HOUSEHOLDS' SHORT-RUN HETEROGENEOUS USE OF ELECTRIC VEHICLES: IMPLICATIONS FOR PUBLIC POLICY

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1. Introduction

A long-standing component of environmental policy has attempted to reduce automobile pollutants by a combination of taxes to encourage households to drive less and subsidies to encourage them to use alternative modes that have smaller environmental footprints. Because electric vehicles generally produce far fewer pollutants than vehicles with internal combustion engines (ICEs) produce and because policymakers believe it is imperative to slow climate change, they have expanded environmental policy to include subsidies to encourage households to adopt electric vehicles.[1] The Inflation Reduction Act of 2022 provides new opportunities for savings on buying an EV by extending the current $7,500 tax credit for a new vehicle and by providing a $4,000 tax credit for a used EV. It also eliminates the current cap that cuts automakers off tax credits after they have sold 200,000 EVs, and it is written so buyers can get an immediate discount at the dealership, instead of waiting weeks or months for their tax credit to come through.[2]

Consumers' interest in EVs has grown significantly as the share of new car sales in the United States that are EVs has increased from roughly 2% in 2020 to more than 10% in 2023. Surveys indicate that 36% of Americans are considering an EV as their next vehicle purchase with 25% saying that their next vehicle purchase *will* be an EV.[3]

Given the majority of US households own multiple vehicles, a fundamental behavioral question is how those households will integrate their use of EVs with their use of ICE vehicles. For example, if households use their EVs more than they use their ICE vehicle(s), they will expedite the environmental benefits of EVs. Conversely, households could delay those benefits if they use their EVs infrequently.

From a policy perspective, households' adoption and use of EVs could affect the efficiency and distributional effects of the current policy of subsidizing the purchase of EVs. For example, Winston (2021) summarizes evidence that subsidies to encourage the purchase of fuel efficient vehicles and energy efficient appliances have been wasteful because they were provided to affluent households who would have purchased those durable goods without subsidies. Subsidies for EVs could suffer from the same inefficiency or could create inefficiencies by encouraging less affluent

[1] Electric vehicles' consumption of electricity for charging generates emissions, but an EV's carbon footprint is smaller than an ICE vehicle's carbon footprint because EVs have no tailpipe emissions.
[2] All purchasers of EVs with a manufacturer's suggested retail price (MSRP) less than $55,000 for passenger cars and less than $80,000 for vans, SUVs, and light trucks qualify for a tax credit regardless of household income.
[3] https://www.bloomberg.com/news/articles/2022-07-13/a-quarter-of-americans-say-their-next-car-will-be-an-ev?leadSource=uverify%20wall

households to purchase an EV when those household value EVs less than their unsubsidized price. Such inefficiencies motivate interest in a potentially more efficient policy to improve the environment by charging drivers a vehicle-miles-travelled (VMT) tax to reduce EVs and ICE vehicles' road mileage.

In what follows, we first document that households drive EVs less, on average, than they drive their ICE counterparts and that we can partially explain this mileage gap by differences in the vehicles' technologies. Previous work by Davis (2019) and Burlig et al. (2021) on households' substitution of EVs and ICE vehicles have obtained a similar finding.

We further the analysis of households' EV and ICE vehicle utilization by collecting a large, disaggregated panel of households in Texas, which includes their demographic information, vehicle portfolios composed of electric and ICE vehicles, and the exact annual miles households drive each vehicle based on the vehicles' odometer readings. The demographic data provide suggestive evidence that it is both vehicle technology and owners' characteristics that explains the mileage gap in EV and ICE driving. Further, the disaggregated data enable us to provide evidence on the causal impact of EV adoption on total household driving in the short run. A long-run analysis would account for households' joint choice and use of vehicles and would allow households to change their vehicle portfolio and use in response to demographic and macroeconomic changes and new vehicle offerings (Mannering and Winston, 1985).

To achieve plausible identification, we analyze EV adoption by applying a matching procedure where we include only households in the sample who have adopted an EV or a "similar" ICE vehicle in the same year and in the same metropolitan area and who share similar demographics and pre-purchase driving/vehicle choices.[4] We find that in the short run a households' adoption of an EV is associated with a reduction in both annual ICE mileage and gasoline consumption, and a slight change in the total mileage across all household vehicles. Gillingham, Spiller, and Talevi (2023a) report a similar finding based on data for Massachusetts households. Using our disaggregated data, we also document differences in household EV use according to education, age, and income levels. We find that among EV buyers, lower-income households reduce gasoline consumption more than higher-income households do by either substituting an EV for a less fuel-efficient vehicle in their portfolio or by using EVs for a greater

[4] Muehlegger and Rapson (2023) use a similar matching procedure to determine the alternative fuel efficient vehicle for households that purchase EVs

share of household driving.[5] We corroborate those findings with evidence from an instrumental variables regression approach that uses gasoline prices in the year that a new vehicle was purchased as an instrument for EV adoption.[6]

Our findings are important for two reasons. First, they imply that the environmental improvements from EV adoption may accrue more quickly than expected because lower-income households will comprise a greater share of new EV purchasers over time. Second, they raise the possibility that instead of imposing no income limit on households who are eligible for taxpayer funded EV subsidies, there may be an efficiency gain to targeting the subsides toward lower-income households because those subsidies would produce greater environmental benefits than would untargeted subsidies, and they would eliminate the welfare cost from subsidizing higher-income households who may have purchased EVs without any subsidies. In addition, targeting subsidies toward lower-income households would raise fewer distributional objections than would untargeted subsidies that enable affluent households to receive them.

Finally, our analysis differs from previous research on electric vehicles by showing that policymakers face an important policy choice.[7] Although economic theory indicates that to achieve a given reduction in emissions by increasing EV adoption, it is more efficient to charge motorists with homogeneous behavior a vehicle-miles-traveled (VMT) tax that includes an emissions externality component (Langer, Maheshri, and Winston (2017)) than to subsidize motorists, it is not clear that a VMT tax is more efficient than a subsidy if motorists have heterogenous behavior. We provide suggestive empirical evidence that a VMT tax on miles driven by motorists with heterogeneous behavior would be a more efficient policy than an untargeted or

[5] We define lower income households as those with an annual income below $50,000, the median annual income of U.S. households at the very beginning of our sample in 2011 (Bank, 2021). The median annual income of households who purchase EVs is likely to be considerably greater than $50,000. As noted, current EV subsidy policy does not have an income limit on households who are eligible for a subsidy.

[6] Because we control for gas and electricity prices in the period after a household purchases an EV, our instrument of gas prices in the year an EV is purchased influences post-purchase driving behavior only by increasing the likelihood of EV adoption.

[7] Previous research on electric vehicles has addressed various positive issues but has not used their empirical findings to clarify the choice facing policymakers that we clarify here. Recent studies, for example, have assessed the benefits of EVs (Davis, 2019, Burlig et al. 2021, Muehlegger and Rapson, 2022, and Langford and Gillingham, 2023); the effect of demographics on EV adoption (Gillingham et al. 2023b); and the importance of EV technology (Forsythe et al. 2023). Gillingham et al. 2023a discuss policy issues but they do not compare the efficiency and distributional effects of VMT taxes versus EV subsidies. Rubin et al. (2021) consider the impacts of altering income requirements for EV subsidies but do not consider heterogeneity in use across groups or efficiency comparisons to other transportation policies. Jacqz and Johnston (2023) do compare the distribution in local pollutants depending on a targeted versus a non-targeted EV subsidy.

targeted EV subsidy. This is partly due to the large benefits that would accrue from decreased congestion and vehicle accident costs from a large reduction in households' total vehicle miles driven in response to a VMT tax. However, we also provide evidence that a VMT tax would be less effective at expediting environmental improvements, as measured by a reduction in climate costs, especially when compared with targeted subsidies because lower-income households' driving comprises a disproportionately larger share of the environmental benefits from EV adoption.

We therefore clarify a choice facing policymakers of whether to implement the more efficient VMT tax, which received funding as part of the 2021 Infrastructure Investment and Jobs Act for nationwide testing, or to provide the more environmentally effective EV subsidies to a subset of consumers. Policymakers have indicated a preference to subsidize all consumers on the grounds that it is imperative to expedite the adoption of EVs to improve the environment as soon as possible to meet an existential threat to future generations. However, our findings suggest that by modifying the subsidies to target low-income households, policymakers may increase the benefits that they prioritize and may produce a larger improvement in welfare than they would produce with untargeted subsidies.

2. Sample, Data Sources, and the Endogeneity of EV Adoption

We conduct our analysis by collecting a comprehensive data set of Texas households.[8] For the period covering 2013 to 2018, we obtained from AIB, Incorporated a sample of households living in the seventeen counties that comprise the Houston-Galveston-Brazoria, Dallas-Fort Worth, Austin, and El Paso areas. The sample included the make, model, vintage, and trim of the automobiles the households owned, including ICE and electric vehicles. We supplemented this information with the manufacturer suggested retail price (MSRP) for each vehicle, the electric vehicle characteristics of range, driving costs, and charging time from the Environmental Protection Agency (EPA), and energy prices for the households' vehicles. Gasoline prices at the city level are from *Gas Buddy* from 2013 to 2018[9] and electricity prices are from the Open Data

[8] Gillingham, Spiller, and Talevi (2023a) construct a detailed data set of Massachusetts households to assess the heterogeneous electric vehicle rebound effect. However, they do not address heterogeneous motorists' use of EVs and public policy tradeoffs, which we address here.
[9] https://www.gasbuddy.com/

Energy Initiative at the residential zip code level for the Texas households in our sample.[10] Residential electricity prices are appropriate because the majority of EV owners charge their vehicles at home.[11]

We used the Vehicle Identification Numbers (VINs) of the vehicles to obtain each vehicle's annual vehicle miles traveled (VMT) from the Texas Commission on Environmental Quality, which we computed from the difference in odometer readings between annual safety checks. Finally, because our sample included the households' addresses, we obtained a 2019 snapshot of their socioeconomic characteristics, such as income, number of family members, and other information from Acxiom.

A simple descriptive analysis of the data helps to identify certain sources of the endogeneity of EV adoption, which motivate the methodological approach we take in the next section to control for those sources. Table 1 presents means and standard deviations of the demographic characteristics of the households in our sample that reveal differences between households whose vehicle portfolios include only ICE vehicles, column (1), and households who eventually purchase an EV, column (2). Note the summary statistics in column (2) are from the year or years before the household purchases an EV; for example, if a household purchases an EV in 2018, then the household's average driving characteristics are for the years 2013 through 2017. Roughly 8% of the households in our sample eventually purchase an EV by the end of 2018.

Column (3) shows that households who eventually purchase an EV during our sample period have greater incomes, which exceed the U.S. median income, are more likely to own a home and have a college education, and are more likely to be white than are households who never purchase an EV during our sample period. The differences in demographic characteristics are consistent with the findings using zip-code sociographic information (Muehlegger and Rapson, 2022) and with using restricted public-use micro data (Borenstein and Davis, 2016). The table also shows that households who eventually purchase an EV drive roughly 13% fewer miles annually and are more likely to own a truck, which is less fuel-efficient than a car, compared with households who never purchase an EV. In sum, households who eventually purchase an EV differ from households who never purchase an EV both in their demographics and driving behavior.

