The Urban Equilibrium Effects of Electric Vehicle Tax Credits

Weihua Zhao*†
William Larson*‡
Becka Brolinson*§

November 3, 2023

Abstract

This paper extends the monocentric city model to incorporate endogenous automobile fuel choice and household energy consumption. Electric vehicles (EVs) have lower marginal commuting costs, making them optimal in suburban locations. EV tax credits cause energy consumption and carbon emissions to fall due to more efficient commutes. However, in the long-run, EV credits induce substantial sprawl and a 30% energy rebound effect consisting of larger homes, longer commutes, and greater numeraire consumption. Nevertheless, unless electricity production is heavily tilted towards coal, EV credits are benefit-neutral under a social cost of CO_2 between \$190 and \$230 per ton.

JEL Codes: R41, R48, R28, R21, R31, R38
Keywords: monocentric city model, electric vehicle, tax credit, urban sprawl

*Disclosure statement: The authors declare no relevant or material financial interests that relate to the research described in this paper. Corresponding author: William Larson, larsonwd@gmail.com.

†Assistant Professor, Department of Economics, University of Louisville, weihua.zhao@louisville.edu.

‡Research Fellow, Center for Economic Research, George Washington University

§Senior Economist, Federal Housing Finance Agency (FHFA), Becka.Brolinson@fhfa.gov. The analysis and conclusions are those of the authors alone, and should not be represented or interpreted as conveying an official FHFA position, policy, analysis, opinion, or endorsement. Any errors or omissions are the sole responsibility of the authors.

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. However, by reducing per-mile commuting costs, EVs are likely to cause urban sprawl, with associated increases to commute length, dwelling size and reductions to dwelling energy efficiency. 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. Two questions motivate this paper. First, what are the effects of EV tax credits on the long-run urban form of the city, and second, do EV tax credits reduce overall emissions, and if so, by how much?

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 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 the short-run, holding the urban form of the city and all other parameters fixed, and then in long-run 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 long-run EV adoption in response to purchase tax credits.

In the long-run, identical households choose EVs in more suburban locations because EVs have lower marginal commuting costs. Accordingly, the introduction of EVs causes sprawl, and EV tax credits encourage such sprawl. This rotation of the price gradient makes housing more affordable by increasing effective land supply. Savings from EVs are reallocated to other housing and non-housing consumption, and this consumption embodies energy consumption and carbon emissions. This reduces the total energy reduction effect of EV adoption and demonstrates the need to model EV tax credit effects in local general equilibrium. Because EVs are adopted in more suburban locations, they effectively remove gasoline-powered cars that are driven the most. So, while EVs cause sprawl in the model, they still substantially reduce energy consumption because they take the most highly utilized gasoline vehicles off the road.

We also offer findings of differential effects across cities of identical size 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 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.

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 more quantitative equilibrium 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.

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 Background

To frame the model presented in this paper, we first discuss several facts in the data concerning EVs before moving on to an overview of government policies designed to encourage their purchase by households. The overall theme is that EVs are a nascent technology, and this presents a serious modeling challenge both in terms of understanding household behavior in laissez faire and in response to purchase tax credits.

2.1 Stylized Facts

While EVs show great promise in achieving 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. 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.

One survey by the AP-NORC Center for Public Affairs Research (2023) offers some insights driving this 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 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, current EV statistics may be difficult to generalize to the wider population and in the long-run.

Despite these challenges with the data, there are two useful—but conflicting—facts we would like to introduce here. The first fact in the data is that the EV market share declines with distance from the center of the city, both unconditionally and conditional on socioeconomic characteristics and voting behavior (see Figure 1). The second fact is that electric vehicles have higher fixed costs but lower marginal costs of ownership than gasoline-powered vehicles, both unconditionally and conditional on vehicle make and model (see Table 1 and the Online Appendix). These facts are in apparent conflict because virtually all textbook urban models predict that for identical households, the cheaper commuting method will be chosen at each location in the city, *ceteris paribus*. Accordingly, the empirical EV market share gradient should be upward sloping, not downward sloping were fuel technology choice to be due exclusively to direct costs.

Fact 1: EV registrations decline with distance to the CBD

The first fact we would like to introduce relates to the EV registration gradient in large U.S. cities. To our knowledge, this gradient has not been explored elsewhere in the literature. 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 [1] 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 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.[2]

Fact 2: EVs are cheaper for longer commutes but not for shorter commutes

The second set of facts we wish to present involve costs of EV versus gasoline vehicle ownership. Prior research has used information from the American Automobile Association (AAA) and engineering studies for cost breakdowns (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 is 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

[1] 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.

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

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. Parameter estimates are shown below in Table 1.[3]

Table 1: Automobile Costs

	Electric	Gasoline	Source
Fixed Annual Costs	8,709	7,494	
Insurance	1,588	1,588	AAA (2022)
License, Registration, Taxes	675	675	AAA (2022)
Obsolecense	3,882	3,231	Cars.com, Authors' calculations
Finance cost	2,000	2,000	5% rate × 40k cost
Charger depreciation	300	-	10% per year
Charger finance cost	150	-	5% rate × 3k cost
Per-mile costs	0.147	0.277	
Maintenance	0.079	0.106	AAA (2022)
Depreciation	0.022	0.012	Cars.com, Authors' calculations
Avg fuel cost	0.046	0.159	Idaho National Laboratory (2010)
			($3.50 per gallon; $0.14 per kWh)

Notes: Parameters using Cars.com listings data are described in appendix Table 1. Cost of capital is assumed 5% per year. For more details, consult the appendix.

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 commuting 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. While the fuel economy functions we use in the model are non-linear functions of speed, in this table we report average fuel costs from a U.S. government engineering study which show average electric vehicle fuel costs are less

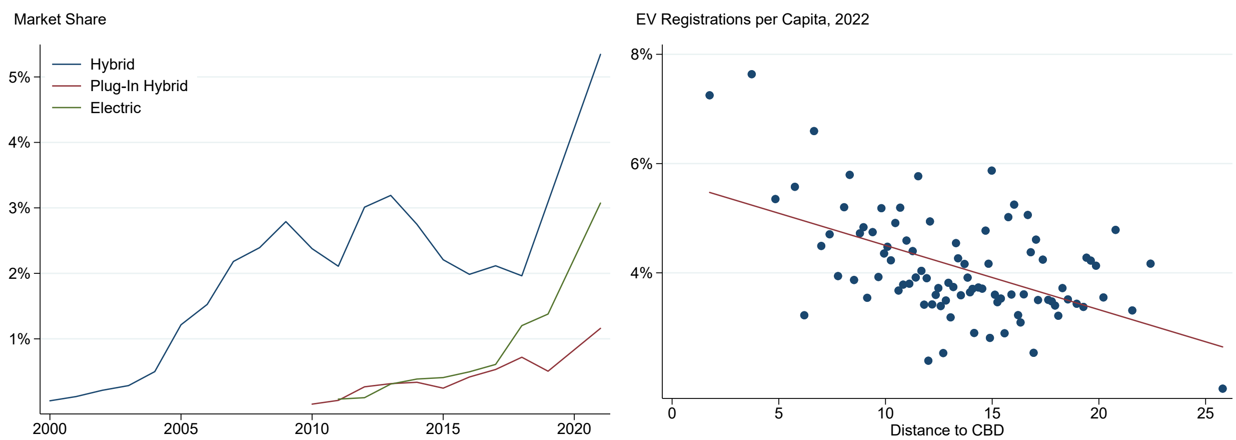
[3]We focus on Teslas for per-mile costs for two reasons. First, fuel cost curve data are public, and second, we have no reason to believe the shape of the fuel cost curves for Teslas are not representative of EVs as a whole. The risk of this approach is that there may be some shifter that affects the entire cost curve that is unique to Teslas.

than 1/3 of gasoline-powered vehicles.

