Does Air Pollution Increase Electric Vehicle Adoption? Evidence from U.S. Metropolitan Areas, 2011-2018

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Abstract

We estimate a model for adoption of electric vehicles in 427 of the largest metropolitan areas in the 48 contiguous U.S. states. We use a data set with new registrations for battery electric vehicles (BEV) and plug-in electric vehicles (PHEV) by metro area over the 2011-2018 period, and investigate whether adoption of new EVs is affected by multiple types of air pollution - both long-term metro air pollution as measured by PM2.5 and more temporary metro events as measured by the presence of lower-level and upper-level atmosphere smoke plumes. Regression results show that both PM2.5 pollution and smoke plumes affect BEV and PHEV adoptions by metro area.

Keywords: electric vehicles; pollution; smoke plumes; state EV policies; psuedo-Poisson estimates; high dimensional fixed effects

JEL codes: Q52, Q48, O33, R40

1. Introduction

In this paper we investigate whether people living in U.S. metropolitan areas with higher levels of local air pollution, both persistent and temporary, are more likely to adopt electric vehicles (EVs). EVs have the potential to reduce multiple sources of air pollution, including smog-forming emissions. Both battery electric vehicles (BEVs) and plug-in hybrid electric vehicles (PHEVs) are commonly referred to as Zero Emissions Vehicles (ZEVs) - reflecting that electricity-based fuel contributes no direct exhaust emissions.[1] The marketing of EVs as ZEVs show a clear transmission of information about air pollution and vehicle type that might influence consumer purchases. A substantial portion of local air pollution, in addition to global air pollution in the form of greenhouse gases (GHG), comes from the combustion of fossil fuels in vehicular transport (Holland et al., 2016 and 2020; Lei et al., 2021; Shi et al. 2017). A range of local air pollutants is well-documented to have deleterious health effects (Berhane et al, 2016; EPA, 2021; Halliday et al., 2018; Soriano et al., 2020). Consumers who experience increases in persistent or temporary sources of local air pollution could be motivated to switch from a fossil-fuel-powered vehicle to a partly electric-powered PHEV or fully electric-powered BEV. In a similar inquiry for China, Guo et al (2020) use PM2.5 levels as a proxy for local air pollution and find a robust positive and statistically significant relationship between PM2.5 levels and EV sales using data for 20 major cities between 2014 and 2018.

We additionally inquire whether consumers adopt EVs in response to more temporary sources of air pollution, via smoke plumes. For the United States, Larsen et al. (2018) find that smoke plumes relate to increased measures of PM2.5 and the number of unhealthy air quality days. Burke et al. (2021, 1-2) found that in the United States "[o]ver the last four decades, burned area from wildfires has roughly quadrupled," while smoke days per year increased by almost two days per year on average from 2005 to 2020. Here the transmission of information regarding air quality and EVs is more indirect, though exacerbated levels of poor air quality days, visible smoke haze, and media reports might heighten consumer awareness of air pollution more generally, as well as prompt consumers to make the connection between air quality and climate change.

To assess whether temporary and persistent local air pollution affect EV adoption, we use panel data on EV registrations covering 427 U.S. metropolitan areas from 2011 to 2018 to estimate the effect of PM2.5 pollution levels and the presence of smoke plumes on EV adoption within metro areas. Our econometric model accounts for the number of publicly accessible charging stations within a state as well as measures of state-level EV policies that could contribute to regional variation in EV adoption. Metro-year fixed effects absorb year-over-year changes within metro areas and quarterly fixed effects absorb idiosyncratic macroeconomic shocks to the U.S. economy and automobile market. We use a Poisson psuedomaximum likelihood high

[1] The federal government has provided waivers to some states from its Corporate Average Fuel Economy (CAFE) standards on the grounds that these states need more stringent local air pollution measures to meet clean air standards set by the Clean Air Act. By 2018 nine states had adopted California's clean air standards and its ZEV mandate: Connecticut, Maine, Maryland, Massachusetts, New Jersey, New York, Oregon, Rhode Island, and Vermont. Colorado enacted a ZEV mandate in 2019 and Washington State in 2020.

dimensional fixed effects estimator to obtain results from samples of new BEV and PHEV registrations.

Our results show that changes in local air pollution within U.S. metropolitan areas are associated with changes in consumer purchases of new EVs, with a complex pattern of findings for BEVs and PHEVs. We find that increases in PM2.5 air pollution within metro areas are associated with increased adoption of BEVs and decreased adoption of PHEVs. The importance of this result is amplified by the large average decline (19 percent) in quarterly PM2.5 air pollution within the 427 metro areas in our sample between 2011 and 2018. From this perspective, declines in metro area air pollution during the 2010s depressed adoptions of BEVs and raised adoptions of PHEVs. We also find that changes in smoke plume pollution within metro areas affected EV purchases, but that the effect was relatively small compared to that generated by PM2.5 pollution. Smoke plumes had a positive and statistically significant relationship to PHEV sales, and a negative and statistically significant relationship to BEV sales. These results are important because our measure of annual smoke plume days in metro areas declined from 2011 to 2016 before registering increases in 2017 and 2018 (Figure 2). The overall effect of this exogenous decline in smoke plumes is to depress PHEV adoptions, increase BEV adoptions, and decrease overall EV adoptions, as consumers saw less need to take action towards mitigating air pollution through their vehicle purchase. We conclude that consumers in the new vehicle market are rationally more receptive to signals about the environment generated by changes in persistent PM2.5 pollution in their metro area relative to changes in temporary smoke plume pollution typically originating outside their metro area.

2. Literature Review

EVs negate or reduce tailpipe emissions depending on whether they are BEVs or PHEVs. Whether they reduce net air pollution, including GHGs, depends on the type of energy used to create the electricity used to recharge the EV[2] and the vehicles they replace. Several simulation studies have shown that high levels of EV adoption have the potential to yield substantial public health benefits by reducing several types of local air pollution (Brady and O'Mahony, 2011; Ferrero et al., 2016; Soret et al., 2014). Holland et al. (2020) document a dramatic decline in local air pollutants from power plants across the United States from 2010 to 2017 due to integration of renewable energy and natural gas into electricity grids. The most notable drop is for sulfur dioxide (SO2), which fell by 75 percent. Fine particulate matter (PM2.5) declined by about 35 percent. Carbon dioxide (CO2), a GHG, declined by about 20 percent. With this drop in stationary sources of air pollution, the net benefits of electrifying transportation systems substantially increased. Dividing the country into three large regions—East, West, and Texas – Holland et al. (2020) estimated the net environmental benefit from an electric-powered Ford Focus driven 15,000 miles per year replacing a gasoline-powered Ford Focus for 2010 and 2017. They found that the average annual net benefit was positive in 2010 for Texas and the West but

[2] Based on the average mix of energy sources in U.S. electricity generation during 2019, the U.S. Department of Energy (DOE) estimates that a BEV typically produces the least GHG emissions, followed by a PHEV, a hybrid electric vehicle (HEV) and, lastly, a gasoline vehicle (AFDC, 2019a). Vehicle rankings by GHG emissions are somewhat different at the state level. EVs are an improvement over HEVs in most states, though in 15 coal-dependent states, HEVs still outperform EVs in terms of GHG emissions. The DOE does not provide the same level of information for local air pollutants.

negative for the East. By 2017 net benefits had increased substantially in each region, and become positive in the East.[3] Overall, these findings suggest that stationary sources of PM2.5 pollution declined across the U.S. over our study's time-period (Figure 2).