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[10] https://data.openei.org/
[11] file:///C:/Users/cwinston/Downloads/2016_UCD-ITS-RP-16-05.pdf

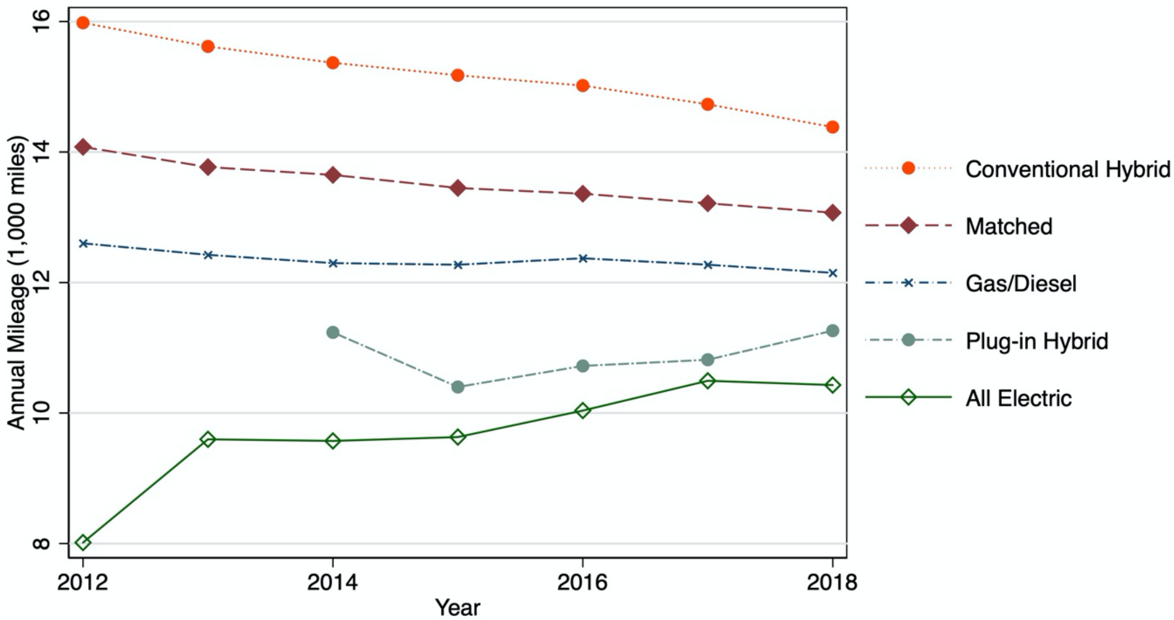
Table 1: Summary Statistics All Households

	(1) No EV Mean/S.D.	(2) EV Mean/S.D.	(3) Difference Diff./(S.E)
# Adults	2.25	2.28	-0.03*
	1.23	1.22	0.01
White	0.61	0.72	-0.11***
	0.49	0.45	0.01
Age	52.44	51.89	0.56***
	13.85	12.49	0.17
# People	2.90	3.00	-0.10***
	1.65	1.68	0.02
Income	78241.00	104895.54	-26654***
	48800.33	44531.78	585.80
Home Ownership	0.80	0.87	-0.07***
	0.40	0.34	0.00
College	0.40	0.63	-0.23***
	0.49	0.48	0.01
# Trucks	0.05	0.16	-0.11***
	0.28	0.35	0.00
Miles Driven	22,422.55	19,604.22	2818.33***
	12642.63	11295.88	151.74
# Vehicles	1.87	1.83	0.04***
	0.93	0.83	0.01
Avg MPG	26.00	23.64	2.36
	642.78	18.02	7.69
Observations	836,746	6,988	

Notes: This table shows summary stats for the households we observe complete demographic data for. Column (1) is households that are only observed with ICE vehicles. Column (2) displays the summary statistics for the households that are observed with a BEV vehicle. Finally, column (3) displays differences in the values between the two groups. # Trucks, # Vehicles, Miles Driven, and Avg. MPG are averages taken across all years the household is observed pre purchase. Time period is 2013 – 2019.

The preceding differences among households appear to be reflected in their use of an EV when they adopt one because figure 1 shows that Texas households use EVs less, based on annual mileage, than they use vehicles with other technologies, including ICE vehicles and hybrids. This finding is not specific to Texas households as Davis (2019) obtains a similar finding based on the National Household Travel Survey.

Figure 1. Annual Miles Driven By Vehicle Model Year And Type



Notes: This figure displays the average annual number of miles driven by vehicle type and model year. Data is based on 69,041,488 annual Texas vehicle odometer readings from 2011 to 2019.

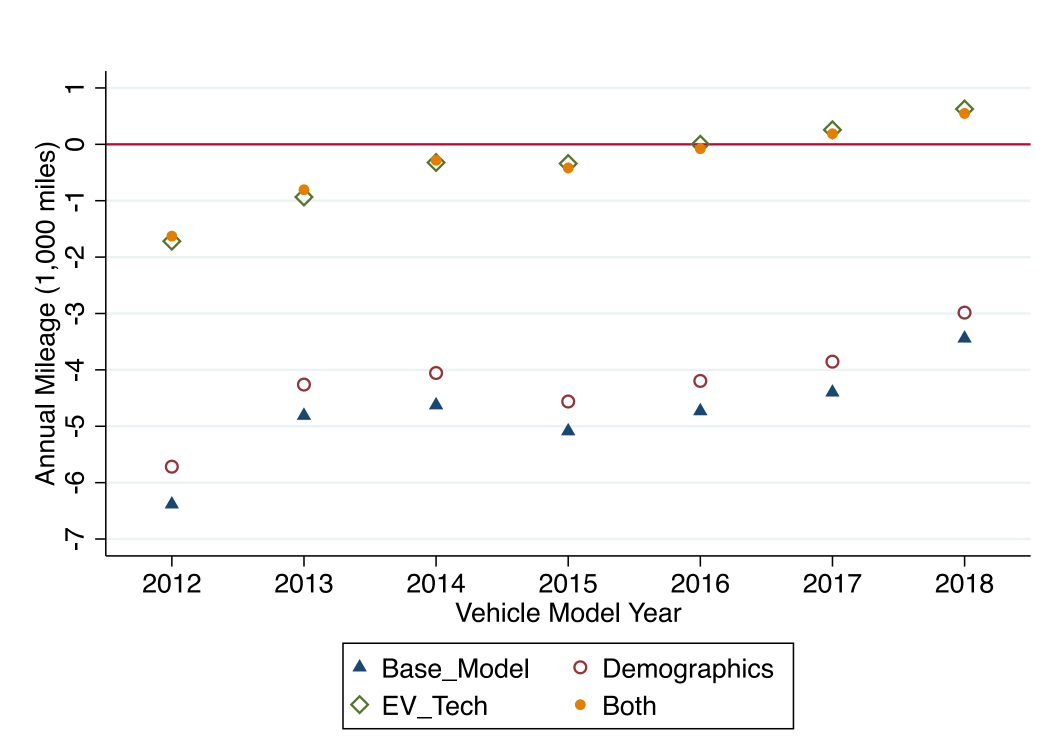
The sources of the so-called mileage gap are important to understand because they are likely to be related to households' choices of whether to adopt an EV and after their EV purchases, how they allocate miles driven in the EV and ICE vehicles in their vehicle portfolios. We therefore assess the potential influences on the mileage gap by introducing them separately in a specification of vehicle miles driven. Equation (1) includes vehicle type and other controls.

$$MilesDriven_{i,t} = \beta_0 + \gamma_m + \omega_y + \sum_{y=2012}^{2018} \alpha_y \cdot 1\{IsEV_i\} \cdot 1\{ModelYear_i = y\} + \varepsilon_{i,t}, \qquad (1)$$

where the dependent variable is the miles vehicle i was driven in year t, γ_m is the vehicle make fixed effect, and ω_y is the model year of the vehicle fixed effect. The gap in EV utilization is measured by the interactions between vehicle model-year α_y and whether vehicle i is an EV. Based on the parameter estimates, figure 2 confirms the existence of the EV mileage gap, which fluctuates during our sample period.

Figure 2 also shows that the mileage gap notably shrinks by at least two-thirds when we account for EV technology by adding interactions between whether the vehicle is an EV and charging cost, charging time, and range. As the figure shows, the mileage gap shrinks further when

Figure 2: Determinants of the EV Mileage Gap



Notes: This figure displays the coefficient value and standard error bars for the BEV model year indicator variables. We display four sets of interactions, those based on: (i) a base regression predicting annual mileage on model year and make fixed effects; (ii) a demographics model that adds household demographic and location characteristics; (iii) a technology model that incorporates BEV characteristics as additional covariates; and (iv) a model that includes both demographic and technology characteristics. Data is based on 4,425,616 annual vehicle miles traveled observations for the 843,734 households discussed in table 1.

we include the full vector of household characteristics presented in table 1 as well as the city year fixed effects in the miles driven model.

The implication of this exercise is that one must control for households' demographics as well as vehicle technology to accurately identify the causal impact of EV adoption on households' driving behavior. The failure to do so could cause the estimated environmental benefits of EVs to be biased. Recall, we found that households who purchase EVs generally drive less than non-EV households, so a research design that fails to account for demographic differences among households would erroneously attribute a decrease in driving, and the associated environmental benefits, to the adoption of an EV. At the same time, households who adopt an EV prefer to own relatively fuel-efficient ICE vehicles, which could reduce the incremental environmental benefits from EV adoption.

In appendix table A1, we estimate a simple OLS regression of gasoline consumption on EV adoption to show the bias from failing to account for the sources of endogenous EV adoption. Those sources lead to greater adoption by households who tend to drive relatively fewer annual miles in relatively fuel-efficient vehicles. We find that failing to control for the relatively smaller automobile environmental footprint of these households leads to an implausibly large reduction in gasoline consumption from EV adoption and to an upward bias in the environmental benefits. We therefore propose a matching procedure to eliminate the bias and to identify the effect of EV adoption on the factors affecting environmental quality.

3. Matching Procedure

To estimate the impact of EV ownership on household driving behavior, we would ideally assign the treatment variable (EV ownership) randomly to observationally equivalent households, with the control households using only ICE vehicles during the sample period. However, it is clear from the preceding discussion that EV ownership is not random.

The estimation strategy we employ to address this concern is to define a set of counterfactual ICE vehicles; that is, vehicles that are equivalent to EVs. We then match the non-EV purchasers in our sample according to whether they purchased a vehicle from this set with the EV purchasers in our sample who purchased the equivalent EV, lived in the same metropolitan area when they made the purchase, and had similar pre-purchase characteristics.

Table 2 lists the EVs in our data from 2013-2018 and the equivalently matched ICE vehicles, which were determined from a survey in Holland et al. (2016). The survey solicitated consumers' alternative ICE choices if their preferred EVs were not available. Note many of the matches are the electric version of an ICE vehicle, such as the Chevrolet Spark EV and Chevrolet Spark. For EV models not listed in that survey, we formed matches based on a model’s brand, suggested retail price (MSRP), and vehicle size so that the matches were consistent with the logic of the survey.