Panel (a) in Figure 2 uses the top-line fixed annual costs and linear per-mile costs to construct annual commuting cost curves. These curves make the implausible assumptions of all households commuting to the CBD and no traffic congestion, to name the most heroic. Nevertheless, these figures serve to illustrate qualitatively the gradient of commuting costs between EVs and gasoline-powered cars. In central locations, gasoline-powered cars are cheaper because they are driven shorter distances. In suburban locations, EVs are cheaper because they must drive the entire distance. In later sections, we show this prediction is maintained in the presence of congestion and non-linear commuting costs.

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.

Resolving these conflicting facts

These two stylized facts present an apparent conflict. Fact 1 shows EV market shares decline with distance from the CBD. Fact 2 suggests EV market share should rise with distance from the CBD. Why does the theory not match with the data, and how can this supposed conflict be resolved?

We believe the answer lies in the newness of EVs as a technology, which drives locationvarying non-pecuniary costs. Suppose the cost difference between EVs and gasoline-powered vehicles $\Delta(k)$ at distance k from the CBD can be decomposed into a pecuniary commuting cost differential $\Delta T(k)$ and a non-pecuniary location cost $\ell(k)$ that is additive with respect to pecuniary costs, and may increase or decrease EV adoption. This location cost is a stand-in for factors such as suitability of infrastructure, deviation of available EV types from optimal vehicle types, range limitations, and deviation of available EV quality from optimal vehicle quality.[4] Adding this location cost to the cost differential gives $\Delta(k) = \Delta T(k) + \ell(k)$. We need $\Delta' > 0$ to replicate Fact 1. We know that $\Delta T' < 0$ because EVs have lower marginal commuting costs, meaning the cost differential widens with k and $\ell' > 0$. This implies total location costs for EVs start low at the CBD and rise with distance from the CBD such that $\ell' > -\Delta T'$.

We also propose that $\ell(k)$ 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. Generally, if the mean location cost of EV ownership falls to zero over time, 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).

To illustrate how location costs can help resolve these supposedly conflicting facts, see Figure 2. This figure shows annual pecuniary commuting costs for EVs and gasoline cars, denoted as T_E and T_G, respectively. With no other costs or preferences, the commuting cost differential resulting from panel (a) would give corner solutions, with 0% EVs until about 16 miles from the CBD, where it would switch to 100%. Panel (b) shows how EV shares vary by distance to the CBD under a specific form of cost and preference heterogeneity. First, we include a so-called "range cost" that increases with k. This includes all factors listed above that may affect all households in a given location. Second, we include household preference heterogeneity that is drawn from a normal distribution. Combined, these give location costs for household i at radius k of $\ell(i, k) \sim \mathcal{N}(\mu(k), s^2)$, where $\mu(k) = 85k$ and $s = 800$, both

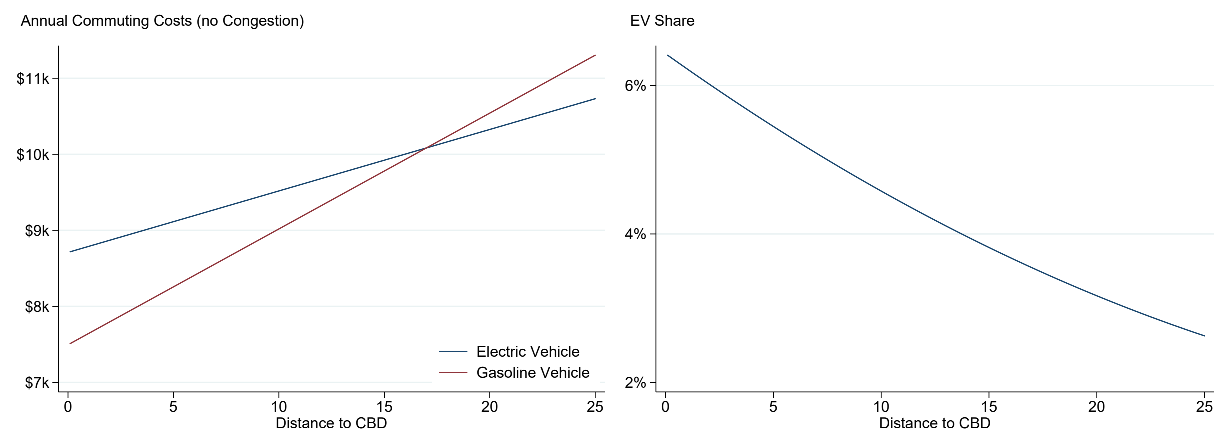
[4] For instance, (Gillingham et al., 2023) show that EVs up until 2020 were primarily hatchbacks and sedans, but included virtually no SUVs, minivans, coupes, or convertibles. Additionally, there were no EV pickup trucks available until 2021.

calibrated.[5] The EV share is calculated as $\lambda(k) = 1 - F(T_E(k) - T_G(k) + \ell(k))/s)$, where F is the cumulative standard normal density function.

At the CBD, despite a cost of EVs that is higher than gasoline-powered vehicles, the EV share is just above 6% because some households prefer EV ownership. As range costs increase with k, the market share declines to about 2.5% at 25 miles from the CBD. This parameterization creates an EV market share curve that matches Figure 1, panel (b).

Figure 2: Numerical Illustration

(a) Direct Commuting Costs | (b) EV Share with Location Costs



Note: Author's calculations based on American Automobile Association and Cars.com data. Panel (a) is a simple calculation that uses annual fixed costs of ownership plus two-way annual commuting cost to the CBD under a fixed cost per mile taken from Idaho National Laboratory (2010). See also, Table 1. Panel (b) incorporates location-based cost heterogeneity for EVs drawn from $\ell(i,k) \sim \mathcal{N}(\mu(k), s^2)$, where $\mu(k) = 85k$ and $s = 800$. The EV share is calculated as $\lambda(k) = 1 - F(T_E(k) - T_G(k) + \ell(k))/s)$, where F is the cumulative standard normal density function and T_E and T_G are pecuniary costs of EVs and gasoline vehicles, respectively.

This numerical illustration is helpful to reconcile the lower relative EV costs in the suburbs and the higher EV adoption near the CBD. This simple exercise requires at least three

[5] In most of the models in this paper, we implement EV cost heterogeneity as an additively separable location cost that is common to each annulus (a "range cost"), and an idiosyncratic household-specific cost (i.e. preference). We assume no sorting based on household preferences occurs in the short-run. Then we explore cases where sorting does or does not occur in the long run. In the simple illustration here, we assume no sorting.

major assumptions: linear commuting costs that do not reflect traffic congestion, omission of important endogenous responses of vehicle choice to optimal location, dwelling type, housing unit size, and other consumption patterns, and lack of sorting behavior related to EV preferences. After describing the relevant policy environment, in the following sections, we use concept of location-based costs introduced here to calibrate a model EV market shares in urban general equilibrium. The model is calibrated to fit the short-run facts described above, with long-run representations setting mean range costs to zero. Parameters in the model are then altered to give effects of EV tax credits on the urban form, energy consumption, and carbon emissions under different scenarios.