Though EVs clearly lead to a reduction in pollutants via a reduction in combustion of fossil fuels, the net effect of switching to an EV on mobile sources of particulate matter pollution is more uncertain (Shi et al., 2017; Schöllnhammer et al. 2014). Soret et al. (2014) and Timmers and Achten (2016) conclude that the reduction in particulate pollution from an EV that replaces an internal combustion engine (ICE) vehicle is substantially lower than conventionally conceived, just a 1.0% - 5.0% reduction. Timmers and Achten (2016) find that 90% of PM10 and 85% of PM2.5 pollution are not exhaust-related and that the increased weight of EVs relative to similar size fossil-fuel-powered vehicles results in more non-exhaust particulate-related emissions due to greater tire wear and road wear. The basis for this finding is extended in Ambrose et al. (2020) who find that BEV size--think the movement of the market to new Tesla models--and battery weight increased from 2012-2018.

Our research abstracts from the degree to which EVs reduce different types of local air pollution, and focuses instead on determining whether the presence of local air pollutants motivates an EV purchase in metro areas across the United States. While ours is the first study to examine this question for the U.S. EV market, Guo et al. (2020) have investigated this question for China's EV market. Using panel data for 20 major cities in China, they show that a positive relationship exists between average PM2.5 concentration levels and EV purchases for 20 major cities in China. Their use of PM2.5 data, similar to ours, serves as a proxy for changes in local air quality conditions.

More broadly, there is evidence that some car buyers choose more environmentally friendly cars because car purchases are highly visible to others, and send "green signals" to other consumers about the car owner's environmental bona fides (Sexton and Sexton, 2014; White and Sintov, 2017). There are numerous survey-based studies conducted during our study period that investigate the role of environmental awareness, attitudes and symbolic attributes, including concern about climate change, in shaping intention to purchase an EV. Survey work conducted when contemporary EVs first came to market in the early 2010s found that potential early adopters tended to be motivated by concerns about the environment and oil dependence as well as pollution reduction (Carley et al., 2013; Hackbarth and Madlener, 2013; Hidrue et al., 2011; Zhang et al., 2011). Carley et al. (2019) compare 2011 and 2017 survey results for residents in the 21 largest U.S. cities. They find that consumer intent to purchase an EV increased over this 6-year interval, though environmental factors, including concerns about climate change and environmental signaling, do not explain much of this increase. Using surveys of residents in three different regions of China, Shi et al. (2017) identify multiple ways that travelers (including drivers) might be influenced in their decision-making about travel mode and technology by

[3] Muehlleger and Rapson (2021) find that the relevant replacement car in California was not an ICE Ford Focus but a very fuel efficient car. They conclude that "[t]he actual incremental pollution abatement arising from EVs today is thus substantially smaller than one would predict using the fleet average as the counterfactual vehicle." Moreover, Burlig, Bushnell, Rapson, Wolfram (2021) find that EVs are driven just 5,500 miles per year in California and find some evidence for substitution into ICE vehicles in a family's vehicle portfolio.

PM2.5 levels, including attitudes, norms, and expectation that individual actions matter in pollution reduction. They find that respondent attitudes towards haze pollution was the strongest factor relating to the intent to adopt an EV. In a survey of Japanese drivers, Okada et al. (2019) find that environmental awareness has a small direct impact on their intention to purchase an EV but a larger impact on post-purchase satisfaction of EV drivers.

There are numerous policy, geographic, consumer, and economic factors that could influence variation in U.S. metro-level EV adoption. Coffman et al. (2017) survey the literature through 2015 on factors affecting EV adoption. The adequacy of public charging networks and uneven policy support for EV adoptions stand out as particularly important factors. Using panel data for 2011-2015, Wee et al. (2018) and Jenn et al. (2018) study various policy instruments used by state governments to support EV adoption including vehicle purchase incentives, home charger subsidies, reduced vehicle license taxes, and preferential lane access. Though preferential lane access accrues benefits to a much smaller set of area residents, prior studies have found it to be highly valued by drivers who use those highways (Bento et al., 2014; Jenn et al. 2020; Shewmake and Jarvis, 2014). Wee et al. (2018) find that a $1,000 increase in the value of EV net subsidies increases new EV registrations by 5-11%, while Jenn et al. (2018) find a 2.6% increase. In the first half of the 2010s, an increasing number of states adopted supportive EV policies, but in the second half of the decade, the number with home charger subsidies declined from eight to two, the number with purchase subsidies declined from 17 to 13, while the number with an annual EV fee, a disincentive to EV adoption, increased from six to 20 (Hayashida, La Croix, and Coffman, 2021).

Lastly, there are also supply-side constraints that could be important factors underlying changes in EV adoption at the municipal level. Federal corporate average fuel economy (CAFE) standards are set nationwide, but allow states that are non-compliant with Clean Air Act standards for local air pollutants to follow California's more stringent policies. The federal government enabled this exemption in 2013 via a waiver to CAFE. Eleven states, often referred to as "Section 177 states," have adopted ZEV mandates that require vehicle manufacturers to hit annual targets on ZEV car sales. BEVs are given full credit as a ZEV, while PHEVs are discounted in meeting the target because they are still run partially on fossil fuels. These targets could limit the ability of vehicle manufacturers to change their supply of EVs in response to changes in consumer demand for EVs generally or for BEVs relative to PHEVS.

3. Data

We construct our data set from five separate data sets covering the 48 contiguous states and the 374 largest metropolitan areas. The five data sets are (1) registrations of new BEV and PHEV cars, (2) estimates for PM2.5 pollution, (3) days of landscape fire smoke plumes, (4) state-level variables, including measures of subsidies and fees for EVs and charging stations, and (5) metro-level variables, including income and population.