Following the notation of the matching literature (Heckman et al. 1997; Dehejia and Wahba, 1999; Abadie and Imbens, 2006), we consider the set of characteristics, X_i, for household i that purchases an EV. The control household j is the mth closest match to household i if it solves:

$$\sum_{l \in L} 1\{\| X_l - X_i \| \leq \| X_j - X_i \|\} = m \qquad (2)$$

where L is the set of individual households l from the same metropolitan area that purchased the matched equivalent ICE vehicle during the same year household i purchased its EV; $1\{\cdot\}$ is an indicator equal to 1 if and only if the expression in brackets is true for all potential matches from the set L; and household j is the closest household in terms of pre-purchase characteristics, including household income, number of vehicles, total driving, number of trucks, number of adults, number of people, as well as the head of household's education level, age, and race.

Table 2: Sample EVs and their Matched Counterparts

EV	Matched Counterparts
Tesla Model S	Mercedes-Benz 550/BMW 740I/750I
Nissan Leaf	Toyota Prius-501.8
Tesla Model X	BMW X5
BMW I3	AUDI A4
Fiat 500e	Fiat 500
Mitsubishi MIEV	Chevrolet Spark
Ford Focus Electric	Ford Focus
Smart Fortwo Electric Drive	Smart Fortwo
Chevrolet Spark EV	Chevrolet Spark
Chevrolet Bolt	Chevrolet Cruze
Mercedes-Benz B-Class	Mercedes-Benz C-CLASS
Volkswagen E-Golf	Volkswagen Golf
Tesla Model 3	BMW 320I
Toyota Rav4 (EV)	Toyota Rav4

Notes: This table lists the BEVs in our data from 2013 – 2018 along with the equivalent matched ICE vehicle. Order of vehicle is based on number of observations we get at least one year of driving mileage.

Distance is measured according to the Mahalanobis distance metric, which accounts for differences in the scale of each variable. The matching criterion yields a control group of 2,150 households for 3,434 EV purchasers with some control households determined as the closest match for multiple EV households. Some EV purchasers in our sample are not included because they did not have an alternative ICE vehicle in their metropolitan area during the purchase year and because they did not own an EV long enough for us to measure their annual VMT.

Table 3 shows the matching procedure was successful because the difference between the summary statistics of the two matched groups of households is much closer than the difference between the households' summary statistics in table 1. With the exception of household size, the

Table 3: Matched Summary Statistics

	(1) No EV Mean	(2) EV Mean	(3) Difference Diff/(S.E.)
# Adults	2.27	2.35	0.08**
			(0.035)
White	0.73	0.73	-0.006
			(0.015)
Age	52.94	52.56	-0.38
			(0.366)
# People	2.95	3.10	0.15***
			(0.048)
Income	110356.73	109282.18	-1074.54
			(1391.06)
Home Ownership	0.88	0.87	-0.008
			(0.011)
College	0.68	0.67	-0.013
			(0.014)
# Trucks	0.12	0.17	0.049***
			(0.002)
Miles Driven	20355.94	21752.22	1396.28*
			(653.70)
# Vehicles	1.81	1.95	0.13***
			(0.042)
Avg MPG	25.24	25.01	-0.226
			(0.77)
Observations	2150	3434	

Notes: This table shows summary stats for the households we observe purchase a BEV that also have a comparable ICE purchase matching household. Column (1) is households that are only observed with ICE vehicles and purchase a comparable ICE vehicle to a BEV household in the same metro area and year. Column (2) displays the summary statistics for the households that are observed with a BEV vehicle and with a suitable ICE match. Finally, column (3) displays differences in the values between the two groups. # Trucks, # Vehicles, Miles Driven, and Avg. MPG are averages taken across all years the household is observed pre purchase. Standard errors for the difference in household demographic characteristics in column 3 are robust heteroskedastic consistent.

differences in household demographics are no longer statistically indistinguishable from zero. Importantly, if households own an EV, their annual mileage is *higher* than the annual mileage of households who do not own an EV, indicating an EV mileage *surplus* not a gap.

We use the matched sample of households and the following specification to estimate the average treatment effect for a treated household i on outcomes Y_i:

$$Y_i = \alpha_0 + \alpha_1 \cdot 1\{EV_i\} + \varepsilon_i \tag{3}$$

where the two primary household outcomes we consider for our analysis are total annual ICE miles driven and gallons of gas consumed two years after the new EV vehicle purchase. We later conduct sensitivity analysis of the findings where we measure ICE miles driven and gallons of gas consumed one year after the new EV vehicle purchase. The estimated parameter $\widehat{\alpha_1} = \frac{1}{N_1}\sum_{i:EV=1}\{Y_i - \widehat{Y_i}(0)\}$, where $\widehat{Y_i}(0)$ is the weighted average outcome of the matched control group; and ε_i is an idiosyncratic household-level shock. We cluster our standard errors at the household level, consistent with the level of treatment assignment.

Tables A2 and A3 in the appendix provide summary statistics and estimates under alternative matching criteria, with some of the alternative control groups displaying no statistically significant differences in pre-purchase driving behavior or in vehicle portfolios compared with EV-owning households. Additionally, we provide a full set of analysis for all outcomes considered only one year after the new vehicle purchase. None of those alternative approaches yielded estimates that differed qualitatively from the primary matched results presented below.

4. Matching Estimation Results

We present the OLS matching estimation results in table 4 with the effect of EV adoption on gasoline consumption in panel A and its effect on ICE miles in panel B. The parameter estimates for the basic specification in equation (3), which does not include any interactions between household demographic characteristics and EV adoption, are in column (1). The estimates in columns (2) through (5) incrementally include various interactions. Our central finding is that EV adoption reduces both gasoline consumption and ICE miles driven, and the effects are large and statistically significant. For example, the estimated coefficient in column (1) of panel A indicates that EV adoption is associated with a 49% reduction in total household gasoline consumption or a reduction equal to 95% of the average gasoline consumption per vehicle, relative to the pre-purchase averages for these households. Given that EV adopters drove an average of 11,155 miles in an ICE vehicle prior to EV adoption, the estimated coefficient in column (1) of panel B indicates that EV mileage reduces per vehicle ICE mileage by 99% to 104%, or roughly 53% of pre-purchase average total household ICE mileage.

We also find statistically significant heterogeneity in the effect of EV adoption, especially by household income level. The estimates in columns (2) and (5) of panels A and B indicate that for lower-income households, the reduction in gasoline consumption is 20% to 24% larger and the reduction in total miles driven is more than 10% larger. The estimates in column (5) of panels A and B indicate larger reductions in gasoline consumption and total miles driven when the head of

Table 4: Matching Estimation Results

	(1) b/se	(2) b/se	(3) b/se	(4) b/se	(5) b/se
Panel A: Gallons Consumed					
BEV	-427.258***	-417.283***	-400.115***	-405.300***	-378.494***
	(21.586)	(21.972)	(47.901)	(27.419)	(48.904)
BEVxLowInc		-84.791**			-92.526***
		(33.487)			(33.780)
BEVxAge			-0.516		-0.227
			(0.839)		(0.881)
BEVxCollege				-34.479	-40.746*
				(23.946)	(24.702)
R-squared	0.089	0.090	0.089	0.090	0.091
Panel B: Combustion Miles					
BEV	-11,610.599***	-11,451.122***	-11,577.273***	-11,055.923***	-11,157.471***
	(438.012)	(446.848)	(1,031.998)	(570.124)	(1,054.265)
BEVxLowInc		-1,355.555*			-1,537.377**
		(705.357)			(712.217)
BEVxAge			-0.634		7.437
			(18.424)		(19.502)
BEVxCollege				-870.945*	-1,041.267*
				(511.698)	(543.269)
R-squared	0.141	0.141	0.141	0.141	0.142
Observations	6,868	6,868	6,868	6,868	6,868

Notes: This table reports estimates of the impact of EV ownership on household driving outcomes for the first two years of EV ownership. Estimates are obtained using the Abadie et al. (2004) matching estimator with the Mahalanobis distance metric to select a control household (also bought a new vehicle) for each treated (bought an EV) household. All specifications match exactly on the year of purchase, metro area, and class of new vehicle. We also match on total household miles driven in the year prior to purchase, the number of trucks owned by the household in the year prior to purchase, and the total number of vehicles owned by the household in the year prior to purchase. Finally, we also match on the demographic characteristics of head of household (HoH) age, HoH education, household income, number of adults, total household size, whether the head of household is white, and whether the household owns their home. Time period considered is 2013 - 2019 *** indicates significance at the 1% level, ** at the 5% level, and * at the 10% level. Heteroskedastic consistent standard errors.

a household that adopts an EV has a college education, which in all likelihood reflects a greater concern with climate change compared with those who have less formal education (Lee et al. 2015).

We have found evidence that the adoption of EVs may produce environmental benefits by reducing households' fuel consumption and miles driven in ICE vehicles. We explore the mechanism underlying those findings by estimating the effect of EV adoption on households' total miles driven, the average fuel economy of their ICE vehicles, and the total number of vehicles in their portfolio.

Panel A of table 5 presents estimates from our matched sample that show the adoption of EVs by lower-income households or those with an elderly household head reduces total miles driven in the household's vehicle portfolio and the effect is statistically significant. Although the adoption of an EV reduces a household's vehicle operating costs, it does not produce a rebound

Table 5: The Effect of EV Adoption on Miles Driven, MPG, and Total Vehicles

	(1) b/se	(2) b/se	(3) b/se	(4) b/se	(5) b/se
Panel A: Total Miles					
BEV	-1,060.681**	-816.207*	1,006.617	-683.845	1,456.818
	(451.098)	(461.342)	(1,133.884)	(594.039)	(1,152.689)
BEVxLowInc		-2,078.031***			-2,224.079***
		(778.213)			(786.265)
BEVxAge			-39.332*		-36.119*
			(20.304)		(21.410)
BEVxCollege				-591.702	-561.228
				(556.222)	(588.987)
R-squared	0.001	0.002	0.002	0.001	0.003
Panel B: Avg. ICE MPG					
BEV	-1.425***	-1.480***	-2.888*	-1.387**	-2.929*
	(0.515)	(0.544)	(1.581)	(0.589)	(1.544)
BEVxLowInc		0.467			0.467
		(0.902)			(0.906)
BEVxAge			0.028		0.030
			(0.029)		(0.031)
BEVxCollege				-0.060	-0.199
				(0.723)	(0.795)
R-squared	0.001	0.002	0.002	0.001	0.002
Panel C: Total Vehicles					
BEV	0.114***	0.138***	-0.306***	0.077*	-0.274***
	(0.035)	(0.035)	(0.087)	(0.045)	(0.089)
BEV_lowinc		-0.204***			-0.195***
		(0.063)			(0.063)
BEV_hhage			0.008***		0.008***
			(0.002)		(0.002)
BEV_hhced				0.059	-0.004
				(0.043)	(0.044)
R-squared	0.003	0.004	0.006	0.003	0.008
Observations	6,868	6,868	6,868	6,868	6,868

Notes: This table reports estimates of the impact of EV ownership on household vehicle portfolio characteristics for the first two years of EV ownership. Estimates are obtained using the Abadie et al. (2004) matching estimator with the Mahalanobis distance metric to select a control household (also bought a new vehicle) for each treated (bought an EV) household. All specifications match exactly on year of purchase, metro area, and class of new vehicle. We also match on total household miles driven in the year prior to purchase, the number of trucks owned by the household in the year prior to purchase, and the total number of vehicles owned by the household in the year prior to purchase. Finally, we also match on the demographic characteristics of head of household (HoH) age, HoH education, household income, number of adults, total household size, whether the head of household is white, and whether the household owns their home. Time period considered is 2013 - 2019 *** indicates significance at the 1% level, ** at the 5% level, and * at the 10% level. Heteroskedastic consistent standard errors.

effect because households reduce not increase their total mileage. We speculate that these households reduce overall driving because their workplaces may be less likely to have a convenient EV charging option and because they are more sensitive to the cost of using EV charging stations if they cannot charge their EV at home.