2.2 Policy Environment

EVs and Emissions

In 2021, 28 percent of all energy consumed in the US was used in the transportation sector (Energy Information Administration, 2022b). Despite using around 30 percent of all energy consumed in the US, the transportation sector is responsible for a disproportionate share of CO_2 emissions. Reducing emissions from the transportation sector is a way to meaningfully decrease CO_2 emissions in the US; one potential direct solution is increasing the share of the US' electric vehicle fleet.

How are electric vehicles supposed to reduce emissions? The focus on electric vehicles as a means to reduce greenhouse gas emissions rests on the premise that the emissions per mile for gasoline-powered vehicles is more than that of electric-powered vehicles. This in turn depends squarely on the input mix producing electricity. It also presumes that EVs have no interactive effects with other sectors, which as we show in this paper, can be substantial.

In 2021, the average kilowatt hour (kWh) generated in the U.S. produced around 0.883 pounds of CO_2 (Energy Information Administration, 2022a). The typical electric car uses around 0.34 kWh per mile driven, or 1 kWh per 2.9 miles (O'Dell, 2022). Thus, the typical electric vehicle emits around 0.30 pounds of CO_2 per mile driven. In 2019, the U.S. passenger fleet average for gasoline powered vehicles for CO_2 emissions per mile was 0.47 pounds, or more than 1.5 times as much CO_2 per mile as an electric vehicle (Congressional Budget Office, 2022). The average work commute is around 15 miles (US Department of Transportation, 2003), yielding around 4.5 pounds of CO_2 emissions for a commute with an electric vehicle versus 7.05 pounds of CO_2 emissions for a commute with a gasoline powered vehicle.

While these statistics are averages, there is both intertemporal and cross-sectional variation in electricity generation emissions. Moving forward, shifts in electricity generation from fossil fuels to renewables will likely cause emissions per mile for electric vehicles to decrease. Additionally, 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. In some parts of the country the retail price for residential electricity consumption is higher than the social marginal cost of electricity generation, disincentivizing EV adoption.

Overall, EVs offer the potential to substantially reduce direct emissions in the transportation sector. Responding to this need, a variety of policies have been enacted at the federal, state, and local level.

Federal Policies

The United States has implemented various policies to help reduce emissions in the transportation sector. 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 Section 1341 directing up to $2,400 towards the purchase of electric or hybrid electric vehicles.

[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.

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 Independence and Security Act of 2007 helped encourage consumer adoption of electric and hybrid-electric vehicles through several provisions. First, Section 105 of the law required the Department of Transportation to develop a way to standardize and publicize the fuel economy of vehicles with alternative fuels. Section 131 introduced a grant program to encourage the use of electric vehicles or other technologies. Finally, the substantial increase in CAFE standards in this law, combined with the expansion of the CAFE credit program, led to a dramatic increase in incentives for EV development.

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.

State and Local Policies

State and local policies encouraging EV adoption tend to focus on the consumer. Recognizing the high costs of household infrastructure required to charge electric vehicles, both credits and other assistance for charging stations are popular, with 37 states having some sort of incentive.[9] Utility rebates, inspection waivers, high-occupancy-vehicle (HOV) lane access, free parking, and additional purchase tax credits are also available in some states and communities.

The most widely coordinated interstate program is the Zero Emission Vehicle (ZEV) Program, initially implemented by California in 1990. The ZEV program includes requirements for automakers to sell a certain percentage of electric vehicles, establishes emissions credits and trading programs, and encourages the development of electric vehicle charging infrastructure. Since 1990 the program has been implemented by Colorado, Connecticut, Delaware, Maine, Maryland, Massachusetts, Minnesota, Nevada, New Jersey, New Mexico, New York, Oregon, Pennsylvania, Rhode Island, Vermont, Virginia, Washington, and the District of Columbia. In 2020, California Governor Gavin Newsom's executive order N-79-20 mandated 100% of new vehicle sales be zero emissions by 2035. This was codified into state regulation in a 2022 rule. It has yet to be seen which states may or may not follow California's 2022 rule.

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

This section introduces a version of the monocentric city model with 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

[9] `https://www.kbb.com/car-advice/electric-vehicle-rebates-by-state/`. See also (Canis et al., 2019). For example, in Arizona, Tucson Electric Power customers who buy a Level 2 or DC Fast Charger can get up to $500 in rebates. Some states offer rebates for multiple chargers in a single household, such as Alaska's Chugach Electric Association rebate program which gives $200 bill credits to up to two Level 2 chargers in a single household.

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.

Combined, these two extensions to the monocentric city model allow household and housing producer optimization 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 both the short-run and long-run 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.[10]

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.

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

[10]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).

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 $\bar{k}$.

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

Transportation costs: Annual commuting costs $T(k)$ for a worker living at distance k include fixed costs of owning and operating an automobile 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.[11]

In the short-run, electric vehicles have a location-specific cost drawn from a normal distribution, $\ell_E(k) = \mathcal{N}(z_1 k, z_2^2)$. The mean of this distribution varies by k, with $z_1 k$ interpreted as a "range cost". The variance z_2^2 is interpreted as an annulus-based (money-additive) location-based suitability of EVs, including infrastructure. In the long-run, we assume these location-specific costs are equal to zero. Gasoline-powered vehicles do not have a location-specific cost, so $\ell_G(k) = 0$. Fixed costs for electric vehicles, m_{0E}, include an EV subsidy. Revenue for this credit is outside the model, but may be assumed to be a fixed per-acre tax, making it completely non-distortionary; other tax and revenue cycling regimes are considered later. Households residing at location k choose an optimal vehicle fuel technology such

[11] Residential charging stations are modeled as a fixed cost in m_0. However, it is possible there is a charging cost gradient that follows the land price, due to demands for space for charging. These are subsumed within $\ell(k)$.

that $T(k) = min(T_E(k), T_G(k))$.

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

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, which estimates this parameter to be approximately 0.5 (Small and Verhoef, 2007). 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.

Energy consumption: Energy consumption $e(k)$ is generated in three ways in the model: direct consumption of electricity, 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.

$$e(k) = e^d(k) + e^c(k) + e^n(k) \tag{6}$$

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 $s(q(k))$ which is a function of the floor-area ratio at k,[12]

$$e^d(k) = E_e \exp(g'\Gamma) \tag{7}$$

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

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

$$e^c(k) = E_V \epsilon \int_0^k \frac{1}{G_F(V(M(\kappa)))} d\kappa \tag{8}$$

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.[13] Note that the wage reduction due to time spent commuting is fully incorporated in the reduction in expenditures by $\int_0^k \frac{1}{V(M(\kappa))} d\kappa$.

$$e^n(k) = E_N \left(\epsilon W \left(1 - \int_0^k \frac{1}{V(M(\kappa))} d\kappa \right) - p_V e^c(k)/E_V - p_e e(k)/E_e \right) \tag{9}$$

[12]Heating and cooling degree days are calculated as the annual sum of negative and positive daily differences in average temperature from 65 degrees.

[13]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.

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.[14] 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.

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 $d = 0.001$ mile, or 5.28 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

[14]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`.

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 $k - d$.

$$\begin{bmatrix} T(k) \\ N(k) \end{bmatrix} = \begin{bmatrix} T(k-d) + d(m_{1F} + p_F \frac{1}{G_F(V(M(k)))} + \tau W \frac{1}{V(M(k))}) \\ N(k-d) + 2\pi\theta d D(T(k)) \end{bmatrix} \tag{10}$$

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 Tables 1, 2, and throughout the text. For details about parameter values, see the Online 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.