Our first data set consists of monthly registrations of new BEVs and PHEVs by metro area from 2011 to 2018 (IHS Markit, 2020).[4] Figure 1 displays total monthly registrations by vehicle type

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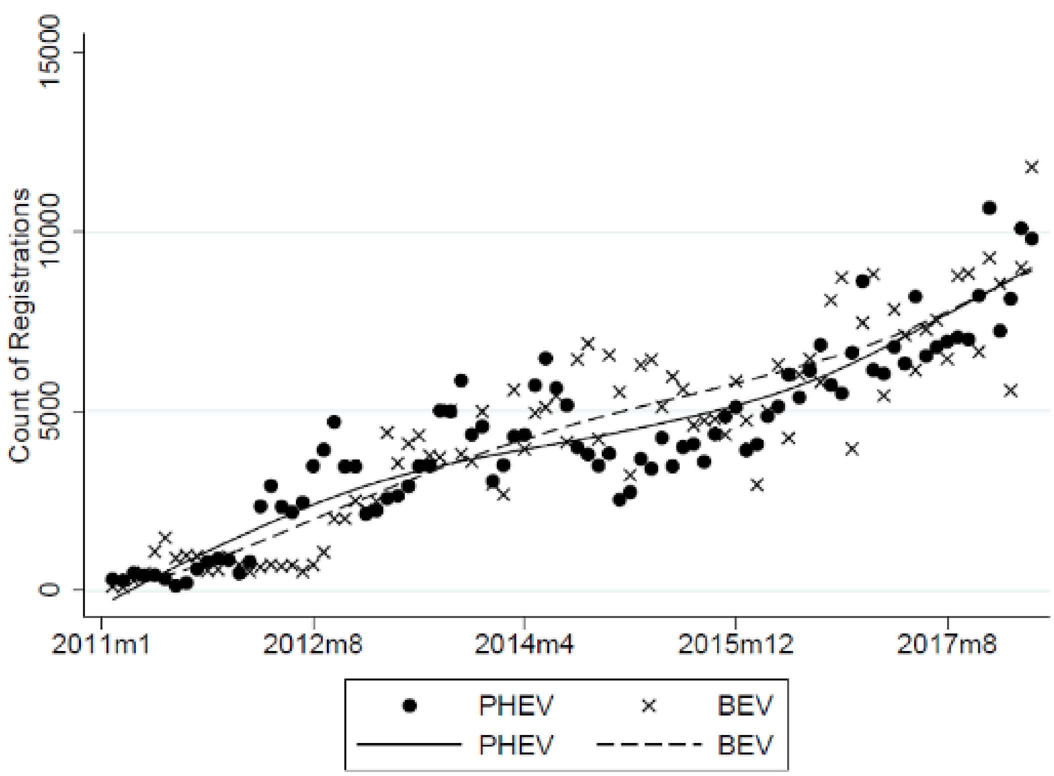
[4] The registration data reports two separate values for vehicles sold in different parts of core-based statistical areas (CBSAs) which consist of metropolitan and micropolitan areas. Some CBSAs are located

in the 374 metro areas in our sample. BEV and PHEV registrations both increased at about the same pace through 2016. BEV registrations jumped in 2017 and 2018, exhibiting exponential growth, while PHEV registrations increased at a more gradual pace in 2017 and 2018. Table 1 shows that there was wide variation in BEV and PHEV adoption between U.S. metro areas during our study period. It is notable that in 39% of metro areas, there were no sales of BEVs or PHEVs over the entire 2011-2018 period. In 2015, the median values of BEV and PHEV sales by metro area were just 2 vehicles each.

Our second data set consists of PM2.5 estimates for the 374 largest U.S. metropolitan areas from 2011 to 2018. The estimates are constructed from gridded daily PM2.5 levels (approximately 15 km resolution) across the 48 contiguous states (EPA, 2018; Lassman et al. 2017; Burkhardt et al. 2018). We aggregate the gridded PM2.5 data by calculating the population-weighted mean for each metro area (374 counties) in our sample. We take this measure of PM2.5 pollution as a starting point, naming the variable *PM2.5.* However, because consumers are not likely to contemporaneously respond to air pollution with a large vehicle purchase, we adjust the measure by taking the average of air pollution over the prior four quarters to better capture cumulative impacts, and name this variable *A4LPM2.5*.

Figure 1. New BEV and PHEV Monthly Registrations in 48 U.S. States, 2011 - 2018



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in different states, and have a separate entry for the portion in each state. Once we account for separate entries for each portion of a CBSA in different states, the 374 CBSAs expand into 427 separate CBSAs. Throughout the paper we refer to this expanded set of CBSAs as "metro areas." See U.S. Census Bureau (2016) for a discussion.

Table 1: Mean and SD for Monthly BEV and PHEV Sales Across Metro Areas by Region, 2011, 2015, and 2018

Region	Vehicle Type	2011	2015	2018
CA	BEV	13.6	17.7	42
		(34.1)	(49)	(173)
	PHEV	7.3	17.1	15.6
		(11.4)	(46.2)	(45.9)
West	BEV	9.7	11.9	22.4
		(26.7)	(36.8)	(111.1)
	PHEV	4.7	8.7	7.9
		(7.9)	(30.7)	(29.9)
North	BEV	1.6	4.4	9.6
		(3.9)	(11.6)	(39.8)
	PHEV	3.7	3.2	4.0
		(5.9)	(5.3)	(9.8)
South	BEV	2.8	7.5	8.4
		(4.9)	(51.8)	(28.8)
	PHEV	2.9	2.1	2.2
		(3.9)	(2.4)	(2.8)

Notes: Means and standard deviations (in parentheses) of vehicle registrations by region by year.

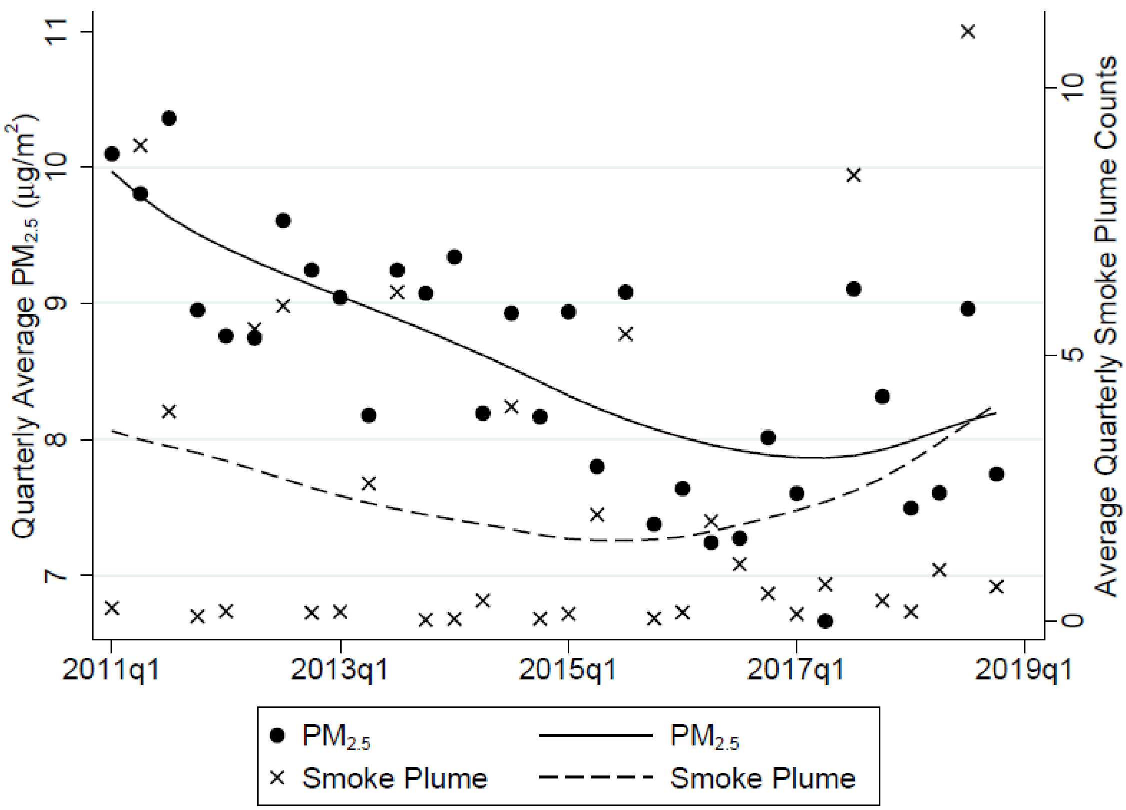
To construct the smoke plume data for the metro areas used in this paper, we follow the procedures detailed in Burkhardt et al. (2020).[5] The raw data is the daily data on landscape fire smoke plumes gathered by the National Oceanic and Atmospheric Administration Hazard Mapping System (HMS, 2018). Wild and prescribed fires, such as agricultural burning, generate plumes that spread across the country for hundreds or thousands of miles before dissipating. This can produce elevated levels of PM2.5 (Ruminski et al., 2006; Brey et al., 2018). The Hazard Mapping System provides daily measures of smoke plumes based on satellite imagery for the entire United States (Ruminski et al. 2006; Rolph et al. 2009; HMS 2018). We associate the plume geometries with the PM2.5 grid (approximately 15 kilometers across 48 contiguous states) and assign a value of 1 if a particular grid cell was under a smoke plume for each day and 0 otherwise. We aggregate the grid cells within a metro area by calculating the population-weighted mean by day, which may result in fractions if only part of the metro area was covered