The parameter estimation results in panels B and C of table 5 indicate that when households adopt an EV, they keep their less fuel-efficient vehicle, as indicated by the decrease in average miles per gallon, and that lower-income households decrease the vehicles in their portfolio, although this estimate is not statistically distinguishable from a net effect of zero, given the total number of household vehicles remains the same. Thus, EVs are displacing vehicle mileage that was previously accumulated in a more fuel-efficient ICE vehicle. Such behavior limits to some extent the efficacy of EVs to reduce emissions and helps to explain the finding in table 4 that following EV adoption, gasoline consumption declines by a lesser amount than total ICE mileage declines.

As we noted in the previous section, tables A2 and A3 in the appendix indicate that these results are not sensitive to the choice of matching criteria or based only on two years of post EV purchase. Finally, as a robustness check of our matching methodology, we estimate the impact of EV adoption on household driving behavior using an instrumental variables regression framework. Specifically, we use gasoline prices in the year of new vehicle purchase as a valid instrument for EV adoption, while controlling for energy and gas prices in the year post purchase. This alternative analysis is based on driving behavior one year instead of two years after a household purchases an EV or equivalent ICE vehicle. The results shown in appendix table A5 are qualitatively similar to our initial findings; namely, EV adoption leads to decreased household ICE mileage and gasoline consumption, and the impact of EV adoption on driving behavior is larger for lower-income, college educated, and older households.

5. A Household Model of Vehicle-Miles-Traveled for Policy Analysis

Our findings that EV adoption decreases ICE vehicle use, especially depending on the level of household income, potentially have important implications for the efficiency and distributional effects of subsidies and taxes that seek to increase miles driven in EVs. We draw on our sample of Texas households from 2013 to 2018 to estimate a short-run model of VMT for households with EVs and ICE vehicles, which we subsequently use to assess the effect of a VMT tax and EV subsidies on social welfare and its composition.

Conditional on owning a vehicle, household *i's* use of vehicle *m* for a given time period *t* is measured by the VMT accumulated over that time period, which depends on the household's and vehicle's characteristics, and on contemporaneous economic conditions. We assume VMT_{imt} takes a logarithmic functional given by:

$$Log(VMT_{imt}) = \beta_0 + \alpha_1 \cdot Log(PPM_{imt}) + \alpha_2 \cdot Log(PPM_{imt}) \cdot IsEV_m + \alpha_3 \cdot Log(PPM_{imt}) \cdot IsEV_m \cdot LowInc_i + X'_{i,t} \cdot \gamma + \kappa_i + \rho_m + \delta_t + \varepsilon_{imt}\,, \tag{4}$$

where $Log(PPM_{imt})$ is the log of the price per mile for household i using vehicle m in year t, which is interacted with dummy variables indicating whether vehicle m is an EV ($IsEV_m$) and whether household i is a lower-income household ($LowInc_i$). $X_{i,t}$ contains metropolitan area fixed effects and controls for whether household i has multiple vehicles and whether one of them is an EV, while ρ_m, κ_i, and δ_t are vehicle, household, and year fixed effects. Finally, ε_{imt} is an idiosyncratic household, vehicle, year level shock.

We construct the price per mile of an ICE vehicle for a given metropolitan area and year by combining the data from the EPA discussed previously on a vehicle's miles-per-gallon with data on local gasoline prices. For EVs, we use the charging data provided by the EPA combined with residential electricity price data from the EIA because, as noted, the majority of EV owners charge their vehicles at home. Given the exogenous determination of energy prices and the inclusion of household fixed effects, which capture the unobserved characteristics of individuals in the household that may be correlated with the determinants of VMT, we can identify the effect of energy price changes on households' VMT and estimate a price elasticity of VMT that varies with household characteristics. Note the year fixed effects capture general macroeconomic or weather conditions that may influence both driving and fuel prices and the metropolitan area fixed effects help capture the unobserved effect of a household's residential location on VMT. Finally, by including the household portfolio controls of multiple vehicles and whether they own at least one EV we alleviate concerns that the estimated price response is correlated with some unobserved household factor.

We present OLS estimates of a basic specification in column (1) of table 6 that include the price per mile of travel as well as an interaction term for whether the vehicle is an EV. The estimated VMT price elasticity for ICE vehicles, -0.114, is consistent with the magnitude of other estimated VMT price elasticities in the literature; for example, it is not statistically distinguishable from Langer, Maheshri, and Winston's (2017) estimate.

Table 6: VMT Regressions

	(1)	(2)	(3)
	b/se	b/se	b/se
Log(PPM)	-0.114***	-0.113***	-0.112***
	(0.023)	(0.023)	(0.023)
Log(PPM)xIsEV	0.068***	0.068***	0.063***
	(0.018)	(0.018)	(0.018)
Log(PPM)xLowInc		-0.004	-0.010
		(0.007)	(0.007)
Log(PPM)xLowIncxIsEV			0.028***
			(0.010)
Portfolio Controls	Yes	Yes	Yes
Non-Price Interactions	No	No	Yes
N	399041	399041	399041
adj. R^2	0.423	0.423	0.423
F	39.94	31.98	28.25

Notes: This table reports regressions of the determinants of the log of vehicles VMT. Log(PPM) is the log of the price per mile to drive that vehicle given observed gas or electricity prices in the metro area and year. IsEV is an indicator for whether the vehicle is an EV. Each specification includes vehicle, household, metro area, and year fixed effects. Unit of observation is a vehicle and year. Standard errors are clustered at the household-year level. Time considered is 2013 – 2018. *** indicates significance at the 1% ** at the 5%, and * at the 10% level.

The estimated VMT price elasticity for EVs is roughly half of the VMT price elasticity for ICE vehicles, which is plausible given that the price of electricity has yet to play a notable role in the use of EVs (Bushnell et al, 2022). In addition, the relatively lower price elasticity for EVs may reflect differences in price saliency between electricity and gasoline, or possibly a "green glow" from driving that dampens the price response to EV operating costs (Ma and Burton, 2016). Finally, our estimate of the VMT price elasticity for EV's is not statistically distinguishable from the -0.1 elasticity estimate that Nehiba (2022) obtain for EV drivers in New York.

We expand the specification of VMT in columns (2) and (3) to include interactions that indicate whether the vehicle is driven by a lower-income household. We find in column (2) that lower-income households' VMT responses to changes in energy prices for ICE vehicles are not statistically significantly different from other households' VMT responses to changes in energy prices. However, we find in column (3) that lower-income households are less sensitive than other households to changes in energy prices for EVs, which is consistent with our previous findings that lower-income households tend to use their EVs more than other households. Given the plausibility of the estimates of the VMT specification in column (3), it is appropriate to use it to assess policies that seek to increase EV adoption and use.

6. Policy Analysis

Policymakers have taken an active interest in electric vehicles because they believe their widespread adoption could improve the environment by reducing the share of pollutants produced by ICE vehicles and by eventually eliminating ICE vehicle emissions as a major source of air pollution. Policymakers have therefore attempted to increase the adoption of EVs by offering large subsidies to consumers, which are funded by general taxpayers.

An alternative and potentially more efficient approach is to set a vehicle-miles-traveled tax on automobile externalities to incentivize motorists to switch to electric vehicles to reduce their highway taxes. The relevant externalities include climate change, congestion, accidents, and local pollution. Representative values of the costs of the externalities for ICE vehicles and EVs and their sources are as follows in table 7.

Table 7: Externalities Considered by Vehicle Type

Externality	ICE Vehicles	Electric Vehicles
Climate	\$0.413 per gallon of gasoline, equivalent to a social cost of \$42.14 per ton of CO2 (EPA, 2016).	528 grams of CO2 per KWH of electricity in Texas (EIA, 2017), combined with EPA KWH per mile estimates.
Congestion	\$0.137/mile for urban drivers, Small &Verhoef, 2007.	\$0.137/mile for urban drivers Small &Verhoef, 2007.
Accidents	\$0.077/mile for urban drivers, Small &Verhoef, 2007.	\$0.077/mile, Small & Verhoef, based on urban drivers.
Local-Pollution	\$0.168/mile for urban drivers, Small &Verhoef, 2007.	Not applicable.

Note: All figures are in 2017 USD.

We draw on these estimates and our preceding findings on households' use of EVs after they adopt them and their responsiveness to changes in the price of automobile travel to assess the welfare effects of EV subsidies and a VMT tax to spur adoption of EVs. Our assessment is based on the sample of households who purchased an EV or comparable ICE vehicle, which we used to estimate the VMT specifications in table 6.

We specify taxpayer funded subsidies and VMT taxes for road users that ultimately cost households the same amount, roughly \$100 per household, to provide a fair comparison of the welfare effects of those policies. Consistent with Muehlegger and Rapson (2022), we assume that all households qualify for a subsidy funded by taxpayers of roughly \$9,500 toward a new EV purchase and that the subsidy is completely passed through to consumers. As reported in table 5, an important response by households who are encouraged by the subsidy to adopt an EV is to reduce total mileage, which reduces the cost of all automobile externalities. Although the subsidy is greater than current subsidies, the assumed value will not affect our main conclusions.

We use the estimation results of the VMT equation in column (3) table 6 and the results in Hausman (1981) and framework in Langer, Maheshri, and Winston (2017) to estimate the welfare effects of a VMT tax. We provide an expanded discussion of this framework in the appendix. Based on the estimates above, we assume a tax of 0.38 cents per mile for ICE vehicles and a tax of half that amount for EVs—a ratio that is roughly equivalent to the ratio of the vehicles' climate and local pollution costs when we account for the emissions from electricity generated to power EVs. Based on our VMT price elasticity estimates from Table 6, the annual VMT tax is $100 per household. Thus, as noted, we are comparing the welfare effects of equivalently sized subsidies and taxes that are borne by households.

Because we analyze households with heterogenous behavior and vehicle portfolios, economic theory cannot unambiguously predict whether an EV subsidy or a VMT tax will produce the greatest improvement in social welfare. The subsidy's external benefits depend on the type of households who are induced to purchase an EV and their use of the vehicle, while the subsidy's costs is based on the difference between the marginal purchaser's willingness to pay for the EV and the price of the EV without the subsidy, given we assume the deadweight loss of taxation to finance the subsidy is zero. (This assumption inflates our estimates of the benefits of EV subsidies).