Table 2: 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), Altmann and DeSalvo (1981)
α_1	1	Numeraire parameter	
α_2	0.2	Land parameter	Davis et al. (2021)
A	0.09	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	0.11	Housing parameter	Calibrated
Land Use			
θ	0.33	Fraction of land used for housing	Muth (1975) uses 31.8%
ψ	20	Fraction of land used for roads	Muth (1975) uses 19.7%
k_{CBD}	1	Radius of the CBD	Assumed
p_L^a	1,336	Reservation agricultural land rent per acre	Davis et al. (2021)
Transportation			
v_{low}	5	Minimum commuting speed	Calibrated
v_{high}	55	Maximum commuting speed	Calibrated
c	1.1	Parameter in speed function	Calibrated
τ	0.5	Commuting time cost fraction of income	Small and Verhoef (2007)
p_g	4.0	Auto fuel cost per gallon	Assumed
p_e	0.09	Electricity cost per kWh	Assumed

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.[15]

The baseline model has the option of households using EVs with a stylized pre-Inflation Reduction Act (IRA) subsidy. Prior to the IRA, vehicles were eligible for tax credits until a

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

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 baseline 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 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).

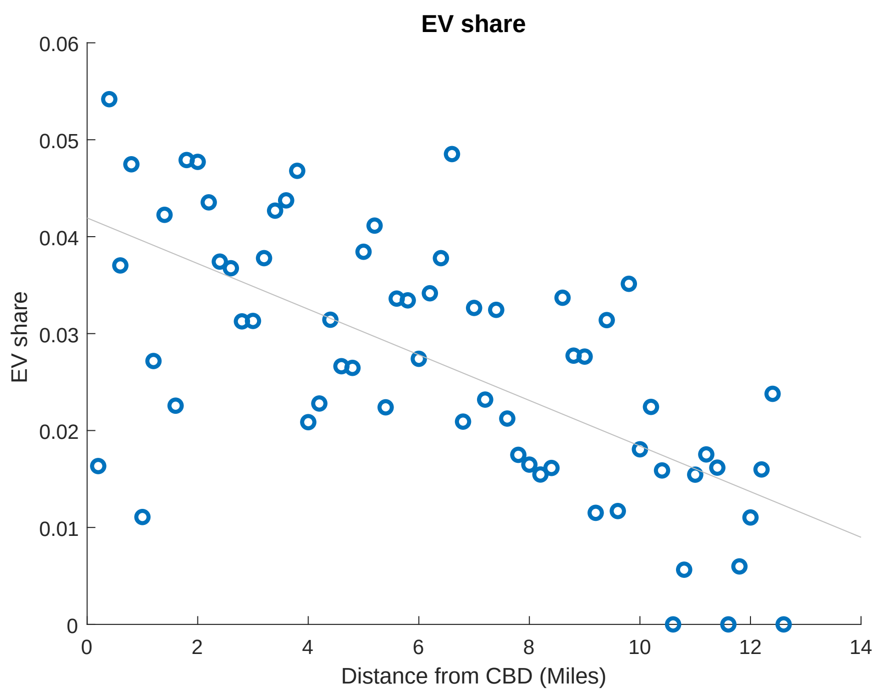
Table 3: Baseline Model Calibration

City **CBSA Code**	**Charlotte** **16740**	**Columbus** **18140**	**Indianapolis** **26900**	**Kansas City** **28140**	**San Antonio** **41700**	**Composite** **Average**	**Calibrated** **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	875,430
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	1,631
Lot Size (acre, single family)[b]	0.46	0.34	0.35	0.30	0.31	0.35	0.25
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%	5%
2-4 unit housing structure[a]	4%	10%	6%	6%	5%	6%	5%
5+ unit housing structure[a]	17%	19%	17%	16%	20%	18%	18%
Area (sq. miles)[a]	741	511	706	678	597	647	585
Radius (assuming circle)	15.4	12.7	15.0	14.7	13.8	14.3	13.7
Time to work[a]	26.0	23.4	24.7	23.0	25.5	24.5	23.2
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 vehicle share[f]						1.4%	2.8%
Dwelling energy per household (mmBTUs)[e]	-	-	-	-	-	75.8	69.8

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 3. In this figure, each circle represents EV shares averaged over an 0.2 mile range of 0.001 width annuli. The solid line is the linear line of best fit (unweighted). EV shares are different at each annulus because of the location-specific EV cost draw from Equation 5. The EV share gradient in this baseline calibration matches closely the empirical gradient in Figure 1, with the line of best fit giving EV shares of about 5% near the CBD, down to about 1.5% at the edge of the city.

Figure 3: Electric Vehicle Adoption in Baseline (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 4 and 5 show solutions under different parametrizations as a function of distance to the CBD. The baseline model reduces the EV tax credit is the solid blue line, the model solution in the long-run without EV tax credits is the solid yellow line, and with EV tax credits is the dashed orange line, the latter two of which will be described shortly. Gradients are monotonic and 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 to increase near the edge of the city as density falls. 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 the numeraire good relative to housing increases with distance, causing consumption to decline. Overall, energy demand increases with distance to the CBD.

