbon tax, emissions fall a further 2.6%. In terms of costs and benefits, however, a carbon tax renders EV tax credits cost ineffective, at a break-even social cost of $653 per ton. This is because the carbon tax does a fairly effective job at incentivizing EV adoption, with the carbon tax alone nearly achieving a similar level of EV adoption as with an EV tax credit and no carbon tax (53% vs 56%).

Congestion tax

The congestion tax is implemented as a marginal tax on the cost an additional driver imposes on other drivers through reduced speeds. This revenue is cycled back to households in the form of a lump-sum transfer as in the case with the carbon tax. The tax and the revenue cycling do not affect the marginal cost of EV versus gasoline-powered vehicles, but these scenarios offer several interesting findings nonetheless.

Alone, the congestion tax actually increases energy consumption by 5.3% by causing households to consume more and by shifting consumption to housing and indirect energy. Offsetting some of the benefits of lower commutes is lower EV adoption. On a net basis, the congestion tax increases CO_2 emissions, suggesting that as a greenhouse gas-fighting tool it may not be a second-best policy, counter to Borck and Brueckner (2018).

When the full EV credit is added to a congestion tax regime, CO_2 changes are similar to the lassez-faire city: emissions fall by about 2.4%, and the city area expands by about 4.5%. Thus, we conclude that effects of EVs are largely invariant with respect to congestion taxes.

Table 8: Effects of EV credits under alternative tax regimes

Funding of EV Tax Credit	External		Driving Tax		External		External	
Additional Tax Regime	None		None		Carbon Tax		Congestion Tax	
EV Purchase Tax Credit	No	Yes	No	Yes	No	Yes	No	Yes
EV Distance Cost	25%	25%	25%	25%	25%	25%	25%	25%
Simulation Output	Level	Level	Level	Level	Level	Level	Level	Level
Fraction of Electric Vehicles	23.7%	53.2%	23.7%	53.1%	56.2%	80.2%	23.6%	53.1%
Urban form	Level	%Δ	Level	%Δ	Level	%Δ	Level	%Δ
City area	840	4.5%	0.1%	3.7%	9.1%	3.2%	-0.4%	4.5%
Time to work	26.2	1.3%	0.0%	1.1%	1.8%	1.3%	-0.3%	1.3%
Energy consumption per household (million BTUs)								
Total	460.68	-1.1%	0.0%	-1.6%	-21.0%	-1.2%	5.3%	-1.0%
Housing Electricity	188.35	0.8%	0.0%	0.1%	-57.3%	0.6%	0.5%	0.8%
Commuting Energy	30.04	-23.8%	0.0%	-23.9%	-27.6%	-24.2%	-0.3%	-23.8%
Indirect Energy	242.29	0.3%	0.0%	-0.1%	8.0%	0.1%	9.7%	0.3%
CO_2 emissions per household (tons)								
Total	22.80	-2.5%	0.0%	-3.0%	-22.0%	-2.6%	5.1%	-2.4%
Housing Electricity	8.99	0.8%	0.0%	0.1%	-57.3%	0.6%	0.5%	0.8%
Commuting Energy	2.24	-30.1%	0.0%	-30.2%	-35.4%	-34.2%	-0.3%	-30.1%
Indirect Energy	11.57	0.3%	0.0%	-0.1%	8.0%	0.1%	9.7%	0.3%
CO_2 cost-benefit								
Cost of credit per hh. ($190/ton)		$200		$199		$301		$199
Benefit of credit per hh. ($190/ton)		$108		$128		$88		$107
Break-even SCC (per ton)		$352		$295		$653		$352

Notes: This table presents solutions to the model described in Section 3. The EV credit is a $7,500 EV credit, giving a flow-subsidy of $375 per year at a 5% cost of capital. The driving tax is a flat per-driver fee that scales with the number of EV credits claimed. The carbon tax prices carbon at $190 per ton, with carbon weights described in the main text. The congestion tax is the marginal cost of the reduction in speed imposed on other drivers from driving. Both carbon and congestion taxes are recycled to households as lump-sum transfers.

5 Conclusion

The model in this paper rests at the intersection of urban, energy, and public economics. Deep parameters affecting commuting costs or home energy consumption have effects on the entire urban system, including the urban form of the city. Thus, it is crucial to model policies affecting commuting costs, such as EV tax credits, in a full urban general equilibrium to fully account for possible rebound or amplification effects. Cost-effectiveness of such policies, should be judged based on effects in totality, not just partial equilibrium.

The model is calibrated to a set of five moderate-sized U.S. cities in 2019. Counterfactual solutions are generated by altering model parameters; to be clear, the model is not generating forecasts, but rather a new city, *ceteris paribus*. This is a strength in our setting, as it allows us a laboratory to perform stylized experiments that cannot be performed using data on real-world cities due to path dependence, partial adjustment processes, immature technologies, and endogenous relations.

Experiments conducted using this model offer several key qualitative insights which may be of use to economists and policymakers. The first major conclusion is that EV tax credits are most cost-effective when EVs are a nascent technology because of their low base adoption rate in absence of the policy. As EV technology matures, subsidy cost-effectiveness declines. Second, there are substantial energy rebound effects of EV tax credits. These rebound effects are due to both higher levels of numeraire good consumption and sprawl, which includes a greater number of large, single-family and longer commutes. Other insights from the model include predictions that EV subsidies are most cost-effective when the electricity input mix embodies lower CO_2 emissions, the climate has less extreme seasonal temperatures, land use regulations are more stringent, and there are no duplicative CO_2 emissions taxes.

The model in this paper could presumably be extended to include heterogeneous preferences, public transportation, decentralized employment, and endogenous electricity input sources, to name several possibilities. It may also be possible to extend this framework to the quantitative urban model of Ahlfeldt et al. (2015), as applied by Delventhal et al. (2022) to the topic of telework in order to generate near-term predictions. But in general, modeling energy consumption in an urban equilibrium framework is surely a useful endeavor for future economics and policy research.

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