[5] This section follows the logic described in Burkhardt et al. (2020, 191).

by a plume. Next we sum the number of days within a quarter that a metro area was under a smoke plume. We name this variable *SmokePlume.*[6] Next we take the average over the prior four quarters, and name this variable *A4LSmokePlume.*

Figure 2 displays average values and trends for all U.S. metro areas in our sample for both *PM2.5* and *SmokePlume*. *PM2.5* exhibits some seasonal volatility and declines by roughly 20 percent through 2016 before recovering about 5 percentage points of the 20 percentage point loss in 2017 and 2018. *SmokePlume* displays extreme seasonal volatility, showing an average decline of roughly 8 percent through 2016 before increasing in 2017 and 2018. Although smoke plumes contribute to *PM2.5*, there is little correlation between our measures of *PM2.5* and *SmokePlume* (see Appendix Figure 1).

Figure 2. *PM2.5* and *SmokePlume*, 2011-2018



[6] Smoke plumes are often transported in the upper atmosphere and may not necessarily affect surface-level air quality (Rolph et al. 2009; Ford et al., 2017; Brey et al. 2018). To address the discrepancy between data from satellite imagery and what people experience on-the-ground, as a sensitivity analysis we operationalize a method described in Burkhardt et al. (2018), to probabilistically detect whether the smoke plume affected human exposure. We compare PM2.5 levels on smoke days to the three-month average PM2.5 level around a specific day. We consider a day truly smoke exposed when the PM2.5 level on that day exceeds one standard deviation of the three-month non-smoke mean. We take the estimate of smoke exposed days in a quarter in a given county, and aggregate counties into the 374 metro areas in our sample. Next we take the average over the prior four quarters, and name this variable *A4LAdjustedSmokePlume.*

As a control variable, we include a measure (*Subsidies*) of the net value of state EV policy instruments, as documented for 2010-2015 in Wee et al. (2018, 2019) and extended to 2016-2018 in Hayashida et al. (2021). This variable is measured on a semi-annual basis, and changes when new policy instruments are implemented or existing policy instruments repealed.[7] States have specified EV policy instruments that often differ in value depending on whether a vehicle is a BEV or PHEV. Thus, we specify two different measures of *Subsidies: BEV-Subsidies* and *PHEV-Subsidies*. Each measure is the sum of the monetary value of six state-level policy instruments: five incentives (vehicle purchase incentives, home charger subsidies, reduced licence and registration fees, and high occupancy vehicle lane access) and one disincentive (annual EV fees). One-time benefits are aggregated with annually accruing benefits and costs by taking the net present value over the average vehicle ownership period of six years, assuming a 5% discount rate (Wee et al., 2018). Appendix Table 1 summarizes the intervals when various state policy instruments are in effect.[8]

Lastly our data includes one additional variable used as a control in regressions and two more variables used to test for heterogeneous effects of *A4LPM2.5* and *A4LSmokePlume* on EV adoptions. *PublicChargers* is the number of charging stations open to the public per 1,000 square miles of land by state. Two more variables, metro income per capita (*Income*) and metro population (*Population*), are used in regression specifications designed to determine whether the effects of *A4LPM2.5* and *A4LSmokePlume* are heterogeneous with respect to metro income and metro population.

Table 2 displays descriptive statistics, definitions and sources for all variables used in the regressions reported in tables in the main text and appendix.

Table 2. Variable Descriptions, Summary Statistics, and Data Sources, 2011 - 2018

Variable	**Description**	**Mean**	**s.d.**	**Min**	**Max**	**Source**
			EV Registrations			
BEV-registrations	New registrations of BEVs sold in	39	262	0	10,152	IHS Markit, 2021.

[7] Policy data from Hayashida et al. (2021) are dated according to the enactment date of a policy. We have updated this data set to date the start of a policy as the period when it becomes effective.

[8] For some state-level policy data--HOV lane access and designated parking, we gather additional data from a number of publicly-available sources. All data were collected at the state level except data on exemptions from emissions inspections. They were usually collected at the county level, but then assigned as a state-level policy based on whether the policy reached at least 50% of the population in the state. Sources include government websites, phone calls and e-mail correspondence, including Alternative Fuels Data Center (AFDC). (2019b). State Laws and Incentives. U.S. Department of Energy. Accessed 5 October 2019. Available at https://afdc.energy.gov/laws/state

	metropolitan area *a* in quarter *q*					
PHEV-registrations	New registrations of PHEVs sold in metropolitan area *a* in quarter *q*	33	208	0	7,475	IHS Markit, 2021.
Pollution						
A4LPM2.5	Population-weighted PM2.5 (mg/m^3) in metropolitan area *a* in quarter *q*, measured as the average the prior four quarters	8.7	1.9	2.9	19	EPA, 2018; Lassman et al., 2017; Burkhardt et al., 2018.
A4LSmoke Plume	Population-weighted smoke plume days in metropolitan area *a* in quarter *q*, measured as the average of the prior four quarters	7.3	4.8	0	27	HMS, 2018.
A4LAdjusted Smoke Plume	Population-weighted smoke plume days (excluding high altitude plumes) in metropolitan area *a* in quarter *q*, measured as the average of the prior four quarters	2.0	2.0	0	15	HMS, 2018.
State EV Policies						
BEV-Subsidies	Dollar value of vehicle purchase incentive, home charger subsidy, reduced registration fee/vehicle license tax, emissions fee abated, annual fee (negative), and HOV access value	1,479	1,837	-1,066	6,000	AFDC, 2019; govt websites; phone calls and email correspondence.
PHEV-Subsidies		1,045	1,551	-533	6,000	AFDC, 2019; govt websites; phone & email correspondences.