Figure 4: Urban Form

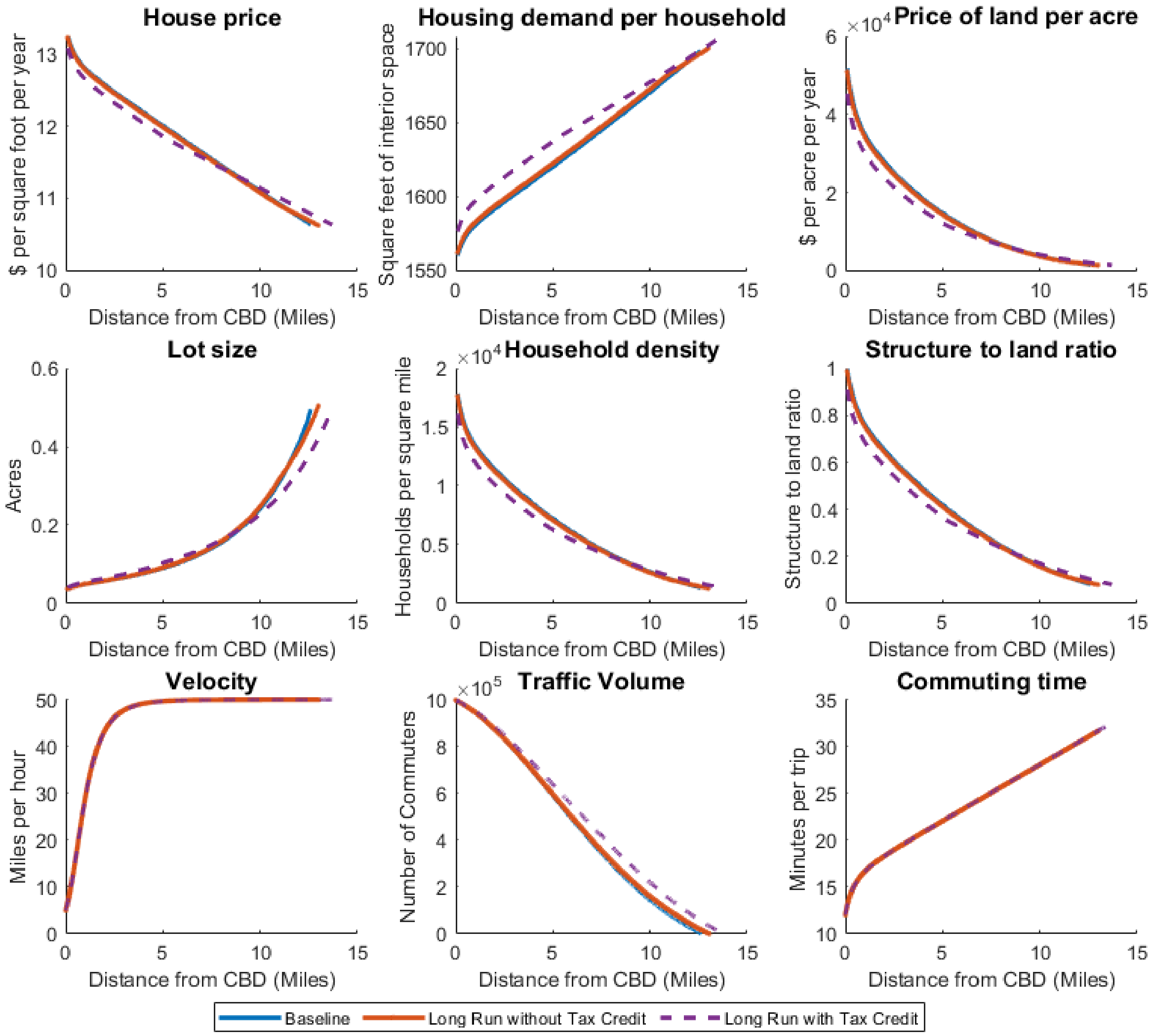
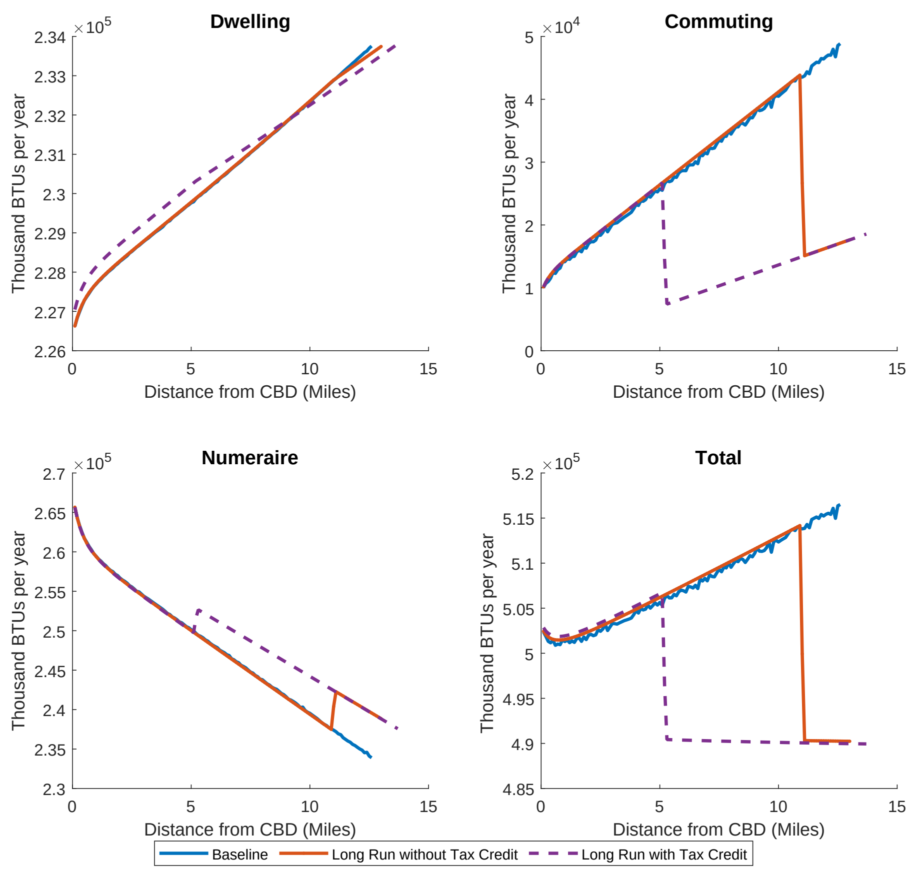


Figure 5: Energy Consumption



Notes: Baseline energy consumption fluctuates with distance to CBD due to EV cost heterogeneity at different locations (smoothed with a bandwidth of 0.5 miles). Long run models reduce location costs to 0; hence there is a single discrete jump when households switch from 100% gasoline vehicles to 100% EVs.

4 Scenario Design and Results

This section uses the calibrated model to perform various counterfactual experiments by altering model parameters. Cities solved under alternative parameterizations are compared to the baseline model solution to generate estimated urban equilibrium effects.

Key parameters of interest are tax credits for EVs, 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 scenarios are designed to provide a range of findings concerning the effects of EV tax credits in various settings. The EV credit is the full amount described in the calibration of a flow-subsidy of \$375 per year.

4.1 Short-run vs long-run effects of EV tax credits

The short-run scenarios are designed to show the effects of EV tax credits holding urban form constant. This parameterization takes the baseline urban form and uses values for unit size, FAR, lot size, and density, and treats them as fixed in the scenario with the tax credits. This scenario gives effects of EVs in partial equilibrium as the change in commuting energy costs, and considering short-run "goods substitution rebound" effects as cost savings from EVs are reallocated to other expenditures.

The long-run scenarios alter both model parameters and adjustment mechanisms. Location-based EV costs from Equation 5 are removed to account for promulgation of EV infrastructure, battery technology, and more widespread EV variety and availability. This flattens the EV cost gradient and reverses the slope of the EV adoption gradient to be increasing with distance to the CBD. In terms of adjustment, long-run scenarios allow producers to respond to the changes in consumer bid-rent curves. This makes it profitable for producers to change the location, density, and structure type of housing supplied over time from what would have been optimal in the baseline model.

Results from the baseline, short-run, and long-run scenarios are found in Table 4. In the baseline model with no EV tax credit, EV adoption is 2.8%. In the short run, the EV tax credit increases adoption to 9.5%. Urban price equilibrium dictates that land and house prices rise to capture the benefits of the tax credits. While energy consumption falls by 0.2%, carbon emissions fall by 0.4% because gasoline is more carbon-intensive than electricity for the same number of BTUs, and gasoline usage falls by 5.9%. There is a substantial short-run rebound effect, however, 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 250 thousand BTUs per household. This is in comparison to the 1 million BTUs per household saved using additional EVs. Dividing one by the other gives the goods substitution rebound effect of about 25%. To summarize, EV tax credits are spent on EVs, but also housing and other consumer goods which offset some of the energy and carbon emission benefits.

In the long run, because households with EVs have flatter bid-rent curves than ones with gasoline-powered vehicles, the adoption of EVs is associated with sprawl. Direct commuting costs for each fuel type are shown in Figure 6. EV shares rise to 10.3% absent EV subsidies because range costs are now gone, making EVs the cheaper option at the urban periphery. The city area expands by about 6%, with commute times rising by 0.7% and average housing consumption increasing by 0.2%. This sprawl causes commuting energy to fall only by 0.2% despite an increase in EVs of about 8 percentage points. Housing affordability increases as lower commuting costs increase accessibility of suburban land.