Depending on motorists' elasticities, a VMT tax will produce external benefits by reducing driving but will reduce individual motorists' welfare by increasing the out-of-pocket cost of driving and by causing motorists to lose utility by reducing driving. Consistent with current policy, we assume all households are eligible for EV subsidies. However, it may be possible to exploit households' heterogenous behavior by targeting an EV subsidy to certain households to potentially increase the subsidy's net benefits. For example, the subsidy could be provided only to lower-income households who, based on our findings reported in table 4, generate the greatest displacement of ICE mileage but may not have purchased an EV without the subsidy. The former effect positively affects welfare by reducing the environmental costs of driving, while the latter effect negatively affects welfare by increasing the loss in consumer surplus. In addition to exploring the static welfare effects of the targeted subsidy, we consider its dynamic effects by incorporating projections of education and population age in the year 2030. Our previous estimates suggest that such dynamics could increase the climate benefits from targeted subsidies because we found in table 5 that age corresponds with a reduction in total miles driven and we found in table 4 that education corresponds with greater ICE displacement, following EV adoption. In the appendix, we include a list of the assumptions and steps used for those back of the envelope calculations.

Table 8 presents the welfare effects of the VMT tax and subsidy policies for all households and for lower-income households. The untargeted subsidy shown in column (1) leads to a modest increase in the share of EV ownership from 4.36% to 5.17%, which reduces annual ICE miles, increases annual EV miles, and reduces discounted climate damages by $2.72 per household-year, making the plausible assumption that EV ownership lasts 11.4 years.[12] The remaining findings indicate that the benefits of the untargeted subsidy significantly increase when we account for the additional external benefits, particularly congestion.

The effect shown in column (2) of the VMT tax on average household ICE mileage is almost the same as the effect of the subsidy. However, the reduction in ICE mileage leads to a smaller reduction in climate costs than the subsidy because the effect of the tax applies only for the years the tax is imposed, rather than 11.4 years for each additional purchase under the EV subsidy. Nonetheless, because EV mileage also is subject to a VMT tax and households do not receive an EV subsidy, EV's market share and mileage is less than its market share and mileage with a subsidy, which enables the VMT tax to reduce total external costs by more than the EV subsidy. Finally, the VMT tax reduces consumer surplus and increases government revenue while the subsidy has the opposite effect, with the overall welfare effect that the annual net benefits of the VMT tax per household exceed the subsidy's annual net benefits per household.[13]

Column (3) shows that the difference in welfare produced by the VMT tax and EV subsidies can be reduced if the subsidies were targeted to lower-income households. In this simulation, we assume lower-income households receive a subsidy of $16,540 to purchase an EV, which maintains the annual cost of the policy at $100 per household. The large subsidy to lower-

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[12] We make this assumption to provide a fair one-year comparison between the VMT tax and subsidies. That is, the climate benefits of the VMT tax are felt immediately and the reduction in driving is observed for one year. After the year is over, the tax effectively goes away. In contrast, the EV subsidy clearly reduces driving in the first year but also for the remaining years the vehicle is owned, so it is appropriate to assume a length of vehicle ownership and discount the subsidy's future effects.

[13] Even if we assume there is no deadweight loss associated with the untargeted subsidy, its net benefits are less than the net benefits of a VMT tax.

Table 8: Policy Simulations

	(1) EV Subsidy	(2) VMT Tax	(3) Targeted EV Subsidy	(4) Targeted EV Subsidy 2030 Demographics
All Households				
HH ICE Miles	26,120	26,115	25,992	25,987
HH EV Miles	540.8	454.0	626.9	628.2
EV Ownership Rate	0.0517	0.0436	0.0609	0.0609
Change in ICE Miles	-94.3	-99.2	-222.6	-226.7
Change in EV Miles	85.7	-1.1	171.7	173.0
Change in CS	87.82	-100.7	50.00	50.00
Government Revenue	-100	100	-100	-100
Climate Cost	-2.724	-1.751	-8.606	-8.884
Local Pol Cost	-5.690	-1.667	-14.87	-15.15
Congestion Cost	-4.191	-13.58	-27.40	-28.93
Accident Cost	-2.372	-7.768	-15.51	-16.37
Total External Cost	-14.98	-24.68	-66.39	-69.33
Net Benefit	2.8	23.98	16.39	19.33
Subsidy or Tax	9,544	0.0038	16,540	16,540
HH Year Obs	162,948	162,948	162,948	162,948

Notes: Column (1) shows the impact of a subsidy per each EV purchase that uses a total amount of government revenue equal to \$100 per household. Column (2) examines the impact of a VMT tax calibrated to extracting \$100 in revenue from each household on average. Column (3) examines the impact of a perfectly targeted subsidy that goes toward those households that would reduce their gasoline consumption the most and wouldn't purchase an EV otherwise. Column (4) incorporates a perfectly targeted EV subsidy using 2030 demographics. To calculate the external benefits of EV purchases, we assume they drive the vehicle for 11.4 years. We also incorporate electricity generation estimations of 528g per of CO_2 per kWh in the climate cost estimates of these policies. The VMT tax in columns (2) averages 0.0038 dollars per mile for each calendar year. The subsidy in column (1) assumes some portion of the subsidy is captured by those that would purchase the vehicle anyway. The subsidies in columns (3) and (4) assumes a perfectly targeted subsidy Climate damages assume 39.3 cents per gallon damages. All numbers are in 2017 USD.

income households leads to a greater EV market share and mileage, less ICE mileage, and lower total external costs compared with the VMT tax and the untargeted subsidy. Recall, that table 5 showed lower-income households who adopted an EV reduced their total annual mileage while other households' total annual mileage was unaffected when they adopted an EV. Finally, the subsidy targeted to low-income households leads to a smaller increase in consumer surplus than the subsidy for all households because when lower-income households adopt an EV, the unsubsidized price of an EV likely exceeds their willingness to pay for an EV. Nonetheless, the targeted subsidy improves upon the welfare effects of the untargeted subsidy, but its net benefits are still lower than the net benefits from the VMT tax.

We acknowledge that our finding that the net benefits from the VMT tax exceed the net benefits from a targeted subsidy may be sensitive to our using a linear demand for travel with an assumed price elasticity of -2.1 and that alternative specifications of demand and assumed price elasticity could reverse our finding. However, our demand assumptions are plausible and, importantly, they do not affect our finding that a VMT tax will produce substantially larger net benefits than an EV subsidy, unless the subsidy is targeted.

Finally, the estimates in column (4) of table 8 indicate that projected increases in education and income will cause the net benefits of targeted subsidies to grow over time because those changes lead to greater EV miles and fewer ICE miles, which reduce climate costs and overall external costs.

7. Final Comments

We have explored the important interplay between households' electric vehicle adoption and use and the implications of their behavior for public policy. We have collected a sample of motorists that has enabled us to document the heterogeneous use of EVs, especially by households with different income levels. We also have shown that our findings can inform policymakers by suggesting a richer menu of policy alternatives that go beyond large EV subsidies for all US households. In particular, we document that in the short run, there is a tradeoff between overall efficiency gains from a VMT tax versus greater climate benefits from a targeted EV subsidy.

In the medium run, that tradeoff is likely to depend on: (1) the extent that larger portions of the subsidy are captured by households who would have purchased an EV without subsidies—an inefficiency noted previously that resulted from other environmental subsidies; and (2) the decarbonization of the electric grid and whether a rebound effect emerges with improved EV technology and infrastructure. However, our findings suggest that the benefits of a VMT tax will still far outweigh those of an untargeted EV subsidy.

In the long run, the tradeoff between EV subsidies and a VMT tax is likely to be eliminated and the VMT tax will be unambiguously preferable to EV subsidies as the population ages, becomes better educated, and EVs evolve into autonomous electric vehicles, which would be shared not owned and would greatly reduce congestion and accident externalities as well as environmental externalities. Winston, Yan, and Associates (2023) point out that the widespread adoption of AEVs could facilitate the introduction of a VMT tax as part of the price that travelers are charged for their use of shared transportation. In a nutshell, if policymakers are flexible, they can pursue their preferred climate policy in the short run and help to facilitate the adoption of AEVs, which will largely eliminate automobile externalities in the long run.

References

Abadie, A. and Imbens, G. W. (2006). Large sample properties of matching estimators for average treatment effects. Econometrica, 74(1):235–267.

Bank, F. R. (2021). Median household income in the United States. Reserved from https://fred.stlouisfed.org/series/MEHOINUSA646N.

Borenstein, S., & Davis, L. W. (2016). The distributional effects of US clean energy tax credits. Tax Policy and the Economy, *30*(1), 191-234.

Burlig, F., Bushnell, J., Rapson, D., & Wolfram, C. (2021, May). Low energy: Estimating electric vehicle electricity use. In *AEA Papers and Proceedings* (Vol. 111, pp. 430-435).

Bushnell, J. B., Muehlegger, E., & Rapson, D. S. (2022). Energy prices and electric vehicle adoption (No. w29842). National Bureau of Economic Research.

Davis, L. W. (2019). How much are electric vehicles driven?. Applied economics letters, 26(18), 1497-1502.

Dehejia, R. H. and Wahba, S. (1999). Causal effects in nonexperimental studies: Reevaluating the evaluation of training programs. *Journal of the American statistical Association*, 94(448):1053–1062.

Forsythe, C. R., Gillingham, K. T., Michalek, J. J., & Whitefoot, K. S. (2023). Technology advancement is driving electric vehicle adoption. *Proceedings of the National Academy of Sciences*, *120*(23), e2219396120.

Gillingham, K.T., Spiller, B., and Talevi, M. (2023a). The Electric Vehicle Rebound Effect. PowerPoint Presentation at Manhattan College, March.

Gillingham, K. T., van Benthem, A. A., Weber, S., Saafi, M. A., & He, X. (2023b). Has Consumer Acceptance of Electric Vehicles Been Increasing? Evidence from Microdata on Every New Vehicle Sale in the United States, *AEA Papers and Proceedings* (Vol. 113, pp. 329-335).

Hausman, J. A. (1981). Exact consumer's surplus and deadweight loss. *The American Economic Review*, *71*(4), 662-676

Heckman, J. J., Ichimura, H., and Todd, P. E. (1997). Matching as an econometric evaluation estimator: Evidence from evaluating a job training programme. *The review of economic studies*, 64(4):605–654.

Holland, S. P., Mansur, E. T., Muller, N. Z., & Yates, A. J. (2016). Are there environmental benefits from driving electric vehicles? The importance of local factors. *American Economic Review*, *106*(12), 3700-3729.

Jacqz, I., Johnston, S. (2023). Disparities and Subsidy Policy. Mimeo.

Langer, A., Maheshri, V., & Winston, C. (2017). From gallons to miles: A disaggregate analysis of automobile travel and externality taxes. *Journal of public Economics*, *152*, 34-46.

Langford, R. P., & Gillingham, K. (2023). Quantifying the benefits of the introduction of the hybrid electric vehicle. *International Journal of Industrial Organization*, *87*, 102904.

Lee, T. M., Markowitz, E. M., Howe, P. D., Ko, C. Y., & Leiserowitz, A. A. (2015). Predictors of public climate change awareness and risk perception around the world. *Nature climate change*, *5*(11), 1014-1020.

Ma, C., & Burton, M. (2016). Warm glow from green power: Evidence from Australian electricity consumers. *Journal of Environmental Economics and Management*, 78, 106-120.