Other Variables						
Population	Population (100,000s) in metropolitan area *a* in year *y*	9.4	22	0.5	203	U.S. Census Bureau, 2010-2018a.
Income	Per capita income (100,000s) in metropolitan area *a* in year *y* (2018$)	0.3	0.1	0.1	0.6	U.S. Census Bureau, 2010-2018b.
Public Chargers	Number of charging stations per 1000 square miles (land) in state *s* in quarter *q*	554	1,179	0	10,128	AFDC, 2020; U.S. Census Bureau, 2012.

Note: Each variable has 13,644 initial observations: 8 years x 4 quarters x 427 metro areas, including separate observations for metro areas spanning several states.

4. Methods

We estimate all regression models using separate samples of quarterly data for BEVs and PHEVs over the 2011-2018 period. Our baseline specification is a model that includes a quarterly fixed effect, a metro area-by-year fixed effect, the two pollution variables (*A4LPM2.5* and *A4LSmokePlume*) and controls for the value of state EV policy instruments (*Subsidies*) and the number of charging stations open to the public in the state (*PublicChargers*).[9] The baseline specification is:

$$EVReg_{it} = \beta_0 + \beta_1 A4LPM2.5 + \beta_2 A4LSmokePlume_{it} + B_3 Subsidies$$

$$+\beta_4 PublicChargers_{st} + \gamma_{iy} + \delta_q + \varepsilon_{it}$$

where $EVReg_{it}$ is the count of BEV registrations in metro area *i* in quarter t for the BEV sample and the count of PHEV registrations for the PHEV sample, γ_{iy} is the fixed effect for metro area *i* in year *t*, δ_q is a quarter fixed effect and ϵ_{it} is an idiosyncratic error term. The quarterly fixed effect absorbs unobservable shocks that are constant across metro areas but vary by quarter such as macroeconomic shocks that affect the overall national market for EVs. The metro-year fixed effect absorbs idiosyncratic shocks affecting each metro area in a given year such as metro-specific changes in vehicle sales, fuel prices, income, and population. All regressions are

[9] Increases in *PublicChargers* could result in consumers substituting a BEV purchase for a PHEV purchase due to the denser charging options available to drivers taking long-distance trips. However, increases or ***expected increases*** in EV registrations could also induce changes in public and private investments in the charging network open to the general public. The positive feedback from EV registrations to *PublicChargers* implies that the estimated coefficient on *PublicChargers* will be biased upwards.

estimated with a Poisson pseudomaximum likelihood estimator to account for zero values on the dependent variables, overdispersion, and heteroskedasticity.[10] Standard errors in all regressions are robust standard errors, and are clustered by metro area.

For identification, each model relies on within-metro area, within-year variation in air pollution levels via either persistent air pollution (*A4LPM2.5*) or more temporary spikes in pollution (*A4LSmokePlume*). Although an EV that replaces a fossil-fuel-powered vehicle will displace some local pollutants, we assume that marginal EV sales are not noticeably affecting local emissions, and will not affect lagged emissions. Moreover, metro area EV sales are unlikely to directly affect the probability of smoke plumes in the metro area over the eight-year interval covered by our PHEV and BEV samples.

Are there *a priori* expectations for the signs on coefficients for the two pollution variables? The first-order effect should likely be that the relationship is positive - that consumers respond to green signals by substituting into a green good. However, in this case there are multiple vehicles from which consumers can choose. Chan and Kotchen (2014) present a generalized impure public (green) good and linear characteristics model that looks at private choice of impure public goods with both private and public characteristics. An EV is an example of an impure public good that generates private transportation services and environmental services. In a model with just one green vehicle, say BEVs with only an electric engine, we would expect the coefficients for both pollution variables to be positive, as an increase in any type of pollution should induce substitution out of gasoline-powered vehicles into green BEVs. However, with two types of green vehicles that are substitutes, say BEVs and PHEVs with an electric engine and a gas-powered engine, coefficients for both pollution variables could be either positive or negative. In response to an increase in either *A4LPM2.5* or *A4LSmokePlume*, we again expect a substitution out of gasoline-powered vehicles into EVs, and therefore we expect that at least one of the coefficients on *A4LPM2.5* will be positive in either the BEV or the PHEV regression. Similarly, we expect that at least one of the coefficients on *A4LSmokePlume* will be positive in either the BEV or PHEV regressions. Chan and Kotchen (2014) show that changes in demand for green goods in their generalized model (m goods and n characteristics) “depend on the implicit cross-price effects among private characteristics, public characteristics, and across both” (p. 13). In addition, when an environmental parameter changes (in this case, the level of metro pollution), there are additional income effects and complications stemming from kinked budget constraints due to the discrete choice between BEVs and PHEVs.[11]

Beyond the baseline regressions, we estimate other regressions to check on the sensitivity of the baseline results to different samples, time periods, and inclusion of variables to account for heterogeneous treatment effects. First, we split the samples of EV sales into the 2011-2014 and 2015-2018 periods to check whether the estimated regression coefficients change as markets for BEVs and PHEVs changed over time. This is an important check as sales in 80 percent of metro areas increased sharply over the eight-year period and the composition of EV models in the

[10] We use the STATA ppmlhdfe estimator in all specifications (Correia, Guimarães, and Zylkin, 2020).

[11] Finally, it is possible that both coefficients on the pollution variables are negative if consumers decide to substitute away from both conventional autos and EVs into non-plug-in hybrid electric vehicles.

market changed rapidly as new models entered and some models exited the market. Second, we estimate the model without California metro areas, which collectively accounted for 42 percent of EV sales over the sample period. This allows us to check whether estimates for *A4LPM2.5* and *A4LSmokePlume* are driven by California metro areas. Third, we estimate the model using a sample that excludes metro areas with sales below the median. This enables us to check whether metro areas in which markets for EVs have not yet emerged on a substantial scale are muting the pollution regression coefficients in the baseline regressions.

Next we examine whether estimates of *A4LPM2.5* and *A4LSmokePlume* are heterogeneous in metro areas with different population sizes (*Population*) and average per capita income (*Income*). We do this by estimating specifications with interaction terms between the two pollution variables and the demographic variables. Estimates could differ across metro areas with different incomes because consumers with higher incomes have more discretion in their budgets to respond voluntarily to environmental signals, and may have different preferences for different types of environmental goods. Estimates could differ across metro areas with different population sizes for a number of reasons, most of which are related to population density. These include greater densities of EV dealers, availability of more EV models, smaller parking spaces, and more media/internet sources drawing attention to changes in PM2.5 and smoke plume pollution within the metro area.

We also examine whether estimates of coefficients for *A4LPM2.5* and *A4LSmokePlume* are heterogeneous within metro areas located in states with Zero Emission Vehicle (ZEV) regulations. Auto dealers and manufacturers in states with ZEV regulations are more constrained in how they adjust supply of internal combustion engine cars and EVs in response to changes in demand than auto dealers and manufacturers in states without ZEV regulations. The ZEV constraints could affect how they respond to changes in consumer demand stemming from changes in metro PM2.5 and smoke plume pollution.