With EV subsidies, long-run EV ownership jumps from 10.3% to 62.7%. Why the dramatic increase where in the short-run the effect of subsidies was relatively modest? The answer lies in the elimination of the location-based factors. This makes the EV versus gasoline decision one of pecuniary costs, and pecuniary costs are very sensitive to changes in subsidies. As the EV cost gradient shifts down in response to the tax credit, the location where households are indifferent between the two technologies shifts towards the CBD. Because the two curves are quite close together (see Figure 6), the $375 flow credit (based on the $7,500 lump-sum purchase credit) marks a substantial change in the relative price.[16] The equilibrium result is a city that sprawls even more than in the no-credit long-run city, with city area expanding 17% versus the no-credit short-run baseline. House prices and density fall by more while time-to-work rises. Energy consumption falls by 2.4% with carbon emissions falling by 4.8%. Overall, EV subsidies have two main effects: the city becomes larger with lower density, but with substantial energy and carbon emissions savings. However, offsetting the -47% change in commuting energy consumption is a 0.2% increase in dwelling energy and 0.5% increase in indirect energy consumption, giving a rebound effect of about 30%.

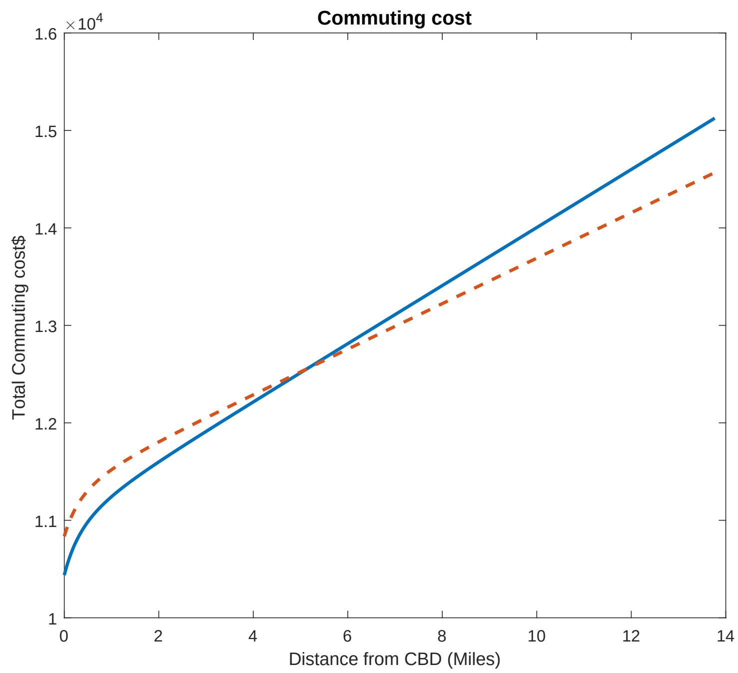
[16]This finding also implies a sensitivity of the model to other assumptions and parameters. Accordingly, we advise a qualitative interpretation of these findings rather than strict quantitative interpretations.

Table 4: Short-run vs long-run effects of EV tax credits

Scenario	[1]	[2]	[3]	[4]
Horizon	Short-run	Short-run	Long-run	Long-run
EV Purchase Tax Credit	No	Yes	No	Yes
Urban form adaptation	No	No	Yes	Yes
Simulation Output				
Fraction of Electric Vehicles	2.8%	9.5%	10.3%	62.7%
Urban form	Level	%Δ	%Δ	%Δ
Unit size (sqft)	1,631	0.0%	0.2%	1.1%
Lot size (acres, single-family)	0.249	-0.1%	4.4%	1.9%
House price per sqft	$11.81	0.0%	-0.4%	-1.5%
Land price per acre	$8,711	0.8%	-7.5%	-19.5%
City area	585	0.0%	5.7%	17.0%
City radius (assuming circle)	13.651	0.0%	2.8%	8.2%
FAR (residential, at CBD)	1.03	0.1%	-1.2%	-8.7%
Density (hh per sq. mi.)	1503.42	0.0%	-5.5%	-14.6%
Time to work (minutes)	23.2	0.0%	0.7%	3.6%
Energy consumption per household (million BTUs)				
Total	507.31	-0.2%	-0.2%	-2.4%
Housing Electricity	230.32	0.0%	0.0%	0.2%
Commuting Energy	29.01	-4.4%	-3.3%	-47.4%
Gasoline	28.81	-6.1%	-6.8%	-73.9%
Electricity (Δ)	0.21	230.7%	481.0%	3656.6%
Indirect Energy	247.97	0.1%	0.0%	0.5%
CO_2 emissions per household				
Total	25.10	-0.4%	-0.4%	-4.8%
Housing Electricity	11.00	0.0%	0.0%	0.2%
Commuting Energy	2.26	-5.1%	-4.6%	-57.6%
Gasoline	2.25	-6.1%	-6.8%	-73.9%
Electricity	0.01	230.7%	481.0%	3656.6%
Indirect Energy	11.84	0.1%	0.0%	0.5%
Social cost	$4,768	-0.4%	-0.4%	-4.8%
Utility per household	3,003	0.0%	0.1%	0.6%

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. The short-run model takes the urban form of the baseline as given and re-solves optimal prices and expenditures. The long-run model solved allowing producers to re-optimize structure provision. Approximate %Δ solution tolerance is +/- 0.1%.

Figure 6: Annual pecuniary commuting costs for gasoline versus electric vehicles



Notes: This figure presents total commuting costs for households in the long-run full-subsidy model solution. The dotted line is for EVs and the solid line is for gasoline vehicles. The cross-point at 5 miles implies the optimal fuel choice switches from gasoline to electric. Past this cross-point 5 miles, EVs are cheaper than gasoline-powered cars.

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 an 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 long-run solutions, 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 Figure 3). 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 619 square miles and time-to-work is 23.3 minutes.[18] When the climate is more moderate such as in the marine climate, the city is larger at 627 square miles, and when the climate is more extreme, such as the cold climate, the city is smaller at 612 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 12% more energy and are responsible for 11% higher emissions before even considering EV tax credits.

Climate interacts 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 2.1% versus 1.9% and 4.4% versus 3.9%.

[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: Long-Run tax credit effects in different climates

	Marine Climate		Hot Climate		Mixed Climate		Cold Climate	
Climate								
IECC zone	3C		1A/2A		4A		6A/7A	
Cooling degree days	498		927		1404		7038	
Heating degree days	2114		3690		3824		610	
	No Credit	EV Credit	No Credit	EV Credit	No Credit	EV Credit	No Credit	EV Credit
Simulation Output	Level	Level	Level	Level	Level	Level	Level	Level
Fraction of Electric Vehicles	10.8%	63.1%	10.4%	62.8%	10.3%	62.7%	9.9%	62.5%
Urban form	Level	%Δ	Level	%Δ	Level	%Δ	Level	%Δ
City area	627	10.6%	622	10.7%	619	10.7%	612	11.4%
Time to work	23.4	2.9%	23.4	2.9%	23.3	2.9%	23.3	2.9%
Energy consumption per household (million BTUs)								
Total	469.35	-2.1%	493.86	-2.0%	505.34	-2.0%	524.51	-1.9%
Housing Electricity	192.86	0.2%	218.43	0.2%	230.39	0.2%	250.36	0.2%
Commuting Energy	26.77	-43.0%	26.78	-43.0%	26.78	-43.0%	26.80	-43.1%
Indirect Energy	249.73	0.4%	248.66	0.4%	248.17	0.4%	247.35	0.4%
CO_2 emissions per household								
Total	23.17	-4.4%	24.34	-4.1%	24.89	-4.1%	25.81	-3.9%
Housing Electricity	9.21	0.2%	10.43	0.2%	11.00	0.2%	11.95	0.2%
Commuting Energy	2.03	-53.1%	2.04	-53.1%	2.04	-53.1%	2.04	-53.1%
Indirect Energy	11.92	0.4%	11.87	0.4%	11.85	0.4%	11.81	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. 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. %Δ is calculated relative to long-run model with no EV subsidy in the particular climate zone. Approximate %Δ solution tolerance is +/- 0.1%.