Mannering, F. & C. Winston (1985). A Dynamic Empirical Analysis of Household Vehicle Ownership and Utilization, *Rand Journal of Economics,* 16, 215-236.

Muehlegger, E., & Rapson, D. S. (2022). Subsidizing low-and middle-income adoption of electric vehicles: Quasi-experimental evidence from California. Journal of Public Economics, 216, 104752.

Muehlegger, E. J., & Rapson, D. S. (2023). Correcting estimates of electric vehicle emissions abatement: Implications for climate policy. Journal of the Association of Environmental and Resource Economists, 10(1), 263-282.

Nehiba, C. (2022). Electric vehicle usage, pollution damages, and the electricity price elasticity of driving. Pollution Damages, and the Electricity Price Elasticity of Driving (October 5, 2022).

ORGANISATION FOR ECONOMIC CO-OPERATION AND DEVELOPMENT. (2019). Benchmarking Higher Education System Performance. OECD.

Rubin, J., Ballingall, K., & Brown, E. (2021). Electric, Hybrid and High Fuel Efficiency Vehicles: Cost-Effective and Equitable GHG Emission Reductions in Maine.

Staiger, D. and Stock, J. H. (1994). Instrumental variables regression with weak instruments. Technical report, National Bureau of Economic Research.

Small, K.A., & Verhoef, E.T. (2007). Urban Transportation Economics, Routledge Press, United Kingdom.

U.S. EPA. (2016). The Social Cost of Carbon. Available at https://web.archive.org/web/20160113170244/http://www3.epa.gov/climatechange/EPAactivities/economics/scc.html

Vespa, J., Armstrong, D. M., & Medina, L. (2018). Demographic turning points for the United States: Population projections for 2020 to 2060 (pp. 25-1144). Washington, DC: US Department of Commerce, Economics and Statistics Administration, US Census Bureau.

Winston, C. (2021). *Gaining Ground: Markets Helping Government,* Brookings Institution Press, Washington, DC

Winston, C., Yan, J. and Associates (2023). *Revitalizing a Nation: Competition and Innovation in the US Transportation System,* Brookings Institution Press.

Appendix

This appendix presents the estimation reported in the text that show the bias from the controlling for the endogeneity of EV adoption; the robustness of our findings based on a matching methodology; an alternative approach to identification based on instrumental variables; and the details of our simulation methodology for assessing alternative policies to increase EV adoption.

A.1: A Simple OLS Analysis of the BEV Household Driving Differential

Table A1 details a simple comparison of various driving outcomes for households that adopt an EV versus the full sample noted in table 1. Specifically, we consider the following regression equation:

$$Y_{i,t} = \alpha_0 + \alpha_1 \cdot 1\{EV_{i,t}\} + X'_i \cdot \beta + \gamma_{m,t} + \varepsilon_{i,t} \qquad \text{(A1)}$$

Here, $Y_{i,t}$ represents the outcomes of total gallons consumed, total miles driven across ICE vehicles, and total miles driven across all vehicles for household i in year t. These are the underlying three outcomes whose estimates from tables 4 and 5 in the primary analysis are used for the counterfactuals in table 8. $1\{EV_{i,t}\}$ is an indicator which takes a value of one if household i owns an electric vehicle in year t. X_i is a vector of household demographic characteristics, number of adults, whether the head of household is white, head of household education level, household income, head of household age, household ownership and total household size. $\gamma_{m,t}$ is a metro area by year fixed effect, which allows us to capture variation electricity prices and gasoline prices in the years where those variables are not available. Finally, $\varepsilon_{i,t}$ represents the household-year level shock, which is clustered at the household level.

We emphasize that results from this framework, although compelling with the extensive sample, are merely suggestive and not causal since adoption of an electric vehicle is nonrandom. However, we consider this secondary analysis useful in providing suggestive evidence of the magnitude of the impact of EV adoption as well as benchmarking the importance of matching on both the counterfactual ICE vehicle and household demographics. Panel A of table A1 presents the results under this simple OLS framework for total gallons consumed, with large and statistically significant reduction in gasoline consumption following EV adoption. Using the baseline pre-purchase statistics for EV households in table 1, the baseline estimate in column (1) indicate that EV adoption lowers household gasoline consumption by 59.1% or more than a single vehicles gasoline consumption. Similar to our primary results in table 4, columns (2) and (5) of table A1 indicate that a household being lower income or college educated is associated with larger reductions in gasoline use following EV adoption.

In contrast to the larger reduction in gasoline estimated under equation (A1), panel B of table A1 shows an estimate that is similar but slightly smaller than the estimated reduction in ICE mileage displayed in table 4. Using the summary statistics found in table 1, the result here is roughly equivalent to 51.6% of the pre-purchase total ICE mileage for these households. Interestingly, the results for total mileage in panel C of table A1 still suggest there is a slightly negative rebound effect following EV adoption, further these estimates are statistically indistinguishable from those presented in table 5. Overall, we attribute the substantially larger reduction in gasoline mileage under this framework to not adequately capturing the counterfactual high miles per gallon vehicle these households would have purchased if not an EV. While the smaller reduction in ICE miles likely reflects the importance in matching on both demographics and the pre-purchase driving behavior.

A.2: Robustness of the Matched Results

Table A2 details matching estimates for the five outcomes considered in our primary analysis, total gallons consumed, ICE miles driven, total household miles across all vehicles, total number of different vehicles driven, and average ICE vehicle miles per gallon. The estimates in column (1) of table A2 are based on a control group matched on total miles driven, total number of household vehicles, and the number of trucks in the household vehicle portfolio. Summary statistics for this first matched control group are found in column (2) of table A3, while column (4) displays the differences between this group and EV purchasing households. Unlike the control group matched on both pre-purchase vehicle portfolio and demographics that is used in our primary analysis, this vehicle portfolio only selected control group does not display any statistically significant differences from the EV households in terms of pre-purchase driving characteristics. Interestingly, the results from column (1) of table A2 using this vehicle only matched control group indicate slightly higher reductions in gallons consumed and ICE mileage following EV adoption. This is likely due to the substantial differences in household demographics between this control and the EV purchasing households noted in column (4) of table A3.

We find a similar result when considering the demographics only matched control group used for comparison in Column (2) of table A2. In this case, columns (3) and (5) of table A3 indicate that there are few differences between this matched control group and EV purchasers in terms of demographics, but substantial differences in terms of pre-purchase driving behavior and vehicle ownership. In particular, this control group drives roughly 10% more than EV purchasers prior to the new vehicle purchase. Therefore, it is no surprise that the results in column (2) of table A2 show EV purchase corresponding with a reduction in gallons consumed that is 20% larger than our primary result reported in table 4.

As one final check on the validity and robustness of our matching approach, we consider instead looking at household driving outcomes just one year post purchase, rather than two years as in our primary analysis. The results from this approach, broken down by control group matching criteria, are displayed in columns (3) to (5) of table A2. Across specified control groups and outcomes, these results are roughly in line with our primary results in tables 4 and 5. Overall, the results from the analysis in table A2 indicates that the qualitative nature of our primary results are not sensitive to the choice of matching criteria or time frame for the outcome considered.

A.3: Alternative Identification

We believe that our matching approach provides a well identified estimate of the treatment effect of EV adoption on household driving behavior. However, to provide additional evidence on the qualitative nature of our results, both the magnitude of ICE displacement and role of demographics, we utilize an alternative identification strategy. Specifically, we consider an instrumental variables design that exploits variation in gas prices in the year of a new vehicle purchase, while controlling for gas and electricity prices in the post-purchase purchase period. We consider the sample of households that purchased an EV or an ICE equivalent vehicle according to table 2 from the 2013 to 2018 time period, one year after the new vehicle purchase (2014 – 2019).

For the baseline analysis, we use two-stage least squares (2SLS) and estimate the following:

$$1\{EV_{i,t}\} = \alpha_0 + \alpha_1 \cdot GasPrice_{i,t-1} + X'_{i,t}\psi + \gamma_m + \delta_t + \upsilon_{i,t} \tag{A2}$$

$$Y_{i,t} = \beta_0 + \beta_1 \cdot \widehat{1\{EV_{i,t}\}} + X'_{i,t}\zeta + \lambda_m + \tau_t + \varepsilon_{i,t} \tag{A3}$$

Equation A3 is the second-stage and equation A2 is the first-stage regression. The dependent variable, $Y_{i,t}$, is either gallons consumed, ICE miles driven, or total miles driven for household i in year t. The primary independent variable of instrument is $1\{EV_{i,t}\}$ whether household i owns an EV in year t. $X_{i,t}$ includes the full set of demographic controls, the maximum observed price of gas in year t, the households average observed price of gas prior to the year of purchase, and electricity prices in year t as additional controls. We also include metro area and year fixed effects, λ_m and τ_t. The metro area fixed effects capture time invariant factors within a metro area and the year fixed effects capture factors that may have impacted driving over time in Texas. We believe our instrumental variables approach addresses many of the concerns regarding the endogeneity of EV purchase discussed in section 2.

We instrument for whether a household purchases an EV using the maximum observed price of gas, $GasPrice_{i,t-1}$ within the household's residential city in the year of new vehicle purchase. There are a number of characteristics that make the max observed gas price in the year of the new vehicle purchase an ideal instrument. First, a household's driving or vehicle choices individually will not influence the gas price within a city, but it will certainly influence the purchase decision. Second, as we are controlling for both a household's pre-purchase history of observed gas prices, current gas prices in the year post purchase, as well as year fixed effects, the gas price in the year of new vehicle purchase should only relate to driving behavior through whether it influences the household to purchase an EV over an equivalent ICE vehicle. Third, it is likely to be a strong driver of whether a household chooses an EV over an equivalent ICE vehicle. Column (1) of table A4 confirms this as the maximum gas price in the year of purchase has a positive and statistically significant impact on whether the household purchases an EV in that year. Further, the K.P. Wald F stat is 47 much higher than the threshold of 10 needed to alleviate concerns about using a weak instrument (Staiger and Stock, 1994).

The results from our instrumental variables analysis are contained in table A5. The estimates in column (1) of table A5 correspond to the initial second stage results as outlined in equation (A3) and are qualitatively similar to our primary results from tables 4 and 5. Following EV adoption, there is a large and statistically significant decrease in household gasoline consumption and ICE vehicle driving, with no evidence of a positive rebound effect in total household driving. Further, these estimates are statistically indistinguishable from the point estimates obtained in tables 4 and 5 for these outcomes, partially due to the very large standard errors for these estimates. Columns (2) to (5) of Table A5 display our estimates of demographic characteristics interacted with EV purchase. To account for the endogeneity of these additional interactions, we expand the first stage equation (A2) to include as additional instruments these same demographic variables interacted with the maximum gas price in the year of the new vehicle purchase. Overall, the estimates from the additional demographic interactions are in line with our primary estimates. Lower incomes correspond with a larger reduction in gasoline use and ICE driving for EV purchasers, with some reductions also observed among older and college educated households. Once these interactions are included, the average net effect on ICE use is still negative across specifications.