We also recognize that the error terms from the PHEV and BEV regressions are likely to be correlated with each other given that the two green vehicles are substitutes (Chan and Kotchen, 2014). To account for this possibility, we estimate a set of regressions on the share of BEV registrations to EV registrations. The ratio measure of market composition removes all information in the dependent variable regarding the overall expansion of the EV market but can potentially provide additional insights into substitution of BEVs for PHEVs, and vice-versa, within metro areas in response to changes in the two pollution measures.

Finally, we conduct two robustness checks. First, we rerun all regression specifications using a different measure of smoke plumes, *A4LAdjustedSmokePlumes*, that incorporates only those smoke plumes that reach surface levels and could directly affect human exposure. Second, we rerun all regression specifications using a more comprehensive measure of air pollution, Air Quality Index (AQI), that incorporates five different measures of air pollution, including PM2.5.

5. Empirical Results

A. Results for Regressions with BEV Sample

Table 3 reports results for eight specifications of regressions with the BEV sample. In the baseline BEV specification (Table 3, column 1), the estimate for *A4LPM2.5* is positive (0.19) and statistically significant at the one percent level. This means that a one unit increase in *A4LPM2.5* (which indicates an increase in PM2.5 pollution) is associated with an average 19 percent increase in BEV sales within metro areas. To put this in perspective, a one-standard deviation increase in within-metro area *A4LPM2.5* (1.1 units) increases BEV registrations within metro areas by an average 20.9%. In contrast, the estimate for *A4LSmokePlume* is negative (-0.0077) and statistically significant at the 10 percent level. A one-standard deviation (within metro areas) increase (3.26 units) in *A4LSmokePlume* decreases BEV registrations within metro areas by an average 2.5%. Thus variations in PM2.5 pollution are much more important in explaining variations in BEV sales than variations in pollution from smoke plumes.

As discussed in Section 4, we estimate seven variations of our baseline regression. First, we split the sample in two at the start of 2015 and re-estimate the baseline regressions with the split samples. Results from regressions using the 2011-2014 and 2015-2018 samples are reported in columns 2 and 3, respectively. In the regression with the 2011-2014 sample (column 2), the estimated coefficient on *A4LPM2.5* is negative and statistically insignificant, while the estimated coefficient on *A4LSmokePlume* is positive and statistically significant at the one percent level. Both results are diametrically opposite to those obtained in estimates with the full sample (column 1). However, estimated coefficients on *A4LPM2.5* and *A4LSmokePlume* from the regression with the 2015-2018 sample (column 3) have the same signs and statistical significance as the coefficients in the baseline full-sample regressions, with the coefficients on *A4LPM2.5* (0.27) and *A4LSmokePlume* (-0.03) both larger in absolute value than the corresponding coefficients in the baseline regressions. These larger estimates provide some indication that consumers in the U.S. vehicle market became more sensitive to environmental signals in the second half of our sample.

The next five variations--excluding California metro areas from the sample, excluding metro areas with below median sales of BEVs, including interaction variables between metro population and the two pollution measures, including interaction variables between metro income and the two pollution measures, and including interaction variables between state ZEV status and the two pollution measures--all yield estimated coefficients on *A4LPM2.5* and *A4LSmokePlume* that follow the same pattern of signs and statistical significance as in the baseline regression. The estimated coefficient on the interaction variable between *A4LPM2.5* and *Population* is positive and statistically significant at the five percent level (column 6), indicating a larger response to PM2.5 pollution in metro areas with higher populations. The interaction variable between *Income* and *A4LSmokePlume* is negative and statistically significant at the ten percent level, indicating a smaller response to changes in SmokePlume in higher-income metro areas (column 7). Similarly, the interaction variable between *ZEV* and *A4LPM2.5* yields a negative but statistically insignificant coefficient, while the interaction term between *ZEV* and *A4LSmokePlume* yields a negative and statistically significant coefficient, indicating the consumer response to increased smoke plumes is larger in ZEV states (column 8). Overall, the estimated coefficients on *A4LPM2.5* and *A4LSmokePlume* are remarkably similar in five of the seven variations on the baseline regression.

All specifications include a measure of state net subsidies (*BEV-Subsidies)* and for the density of the state's public charger network (*PublicChargers*). Estimates on *BEV-Subsidies* are positive albeit statistically insignificant in all eight specifications. Estimated coefficients on *PublicChargers* are positive in seven of eight specifications and statistically significant in just two specifications. We note that the estimated coefficient on *PublicChargers* is positive and statistically significant at the one percent level in the standard specification estimated for a sample that excludes California metro areas (column 4). This result provides narrow evidence that public charger networks may be important to BEV adoption decisions in most states.

B. Results for Regressions with PHEV Sample

Table 4 reports results for eight specifications of regressions with the PHEV sample. In all eight specifications the estimated coefficients on *A4LPM2.5* are negative and statistically significant at least at the five percent level. One possible explanation for this result is that increases in PM2.5 pollution induce a strong substitution by consumers out of PHEVs and into BEVs. Note that the coefficient in the primary specification is -0.105, which is approximately 55% of magnitude of the effect on BEV (0.190). The estimated coefficients on *A4LSmokePlume* tell a similarly consistent story: All are positive and seven of the eight are statistically significant at least at the five percent level. Combined with the negative estimated coefficients on *A4LSmoke Plume* in the BEV regression, these results indicate that increases in smoke plume pollution induce a strong substitution by consumers out of BEVs and into PHEVs. The interaction of *A4LPM2.5* with *Population* suggests that this substitution response is stronger in areas with higher population. The coefficient on the interaction of PM2.5 and income is positive (0.00548) indicating that the substitution effect is less strong in wealthier metro areas. The interaction of *SmokePlume* and population and income are not statistically significant. However, the interaction between *SmokePlume* and *ZEV* is positive and significant (0.02036) indicating that consumers in metro areas with more supply regulations are more responsive to smoke-exposed days.

Similar to the BEV-focused regressions, all specifications include *PHEV-Subsidies* and *PublicChargers*. The estimated coefficients for *PHEV-Subsidies* are negative for all eight specifications, though not statistically significant in any specification. The estimated coefficients for *PublicChargers* are negative for all eight specifications, and statistically significant at least at the ten percent level in five of eight specifications. A possible explanation for the negative sign is that there is substitution into BEVs as public charger networks expand. In metro areas where charging networks are becoming more dense over the sample period, consumers reasonably expect that there will be fewer instances where travel options for BEV drivers are restricted due to range limits and/or range anxiety, allowing consumers to substitute out of PHEVs with their back-up gasoline-powered engines.