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 emissions. Electricity production input type is not internal to the model, but we can layer on emissions coefficients from alternative input mixes and trace effects through the model.[20]

Table 6 shows CO_2 emissions under alternative electricity generation input sources. The

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

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 11.0 tons from housing electricity, 2.0 tons from commuting, and 11.9 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 10.0% versus 1.5% for the dirty mix. But in terms of raw emissions reductions, the figures are much closer, at 1.21 tons of CO_2 per household under clean energy generation and 0.68 tons per household under dirty energy generation. Still, EV tax credits are far more effective if electricity generation is cleaner.

Carbon emissions calculations give us the opportunity to conduct a rudimentary cost-benefit analysis of EV tax credits. From the outset, we wish to be clear that benefits are only calculated considering reduced CO_2 emissions by households, and costs are only calculated considering the direct cost to taxpayers of the EV credits provided. 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.[21]

[21] Prior research has examined Pigouvian carbon taxes in urban systems, including Borck and Brueckner (2018).

Table 6: Long-run emissions, alternative electricity production input mixes

	Clean Electricity		Mixed Electricity		Dirty Electricity	
	No Credit	EV Credit	No Credit	EV Credit	No Credit	EV Credit
Simulation Output	Level	%Δ	Level	%Δ	Level	%Δ
CO_2 emissions per household (tons)						
Total	12.09	-10.0%	24.89	-4.1%	45.56	-1.5%
Housing Electricity	4.86	0.2%	11.00	0.2%	20.92	0.2%
Commuting Energy	1.99	-62.4%	2.04	-53.1%	2.11	-38.9%
Indirect Energy	5.24	0.4%	11.85	0.4%	22.53	0.4%
Break-even social-cost of carbon		\$194		\$233		\$345

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.

When multiplying the average flow-subsidy of \$375 per year by the 62.7% share of drivers with EVs, we get a cost of EV credits of about \$235 per year per household. Dividing this dollar amount by the change in CO_2 emissions gives the break-even social cost of CO_2. For clean electricity, this social cost break-even value is \$194, meaning if the social cost of CO_2 were \$194 per ton, then the EV tax credit would provide emissions reductions exactly equal to the taxpayer cost of the subsidy. For mixed electricity, the implied break-even social cost is \$233 per year, and for dirty electricity, the value is \$345 per year.

These results have two primary implications. The first is that the benefits of EV adoption in terms of CO_2 reductions hinge on the input mix for electricity generation. If paired with a greening of the energy mix, EVs tax credits become more cost-effective. The second is that the break-even social cost of carbon is quite moderate and within the range of current estimates, despite the highly localized nature of the benefits focusing only on CO_2 and only on the household sector. Current U.S. EPA estimates of the social cost of carbon range between \$120 and \$340 per ton, depending on the discount rate used (U.S. Environmental Protection Agency, 2022). This implies EV tax credits in the Inflation Reduction Act are well within the range of cost-effectiveness except in regions that specialize in coal-fired power plants. On the other hand, movements towards home-based solar and a greening of the electricity input mix make EV tax credits increasingly cost-effective.

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 greenbelt increases the effectiveness of the EV credit in incentivizing EV adoption. This is because the purpose of greenbelts is to limit commuting distance, and EV adoption is positively linked to commuting distance. This makes EV adoption rare in a greenbelt city absent tax credits, with the model solution giving less than 1% market share. However, once EV credits are introduced, the EV share rises to 57%, which is lower than the laissez faire solution but a larger increase. Overall, the end results is a larger change in energy consumption of -2.2% and -4.4% carbon emissions compared to the laissez faire case.

Height limits cause sprawl and so do EVs; the city with both is the largest among the various settings considered, with a city area post-subsidy of 648 square miles. Overall, the city has a higher EV market both with and without tax credits of 12.6% and 65.8%, respectively. The reduction in energy consumption and CO_2 emissions is similar to laissez faire at -2.0% and -4.1%, 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.

Table 7: Interactions with land use regulation

	Laissez Faire		Greenbelt		Height Limit	
	No Credit	EV Credit	No Credit	EV Credit	No Credit	EV Credit
Simulation Output	Level	Level	Level	Level	Level	Level
Fraction of Electric Vehicles	10.3%	62.7%	0.4%	57.1%	12.6%	65.8%
Urban form	Level	%Δ	Level	%Δ	Level	%Δ
City area	619	10.7%	452	0.0%	648	8.4%
Time to work	23.3	2.9%	22.6	1.2%	24.0	1.9%
Energy consumption per household (million BTUs)						
Total	505.34	-2.0%	507.05	-2.2%	505.01	-2.0%
Housing Electricity	230.39	0.2%	230.05	0.1%	230.42	0.2%
Commuting Energy	26.78	-43.0%	28.09	-46.8%	27.40	-44.3%
Indirect Energy	248.17	0.4%	248.91	0.8%	247.18	0.6%
CO_2 emissions per household						
Total	24.89	-4.1%	25.06	-4.4%	24.88	-4.2%
Housing Electricity	11.00	0.2%	10.99	0.1%	11.00	0.2%
Commuting Energy	2.04	-53.1%	2.19	-55.4%	2.07	-54.5%
Indirect Energy	11.85	0.4%	11.89	0.8%	11.80	0.6%

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 millieu in which the EV credit exists.

The first policy considered 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. Table 8 shows that under a driver tax, utility falls slightly.

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 \$206 per driver at a cost of \$234 and a fraction of a percent utility loss. So, while private costs are small, the social costs roughly offset the loss.

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 utility gains and 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 numeraire good consumption. Revenue cycling results in an increase in utility of 7.1%. When EV credits are layered onto the carbon tax, emissions fall further and utility increases further. In terms of costs and benefits, however, a carbon tax renders EV tax credits cost ineffective. 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 (54% vs 63%).

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 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, utility increases and CO_2 changes are similar to the lassez-faire city: utility rises by about 0.5%, emissions fall by about 3.9%, and the city area expands by about 11%. Thus, we conclude that effects of EVs are largely invariant with respect to congestion taxes.

Table 8: Long-run effects of EV credits under alternative tax regimes

Funding of EV credits	External		Driving Tax	External		External	
Additional Tax Regime	None		None	Carbon Tax		Congestion Tax	
EV purchase credit	No	Yes	Yes	No	Yes	No	Yes
Simulation Output	Level	Level	Level	Level	Level	Level	Level
Fraction of Electric Vehicles	10.3%	62.7%	62.5%	54.0%	89.1%	9.7%	61.7%
Urban form	Level	%Δ	%Δ	Level	%Δ	Level	%Δ
City area	619	10.7%	10.0%	11.7%	4.5%	-1.3%	11.3%
Time to work	23.3	2.9%	2.7%	2.3%	1.9%	-0.7%	2.9%
Energy consumption per household (million BTUs)							
Total	505.34	-2.0%	-2.3%	-28.3%	-1.5%	4.0%	-1.9%
Housing Electricity	230.39	0.2%	0.0%	-66.0%	0.2%	0.4%	0.2%
Commuting Energy	26.78	-43.0%	-43.0%	-37.2%	-34.2%	-0.5%	-42.8%
Indirect Energy	248.17	0.4%	-0.1%	7.6%	0.1%	7.8%	0.4%
CO_2 emissions per household							
Total	24.89	-4.1%	-4.4%	-29.3%	-2.9%	3.9%	-3.9%
Housing Electricity	11.00	0.2%	0.0%	-66.0%	0.2%	0.4%	0.2%
Commuting Energy	2.04	-53.1%	-53.0%	-46.0%	-47.5%	-0.4%	-52.8%
Indirect Energy	11.85	0.4%	-0.1%	7.6%	0.1%	7.8%	0.4%
Welfare Measures							
Utility	3005.32	0.5%	-0.1%	7.1%	0.7%	-0.22%	0.5%
Per-capita benefit of CO_2 reduction (Δ)		192	206		96		190
Per-capita cost of CO_2 reduction (Δ)		235	234		334		231