Table A1: OLS Results

	(1)	(2)	(3)	(4)	(5)
	b/se	b/se	b/se	b/se	b/se
Panel A: Gallons Consumed					
BEV	-491.799***	-485.734***	-496.940***	-466.476***	-436.420***
	(7.120)	(7.730)	(12.710)	(28.002)	(28.367)
BEVxLowInc		-53.919***			-52.772***
		(19.376)			(19.412)
BEVxCollege			-5.089		-36.401**
			(15.250)		(16.039)
BEVxAge				-0.347	-0.596
				(0.535)	(0.561)
R-squared	0.056	0.056	0.055	0.052	0.051
Panel B: ICE Miles					
BEV	-10143.873***	-10027.002***	-10048.519***	-9992.704***	-9311.773***
	(150.652)	(163.539)	(278.940)	(599.139)	(608.826)
BEVxLowInc		-792.400*			-819.622**
		(412.410)			(414.550)
BEVxCollege			-419.874		-1059.874***
			(328.964)		(348.554)
BEVxAge				-0.186	-2.528
				(11.464)	(12.096)
R-squared	0.053	0.053	0.053	0.050	0.048
Panel C: Total Miles					
BEV	-949.337***	-719.454***	-855.966***	857.298	1661.984**
	(163.876)	(178.119)	(297.269)	(660.370)	(669.292)
BEVxLowInc		-1618.745***			-1653.810***
		(444.070)			(449.157)
BEVxCollege			-416.792		-921.227**
			(354.318)		(377.042)
BEVxAge				-31.704**	-35.964***
				(12.620)	(13.299)
R-squared	0.051	0.051	0.051	0.047	0.046
Metro-Year FEs	Y	Y	Y	Y	Y
Demographic Controls	Y	Y	Y	Y	Y
Observations	3,871,991	3,871,991	3,871,991	3,871,991	3,871,991

Notes: This table reports OLS estimates of the relationship between EV ownership and various household driving outcomes. Observations are at the household-year level aggregating driving across all household vehicles. Each specification includes controls for head of household (HoH) age, HoH education, household income, number of adults, total household size, whether the head of household is white, and whether the household owns their home, as well as metro area by year fixed effects. We exclude households in their first year of observation in the Texas data as not every vehicle in their portfolio may be properly captured in the TCEQ data. Time period considered is 2013 - 2019 *** indicates significance at the 1% level, ** at the 5% level, and * at the 10% level. Heteroskedastic consistent standard errors.

Table A2: Matching Robustness

	(1)	(2)	(3)	(4)	(5)
	Vehicle Portfolio and 2 Years Post	Demographics and 2 Years Post	Vehicle Portfolio and 1 Year Post	Demographics and 1 Year Post	Both 1 Year Post
A: Gallons Consumed					
BEV	-444.232***	-512.843***	-430.939***	-512.281***	-420.496***
	(23.427)	(24.149)	(21.198)	(24.984)	(21.038)
R-squared	0.090	0.109	0.071	0.082	0.069
B: Combustion Miles					
BEV	-12,094.043***	-13,672.148***	-12,182.560***	-13,761.870***	-11,692.220***
	(488.662)	(503.176)	(433.574)	(514.305)	(421.842)
R-squared	0.142	0.162	0.122	0.132	0.119
C: Total Miles					
BEV	-1,544.125***	-3,122.230***	-1,797.886***	-3,377.197***	-1,307.546***
	(500.426)	(514.608)	(445.398)	(524.311)	(433.986)
R-squared	0.141	0.141	0.141	0.141	0.142
D: Total Vehicles					
BEV	0.053	0.001	0.035	0.011	0.123***
	(0.038)	(0.037)	(0.034)	(0.039)	(0.033)
R-squared	0.001	0.000	0.000	0.000	0.002
E: Avg. ICE MPG					
BEV	-1.344**	-1.573***	-1.590**	-1.247*	-0.936
	(0.522)	(0.564)	(0.707)	(0.692)	(0.648)
R-squared	0.001	0.002	0.001	0.000	0.000
Observations	6,868	6,868	9,218	9,218	9,218

Notes: This table reports estimates of the impact of EV ownership on household driving outcomes under various assumptions of the Abadie et al. (2004) matching estimator. All specifications match exactly on year of purchase, metro area, and class of new vehicle. Columns (1), (3), and (5) match on total household miles driven in the year prior to purchase, the number of trucks owned by the household in the year prior to purchase, and the total number of vehicles owned by the household in the year prior to purchase. Columns (2), (4), and (5) match on the demographic characteristics of head of household (HoH) age, HoH education, household income, number of adults, total household size, whether the head of household is white, and whether the household owns their home. Columns (1) and (2) are similar to the main analysis in considering outcomes two years following EV purchase, while columns (3) – (5) consider driving outcomes only one year after purchase. Time period considered is 2013 - 2019 *** indicates significance at the 1% level, ** at the 5% level, and * at the 10% level. Heteroskedastic consistent standard errors.

Table A3: Matched Summary Statistics

	(1) EV Households	(2) Match On Vehicles	(3) Match On Demographics	(4) Diff. With Vehicles	(5) Diff. With Demographics
	Mean	Mean	Mean	diff/(se)	diff/(se)
# Adults	2.35	2.34	2.30	0.012	0.005
				(0.037)	(0.028)
White	0.73	0.74	0.73	-0.008	0.001
				(0.015)	(0.015)
Age	52.56	54.64	52.93	-2.08***	-0.373
				(0.668)	(0.369)
# People	3.10	3.01	3.00	0.09*	0.098**
				(0.051)	(0.048)
Income	109282.2	104741.3	110480.2	4540.8***	-1198.07
				(1575.60)	(1406.42)
Home Ownership	0.87	0.85	0.87	0.0142	-0.006
				(0.010)	(0.011)
College	0.67	0.62	0.68	0.048***	-0.011
				(0.016)	(0.015)
# Trucks	0.17	0.16	0.24	0.011	-0.069***
				(0.012)	(0.015)
Miles Driven	21752.22	21567.9	24220.4	184.36	-2468.12***
				(438.28)	(527.34)
# Vehicles	1.95	1.92	1.88	0.028	0.062*
				(0.033)	(0.034)
Avg MPG	25.01	25.23	25.02	-0.023	-0.005
				(0.72)	(0.81)
Observations	3,434	2,198	2,416		

Notes: This table shows summary stats for the households we observe purchase a BEV that also have a comparable ICE purchase matching household. Column (1) displays the summary statistics for the households that are observed with a BEV vehicle and with a suitable ICE match. Column (2) is the set of ICE only households that purchase a comparable ICE vehicle to a BEV household in the same metro area and year matched according to the pre-purchase vehicle portfolio characteristics of total miles driven, total vehicles, and number of trucks. Column (3) is the set of ICE only households that purchase a comparable ICE vehicle to a BEV household in the same metro area and year matched according to household demographics. Column (4) displays differences in the values between the two groups on columns (1) and (2). Column (5) displays differences in the values between the two groups on columns (1) and (3). # Trucks, # Vehicles, Miles Driven, and Avg. MPG are averages taken across all years the household is observed pre purchase. Standard errors for the difference in household demographic characteristics in columns (4) and (5) are robust heteroskedastic consistent.

Table A4: IV First Stage

	(1)	(2)	(3)	(4)	(5)
EV Purchase					
PreviousGasPrice	0.181***	0.185***	0.047***	0.029***	0.029***
	(0.031)	(0.029)	(0.014)	(0.005)	(0.005)
PreviousGasPricexLowInc		-0.028***			-0.002***
		(0.003)			(0.000)
PreviousGasPricexCollege			-0.018***		-0.001***
			(0.002)		(0.000)
PreviousGasPricexAge				-0.000***	-0.000***
				(0.000)	(0.000)
R-squared	0.066	0.066	0.065	0.062	0.059
Metro Area FEs	Y	Y	Y	Y	Y
Year FEs	Y	Y	Y	Y	Y
Demographic Controls	Y	Y	Y	Y	Y
Observations	79188	79188	79188	79188	79188

Notes: This table reports the first stage regression estimates of the relationship between gas prices in the year of vehicle purchase and the outcome of whether a household purchased a BEV over a comparable ICE vehicle. Each specification includes controls for head of household (HoH) age, HoH education, household income, number of adults, total household size, whether the head of household is white, and whether the household owns their home, as well as metro area and year fixed effects. Time period considered is 2013 - 2019 *** indicates significance at the 1% level, ** at the 5% level, and * at the 10% level. Standard errors clustered at the city level.

Table A5: IV Results

	(1)	(2)	(3)	(4)	(5)
Panel A: Gallons Consumed					
BEV	-673.959*	-690.653*	766.114	4425.648***	4802.801***
	(405.697)	(370.189)	(717.213)	(814.959)	(920.604)
BEVxLowInc		-206.635			-82.294
		(702.962)			(726.903)
BEVxCollege			-1674.242***		-1098.244**
			(518.500)		(554.878)
BEVxAge				-98.059***	-86.845***
				(17.956)	(19.192)
Panel B: Combustion Miles					
BEV	-19180.179**	-19610.201**	15084.541	89878.871***	99757.974***
	(9307.263)	(8351.067)	(17756.317)	(18033.126)	(20949.962)
BEVxLowInc		-8156.977			-5218.163
		(16467.502)			(16942.804)
BEVxCollege			-40001.035***		-28017.185**
			(12729.515)		(13643.745)
BEVxAge				-2100.913***	-1817.722***
				(384.147)	(413.958)
Panel C: Total Miles					
BEV	-7072.573	-7578.660	27891.273	103101.164***	113151.147***
	(9176.205)	(8218.951)	(17741.426)	(18328.474)	(21215.933)
BEVxLowInc		-7259.807			-4263.449
		(16735.902)			(17244.611)
BEVxCollege			-40852.467***		-28757.736**
			(12827.321)		(13711.608)
BEVxAge				-2123.115***	-1831.428***
				(388.584)	(418.529)
Metro Area FEs	Y	Y	Y	Y	Y
Year FEs	Y	Y	Y	Y	Y
Demographic Controls	Y	Y	Y	Y	Y
Energy Price Controls	Y	Y	Y	Y	Y
K.P. Wald F Stat	47.964	17.940	16.501	24.544	5.946
Observations	70,892	70,892	70,892	70,892	70,892

Notes: This table reports IV estimates of the relationship between EV ownership and various household driving outcomes one year after a vehicle purchase. We instrument for BEV ownership by using gas prices the year of new vehicle purchase. Observations are at the household year level aggregating driving across all household vehicles. Each specification includes controls for gas and crude oil prices in the current year, head of household (HoH) age, HoH education, household income, number of adults, total household size, whether the head of household is white, and whether the household owns their home, as well as metro area and year fixed effects. Time period considered is 2013 - 2019 *** indicates significance at the 1% level, ** at the 5% level, and * at the 10% level. Heteroskedastic consistent standard errors.