C. Results for Regressions on BEV Share in Metro EV Sales

We explore the substitution effect further in Table 5, where BEVs are taken as the share of all EVs sold. The coefficients on A4LPM2.5 are positive in all models and statistically significant

Table 3. Poisson Pseudomaximum Likelihood Regressions: BEV Sample

	(1) Full Sample 2011-2018	(2) Split Sample 2011-2014	(3) Split Sample 2015-2018	(4) Without California	(5) With Above Median Sales	(6) Population Interaction	(7) Income Interaction	(8) ZEV Interaction
A4LPM2.5	0.19025***	-0.12757	0.27483***	0.18048***	0.19643***	0.12086***	0.02361	0.20429***
	[0.035]	[0.089]	[0.046]	[0.042]	[0.037]	[0.031]	[0.157]	[0.043]
*A4LPM2.5 * Treatment*						0.00003***	0.00485	-0.04973
						[0.000]	[0.005]	[0.074]
A4LSmokePlume	-0.00771*	0.02550***	-0.02982***	-0.00181	-0.00891*	-0.00648	0.02864	-0.00065
	[0.004]	[0.010]	[0.005]	[0.005]	[0.005]	[0.005]	[0.020]	[0.005]
*A4LSmoke Plume * Treatment*						-0.00000	-0.00106*	-0.02506***
						[0.000]	[0.001]	[0.007]
BEV-Subsidies	0.00018	0.00009	0.00019	0.00019	0.00018	0.00017	0.00018	0.00018
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
PublicChargers	0.00005	-0.00027**	0.00001	0.00131***	0.00005	0.00005	0.00005	0.00006
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Constant	4.24866***	6.60972***	4.06498***	3.52443***	4.32186***	4.07833***	4.19675***	4.25628***
	[0.402]	[0.849]	[0.533]	[0.304]	[0.422]	[0.376]	[0.439]	[0.399]
Obs	11,852	5,416	6,436	11,076	4,699	11,852	11,852	11,852
Metro-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: Robust standard errors in brackets. *** p<0.01, ** p<0.05, * p<0.1

Table 4. Poisson Pseudomaximum Likelihood Regressions: PHEV Sample

	(1) Full Sample 2011-2018	(2) Split Sample 2011-2014	(3) Split Sample 2015-2018	(4) Without California	(5) With Above Median Sales	(6) Population Interaction	(7) Income Interaction	(8) ZEV Interaction
A4LPM2.5	-0.105***	-0.232***	-0.058**	-0.123***	-0.109***	-0.094***	-0.290***	-0.126***
	[0.030]	[0.065]	[0.024]	[0.028]	[0.032]	[0.032]	[0.085]	[0.027]
*A4LPM2.5 * Treatment*						-0.00000*	0.00548**	0.06768
						[0.000]	[0.002]	[0.044]
A4LSmokePlume	0.01460***	0.03003***	0.00903**	0.00999***	0.01305***	0.01386***	0.00259	0.00997***
	[0.004]	[0.010]	[0.004]	[0.002]	[0.004]	[0.005]	[0.016]	[0.002]
*A4LSmokePlume * Treatment*						0.00000	0.00035	0.02036**
						[0.000]	[0.000]	[0.009]
PHEV-Subsidies	-0.00002	-0.00007	-0.00001	-0.00001	-0.00002	-0.00002	-0.00002	-0.00002
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
PublicChargers	-0.00006*	-0.0006***	-0.00002	-0.00022	-0.00005	-0.00006*	-0.00007**	-0.00007**
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Constant	6.77569***	7.70305***	6.58050***	6.77158***	7.01236***	6.80275***	6.73615***	6.79459***
	[0.228]	[0.598]	[0.149]	[0.190]	[0.247]	[0.233]	[0.180]	[0.178]
Obs	12,856	6,328	6,528	12,060	4,699	12,856	12,856	12,856
Metro-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: Robust standard errors in brackets. *** p<0.01, ** p<0.05, * p<0.1

Table 5. Poisson Pseudomaximum Likelihood Estimates for Share of BEVs in Total EVs Sold

	(1) Full Sample 2011-2018	(2) Split Sample 2011-2014	(3) Split Sample 2015-2018	(4) Without California	(5) With Above Median Sales	(6) Population Interaction	(7) Income Interaction	(8) ZEV Interaction	(9) Net Subsidy
A4LPM2.5	0.07145***	0.05390	0.09511***	0.07208***	0.08026***	0.06494***	0.16588*	0.07579***	0.07613***
	[0.020]	[0.036]	[0.024]	[0.022]	[0.019]	[0.022]	[0.089]	[0.025]	[0.020]
*A4LPM2.5 * Treatment*						0.00102*	-0.33028	-0.00617	
						[0.001]	[0.291]	[0.038]	
A$LSmoke Plume	-0.00330	-0.00709	-0.01945**	-0.00228	-0.00304	-0.00372	-0.02086	-0.00149	-0.00283
	[0.008]	[0.011]	[0.009]	[0.008]	[0.005]	[0.008]	[0.036]	[0.008]	[0.007]
*A4LSmoke Plume * Treatment*						0.00008	0.06202	-0.01567	
						[0.000]	[0.111]	[0.016]	
BEV-Subsidies	0.00003	0.00021***	0.00001	0.00003	-0.00000	0.00003	0.00003	0.00003	
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	
Net BEV-PHEV Subsidies									0.00004*
									[0.000]
Public Chargers	0.00014***	-0.00004	0.00007**	0.00078***	0.00012***	0.00013***	0.00014***	0.00014***	
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	
Constant	-1.48923***	-1.67459***	-1.51950***	-1.70100***	-1.46428***	-1.52985***	-1.46974***	-1.52026***	-1.40007***
	[0.170]	[0.343]	[0.188]	[0.184]	[0.156]	[0.164]	[0.166]	[0.179]	[0.165]
Obs	10,760	4,764	5,996	10,035	4,699	10,760	10,760	10,760	10,760
Metro-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: Robust standard errors in brackets. *** p<0.01, ** p<0.05, * p<0.1

at least at the 10 percent level in all specifications but for the one estimated with the 2011-2014 split sample (column 2). The results support the hypothesis of a substitution from PHEV to BEV induced by PM2.5. The estimated coefficients on A4L*SmokePlume* are positive for seven of eight regressions, though only statistically significant in the 2015-2018 sample (Table 5, column 3). We find that during the early part of the sample (2011-2014), BEV subsidies have a positive effect on the share of BEV sold, which suggests that subsidies played an important role during the early phases of BEV adoption relative to metro air quality. We also experimented with an alternative measure of subsidies, which is the difference between BEV and PHEV subsidies, named *NetBEV-PHEV-Subsidies.* Results (column 9) for a specification with this subsidy variable using the full 2011-2018 sample shows an estimated coefficient (0.00004) that is positive, relatively small, and statistically significant at the 10 percent level.

D. Two Robustness Checks

First, we estimated regression specifications with a measure of smoke plumes adjusted to include only plumes that affect surface level air quality: *A4LAdjustedSmokePlumes*. Results are reported in Appendix Table 3 for the BEV sample and Appendix Table 4 for the PHEV sample. Estimates are broadly consistent with those obtained from regressions estimated with *A4LSmokePlume*, with levels of statistical significance for estimated coefficients on pollution variables lower in some specifications.