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 Discussion and Conclusion

The strength of the model in this paper is to highlight the intersection between urban and energy economics present in automotive transportation policies, including EV tax credits. The solutions to the model are meant to be illustrative. While the model solutions do provide precise values, these "simulated" cities do not and will not exist, as they are based on calibrations of cities that are subject to path dependence, partial adjustment processes, and young technologies, and are solved based on full long-run adjustment of urban form and vehicle choices which in reality, would take decades. Despite these shortcomings, this model offers several key qualitative insights which may be of use to economists and policymakers.

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. But in general, modeling energy consumption in an urban equilibrium framework is surely a useful endeavor for future economics and policy research.

References

AAA (2022). Your Driving Costs. Technical report, American Automobile Association.

Agrawal, D. R. and Zhao, W. (2023). Taxing uber. *Journal of Public Economics*, 221:104862.

Ahlfeldt, G. M., Redding, S. J., Sturm, D. M., and Wolf, N. (2015). The economics of density: Evidence from the berlin wall. *Econometrica*, 83(6):2127–2189.

Albouy, D., Ehrlich, G., and Liu, Y. (2016). Housing demand, cost-of-living inequality, and the affordability crisis. Technical report, National Bureau of Economic Research.

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.

AP-NORC Center for Public Affairs Research (2023). Americans' views on climate, energy policy and electric vehicles. https://apnorc.org/projects/americans-views-on-climate-energy-policy-and-electric-vehicles/.

Archsmith, J., Muehlegger, E., and Rapson, D. S. (2022). Future paths of electric vehicle adoption in the united states: predictable determinants, obstacles, and opportunities. *Environmental and Energy Policy and the Economy*, 3(1):71–110.

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.

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

Borck, R. and Brueckner, J. K. (2018). Optimal energy taxation in cities. *Journal of the association of environmental and resource economists*, 5(2):481–516.

Borenstein, S. and Bushnell, J. B. (2022). Headwinds and tailwinds: Implications of inefficient retail energy pricing for energy substitution. *Environmental and energy policy and the economy*, 3(1):37–70.

Brueckner, J. K. (1987). The structure of urban equilibria: A unified treatment of the Muth - Mills model. *Handbook of regional and urban economics*, 2:821 – 845.

Brueckner, J. K. and Selod, H. (2006). The political economy of urban transport-system choice. *Journal of Public Economics*, 90(6-7):983–1005.

Canis, B., Clark, C. E., and Sherlock, M. F. (2019). Vehicle electrification: Federal and state issues affecting deployment. *Congressional Research Service Report*, 45747.

Chetty, R., Friedman, J. N., and Rockoff, J. E. (2014). Measuring the impacts of teachers i: Evaluating bias in teacher value-added estimates. *American economic review*, 104(9):2593–2632.

Congressional Budget Office (2022). Emissions of Carbon Dioxide in the Transportation Sector — Congressional Budget Office. https://www.cbo.gov/publication/58861.

Davis, M. A., Larson, W. D., Oliner, S. D., and Shui, J. (2021). The price of residential land for counties, ZIP codes, and census tracts in the United States. *Journal of Monetary Economics*, 118:413–431.

Delventhal, M. J., Kwon, E., and Parkhomenko, A. (2022). Jue insight: How do cities change when we work from home? *Journal of Urban Economics*, 127:103331.

Egbue, O. and Long, S. (2012). Barriers to widespread adoption of electric vehicles: An analysis of consumer attitudes and perceptions. *Energy policy*, 48:717–729.

Energy Information Administration (2022a). Frequently Asked Questions (FAQs) - U.S. Energy Information Administration (EIA). https://www.eia.gov/tools/faqs/faq.php.

Energy Information Administration (2022b). Use of energy for transportation - U.S. Energy Information Administration (EIA). https://www.eia.gov/energyexplained/use-of-energy/transportation.php.

Gillingham, K. T., van Benthem, A. A., Weber, S., Saafi, M. A., and He, X. (2023). Has Consumer Acceptance of Electric Vehicles Been Increasing? Evidence from Microdata on Every New Vehicle Sale in the United States. In *AEA Papers and Proceedings*, volume 113, pages 329–335. American Economic Association 2014 Broadway, Suite 305, Nashville, TN 37203.

Gyourko, J., Hartley, J. S., and Krimmel, J. (2021). The local residential land use regulatory environment across us housing markets: Evidence from a new wharton index. *Journal of Urban Economics*, 124:103337.

Huang, R. and Kahn, M. E. (2023). Household carbon dioxide emissions engel curve dynamics. *National Bureau of Economic Research*.

Idaho National Laboratory (2010). Comparing energy costs per mile for electric and gasoline-fueled vehicles. Technical report, Idaho National Laboratory, INL/MIS-11-22490.

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 Yezer, A. (2015). The energy implications of city size and density. *Journal of Urban Economics*, 90:35 – 49.

Larson, W. and Zhao, W. (2017). Telework: Urban form, energy consumption, and greenhouse gas implications. *Economic Inquiry*, 55(2):714–735.

Larson, W. and Zhao, W. (2020). Self-driving cars and the city: Effects on sprawl, energy consumption, and housing affordability. *Regional Science and Urban Economics*, 81:103484.

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.

O'Dell, J. (2022). Making The EV Transition: Understanding Kilowatts. https://www.forbes.com/wheels/advice/ev-charging-kilowatts/.

Proque, A. L., dos Santos, G. F., Junior, A. A. B., and Larson, W. D. (2020). Effects of land use and transportation policies on the spatial distribution of urban energy consumption in Brazil. *Energy Economics*, 90:104864.

Rapson, D. S. and Muehlegger, E. (2021). The economics of electric vehicles. Technical report, National Bureau of Economic Research.

Rezvani, Z., Jansson, J., and Bodin, J. (2015). Advances in consumer electric vehicle adoption research: A review and research agenda. *Transportation research part D: transport and environment*, 34:122–136.

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

Sherlock, M. F. (2019). The plug-in electric vehicle tax credit. *Congressional Research Service - In Focus.*

Small, K. A. and Verhoef, E. T. (2007). *The economics of urban transportation.* Routledge.

US Department of Transportation (2003). From Home to Work, the Average Commute is 26.4 Minutes. https://www.nrc.gov/docs/ML1006/ML100621425.pdf.

U.S. Environmental Protection Agency (2022). Report on the social cost of greenhouse gases: Estimates incorporating recent scientific advances. Technical report.

US EPA, OAR. (2022). Assumptions and References for Household Carbon Footprint Calculator. https://www.epa.gov/ghgemissions/assumptions-and-references-household-carbon-footprint-calculator.

West, B. H., McGill, R. N., and Sluder, S. (1999). Development and verification of light-duty modal emissions and fuel consumption values for traffic models. Technical report, U.S. Department of Transportation, Federal Highway Administration, Report FHWA-RD-99-068.