A.4: Demand Framework and Simulation Details

Within the short run, when a household's vehicle portfolio is fixed. We consider household i's utility from vehicle use, in terms of VMT, for vehicle m in year t as having the Cobb-Douglas functional form:

$$VMT_{imt} = f_{im}\delta_t {p_{imt}}^{\beta_{im}} \quad \text{(A4)}$$

Here, we define f_{im} = exp $(\lambda_i + \sigma Z_{im})$, which captures both fixed unobserved determinants of household driving behavior through λ_i and vehicle characteristics including vehicle fixed effects (a model year-make-model fixed effect). Heterogeneity in household price response is captured through $\beta_{im} = \kappa W_{im}$, where W_{im} includes household and vehicle characteristics, particularly whether the household is lower income and whether the vehicle is an EV. p_{imt} is the price of driving vehicle m one mile for household i in year t. For an ICE vehicle we use the average gas price for the metro area of household i in year t divided by vehicle $m's$ fuel economy. Similarly, for an EV, we use the average residential rate per kWh of electricity for the zip code of household i in year t divided by vehicle $m's$ miles per kWh.

The log-linear regression results in Table 6 that are based on equation (4) represent the parameter estimates of equation (A4) after taking natural logs and combining terms. We use these linear regression estimates within the full model of equation (A4) to estimate the impact on social welfare from a VMT tax in terms of changes in household welfare from decreased driving, changes in government revenues, and a change in externalities (congestion, pollution, etc.). Following Hausman (1981) and Langer, Maheshri, and Winston (2017), we assume constant marginal utility of income and apply Roy's identity to the VMT demand equation (A4) to obtain the short-run indirect utility of a household as follows:

$$V_{imt} = f_{im}\delta_t \frac{p_{imt}^{\beta_{im}+1}}{\beta_{im}+1} + C \quad \text{(A5)}$$

Here, C is a constant of integration while all other variables are the same as those defined in equation (A4). For our VMT tax simulation that changes the price of driving one mile from it's original level p_{imt}^0 to the counterfactual price p_{imt}^1, the change in household $i's$ welfare is given by $V_{imt}(p_{imt}^1) - V_{imt}(p_{imt}^0)$. Therefore, we can obtain the change in welfare from decreased vehicle use under the tax by aggregating this change across all households and vehicles as $\Sigma_{im}[V_{imt}(p_{imt}^1) - V_{imt}(p_{imt}^0)]$. By incorporating the heterogeneity in the household vehicle price elasticity β_{im}, this calculation is likely to capture how the changes in consumer surplus from a

VMT tax will vary according to demographic and vehicle characteristics. In the following subsection, we list the steps and calculations for our counterfactual exercises, of which the VMT tax discussion draws heavily from this appendix section.

A.5: Additional Simulation Details

We now describe the steps and calculations undertaken for the counterfactual exercises conducted in section 6. Since we utilize an unbalanced panel of households, we conduct each policy exercise for each year from 2013 to 2018, then average across years within exercise to obtain the results displayed in table 8. For example, the subsidy of $9,544 in column 1 of Table 8 is the average EV subsidy, but this value varied by sample year to meet the constraint of the tax revenue cost equaling $100 per observed household for each year. For simplicity, we describe the calculations and steps for each policy exercise as if it was being conducted for a single year t, unless stated otherwise.

1. **Untargeted EV Subsidy**
    - We take the factual number of EV acquisitions observed in the data Q_t^0, the average MSRP of those EVs P_t^1, the number of households observed that year, HH_t, and the EV price elasticity of demand estimate of -2.1 from Muehlegger and Rapson (2022) to solve for Q_t^1 and P_t^1. We also combine this with the assumption of complete pass through, based on the empirical results from Muehlegger and Rapson (2022) indicating "in no specification can we reject full passthrough." Specifically, we use two equations to solve for the two unknowns P_t^1 and Q_t^1, the first based on the elasticity:

$$\varepsilon_d = -2.1 = \frac{\%\Delta Q}{\%\Delta P} \approx \frac{\frac{(Q_t^1 - Q_t^0)}{Q_t^0}}{\frac{(P_t^1 - P_t^0)}{P_t^0}} \tag{A6}$$

    The second equation is based on the tax budget constraint of $100 \cdot HH_t = -(P_t^1 - P_t^0) \cdot Q_t^1$, where -$(P_t^1 - P_t^0)$ is the size of the subsidy per EV purchase.
    - After solving for Q_t^1 and correspondingly the number of additional vehicles under the counterfactual subsidy $(Q_t^1 - Q_t^0)$. We obtain the change in EV mileage by taking the estimates for total reduced ICE driving and total reduced household driving from tables 4 and 5, since the difference between these coefficient estimates

represents how much the new EV is driven. Thus, we calculate the increase in EV vehicle miles traveled as $\Delta EV\_VMT = -(Q_t^1 - Q_t^0) \cdot (\widehat{\alpha_{ICE}} - \widehat{\alpha_{totOdo}})$.

- To get the change in climate costs from the subsidy, we start with the change in climate cost from the change in electricity use due to the increase in EV driving noted in the previous step. Specifically, we use the average kWh per mile from EVs in that year multiplied by the 528 grams of CO2 per kWh of electricity generated in Texas during our sample time frame, then multiplied by the climate cost per gram of CO2 based on the \$42.14 per damage estimate from the EPA as follows: $\overline{kWhPerMile_t} \cdot \$42.14 \cdot \frac{528}{90718} \cdot \Delta EV\_VMT$. To obtain the overall change in climate costs from the subsidy, we then incorporate the reduction in climate costs from reduced gasoline consumption. This latter component is calculated by taking the estimates for reduced gasoline consumption from EV adoption in Table 4 and a climate cost of \$0.413 per gallon as follows -$(Q_t^1 - Q_t^0) \cdot \widehat{\alpha_{Gas}} \cdot \$0.413$.
- To obtain the reduction in total congestion and accident costs, we take the estimates for the overall reduction in driving from EV adoption in table 5, $\widehat{\alpha_{totOdo}}$, and combine it with the change in EVs from the subsidy and estimated costs per mile from Small and Verhoef (2007) as follows: -$(Q_t^1 - Q_t^0) \cdot \widehat{\alpha_{totOdo}} \cdot (\$0.077 + \$0.137)$.
- To obtain the reduction in local pollution costs, we take the estimates for the reduction in ICE driving from EV adoption in table 4, $\widehat{\alpha_{ICE}}$, and combine it with the change in EVs from the subsidy and estimated costs per mile from Small and Verhoef (2007) as follows: -$(Q_t^1 - Q_t^0) \cdot \widehat{\alpha_{ICE}} \cdot (\$0.168)$. Note that $(Q_t^1 - Q_t^0) \cdot \widehat{\alpha_{ICE}}$ represents the reduction in ICE miles.
- We estimate the change in total consumer surplus from the subsidy as -$(P_t^1 - P_t^0) \cdot Q_t^0 - 0.5 \cdot (P_t^1 - P_t^0) \cdot (Q_t^1 - Q_t^0)$. Therefore, we are assuming that half of the amount spent subsidizing the marginal EV purchasers becomes deadweight loss, $0.5 \cdot (P_t^1 - P_t^0) \cdot (Q_t^1 - Q_t^0)$.
- To account for the full future benefits of EV adoption, in table 8 we present the total discounted value of the annual change in climate costs, local pollution costs, congestion costs, and accident costs as calculated above. With the additional

assumption that these reductions repeat for 11.4 years, the lifespan of a vehicle, and the discount rate is 2%.

- The EV ownership rate presented in table 8 accounts for the nature of the unbalanced sample by multiplying the number of additional purchases $(Q_t^1 - Q_t^0)$ by the expected likelihood a vehicle is observed in a future sample year then replacing that number of ICE vehicles with EVs in the future sample year. This means that an additional EV purchased in 2014 influences the average EV ownership rate for 2015, 2016, etc.

2. VMT Tax

- To solve for the tax that provides exactly $100 of revenue from each household we use a starting value derived from the following:

$$100 \cdot HH_t = \sum_m [Tax_t \cdot VMT_m^0 \cdot 1\{m \neq EV\} + 0.5 \cdot Tax_t \cdot VMT_m^0 \cdot 1\{m = EV\}] \qquad \text{(A7)}$$

Where VMT_m^0 is the factual VMT for vehicle m. Assuming EVs will be taxed at half the rate of ICE vehicles, in proportion to pollution damages. After obtaining the initial guess $\widetilde{Tax_t}$ we raise the tax by $0.00005 and use the estimates from column 3 of table 6 to predict VMT_m^1. We then iterate this process until we achieve a level of the tax revenue$\sum_m [Tax_t \cdot VMT_m^1 \cdot 1\{m \neq EV\} + 0.5 \cdot Tax_t \cdot VMT_m^1 \cdot 1\{m = EV\}]$ within the interval of $[99.9 \cdot HH_t, 100.1 \cdot HH_t]$.

- We define the change in EV miles from the VMT tax as $\Delta EV\_VMT = \sum_m (VMT_m^1 - VMT_m^0) \cdot 1\{m = EV\}$. Similarly, the change in ICE miles is defined as $\Delta ICE\_VMT = \sum_m (VMT_m^1 - VMT_m^0) \cdot 1\{m \neq EV\}$. With these changes in mileage by vehicle type, we repeat the same calculations as the EV subsidy discussed previously to determine the changes in external costs from the tax.
- Following the discussion around equation (A5), we calculate the change in consumer welfare from decreased driving due to the tax as follows $\Sigma_{im}[V_{imt}(p_{imt}^1) - V_{imt}(p_{imt}^0)]$where $p_{imt}^1 = p_{imt}^0 + Tax_t \cdot (1 - 0.5 \cdot 1\{m = EV\})$. The variable Tax_t is the one solved for in the previous steps of this subsection.

3. Targeted EV Subsidy and 2030 Demographics

- The key difference between the targeted and untargeted subsidy counterfactuals is the second equation used to solve for the size of the subsidy and the number of additional vehicles. Specifically, by assuming that the subsidy could be perfectly targeted toward the marginal consumers, the tax budget constraint becomes $100 \cdot HH_t = -(P_t^1 - P_t^0) \cdot (Q_t^1 - Q_t^0)$. Note, since we are focusing on lower income consumers Q_t is the quantity demanded among the lower income consumers.
- Given the previous assumption that half of the subsidy given to the marginal consumers becomes deadweight loss, for this targeted subsidy deadweight loss is $0.5 \cdot (P_t^1 - P_t^0) \cdot (Q_t^1 - Q_t^0)$.
- For the targeted subsidy with factual demographics, all of the calculations for changes in external costs are similar to those of the untargeted subsidy, however with the coefficients for each displacement effect replaced by the sum of the original coefficient and lower income interaction terms from column (2) in tables 4 and 5. For example, in the case of decreased congestion and accident costs we use $-(Q_t^1 - Q_t^0) \cdot (\widehat{\alpha_{totOdo}} + \widehat{\alpha_{totOdo}^{LowInc}}) \cdot (\$0.077 + \$0.137)$. Where $\widehat{\alpha_{totOdo}} + \widehat{\alpha_{totOdo}^{LowInc}}$ is the sum of the two terms from column (2) of panel A in table 5.
- For the targeted subsidy with 2030 demographics, all of the calculations for changes in external costs are roughly similar to those of the targeted subsidy described in the previous step. The differences are two fold, first we use the full set of interactions in column (5) of tables 4 and 5 for the calculations. Specifically, for each demographic characteristic, we assume low income like the prior step, as well as an average age of 53.16 and college education likelihood of 64%. These are in line with expected increases in these characteristics (Vespa et al, 2018; OECD, 2019).