Second, we estimated regression specifications with a broad measure of metro pollution, the Air Quality Index (AQI). The EPA calculates AQI for metro areas from five air pollutants: ground-level ozone, PM2.5, carbon monoxide, sulfur dioxide, and nitrogen dioxide. Results from regression specifications replacing *AL4PM2.5* with *AL4AQI* are reported in Appendix Table 5 for the BEV sample and Appendix Table 6 for the PHEV sample. Estimates are broadly consistent in signs and statistical significance of estimated coefficients with those obtained in regressions with *A4LSmokePlume*.

7. Discussion and Conclusion

Our study shows that changes in local air pollution within U.S. metropolitan areas are associated with changes in consumer purchases of new EVs. We find a positive association between PM2.5 pollution and BEV adoption, and a negative association between PM2.5 pollution and PHEV adoption. Chan and Kotchen's (2014) framework for analyzing choice between multiple green goods points us to the possibility of consumer substitution from PHEVs to BEVs in response to increases in PM 2.5. Over our sample period there was a large average decline (19 percent) in quarterly PM2.5 air pollution within the metropolitan areas in our sample between 2011 and 2018. This means that a decline in PM2.5 levels served to suppress BEV and raise PHEV adoptions.

Smoke plumes caused by wild and agricultural fires that drift over metropolitan areas, on the other hand, are positively associated with PHEV adoption and negatively associated with BEV adoption - though this effect is relatively small in comparison to the consumer response to PM2.5. We speculate that the preference for PHEVs in response to the presence of smoke plumes may be tied to risk-averse consumers substituting into the EV technology which allows more flexibility during an environmental emergency, such as an evacuation from a wildfire. In this case annual smoke plume days in metro areas declined from 2011 through 2016, and then increased through the end of our sample period in 2018.[12] Whereas our measure of PM2.5 pollution represents more persistent air pollution from local sources, our measure of smoke plumes tends to be more sporadic, seasonal, and temporary. As such, we conclude that drivers are rationally more receptive to persistent environmental signals than temporary ones, particularly given that smoke plumes often originate outside of the metropolitan area.

Our results regarding the influence of metro pollution on EV adoption provide useful information for framing the future policy environment. If declines in metro area PM2.5 pollution continue in tandem with increases in smoke pollution, then policymakers may find that the PHEV market is expanding even in the absence of new state and federal EV policies while the BEV market is contracting. In addition, we find that increases in PM2.5 are associated with a net increase in EV adoption (BEV increasing and PHEV decreasing) while state-level BEV net subsidies only induce adoption in the 2011-2014 subsample of our data. This suggests that existing policy interventions may have only induced early adoption of a lesser known technology, whereas voluntary response plays a continued role. This finding adds to the broader literature on the role of voluntary behavior versus policy-induced behavior (e.g., Ostrom, 2020; Bayham et al., 2015; Yan et al., 2021). We emphasize though that our results should not be interpreted as a justification for relaxing emissions regulations because neither state policy nor the presence of local air pollution will prompt EV adoption to the levels set by U.S. goals to curb the climate crisis. The Biden administration has set a goal of EVs accounting for 50% of new car sales by 2030.[13] Achievement of this target clearly depends on whether consumer preferences begin to tilt towards green goods, whether technology underlying BEV and PEV models substantially improves (particularly with respect to battery weight, performance and cost), how the relative prices of EVs and conventional vehicles evolve, and the important role of supply-side interventions.

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[12] Our study does not include 2020 and 2021, which had notoriously bad wildfire smoke seasons.

[13] See "President Biden sets a goal of 50 percent electric vehicle sales by 2030," *New York Times,* Aug. 5, 2021. Available at: https://www.nytimes.com/2021/08/05/business/biden-electric-vehicles.html (last access on 22 August 2021).

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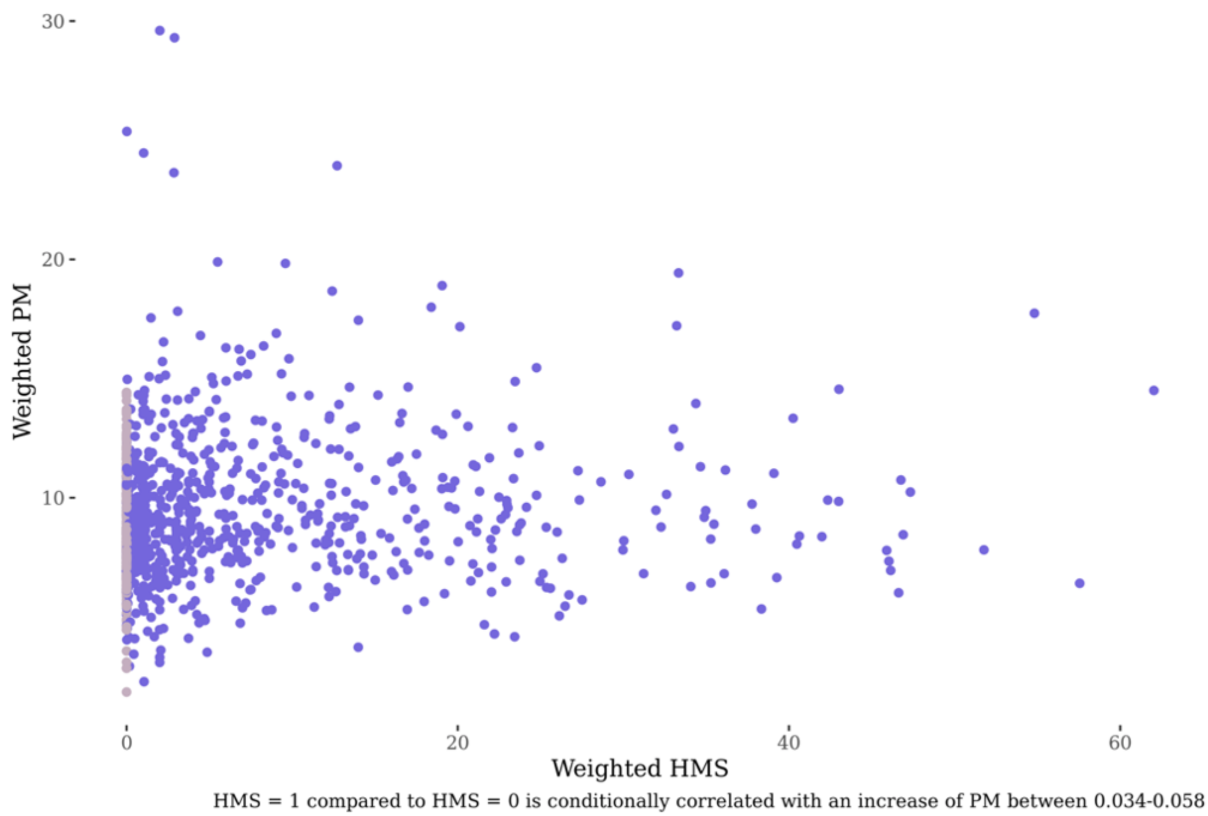
Appendix Figure 1: Scatter plot of quarterly PM levels and weighted smoke plumes



Appendix Table 1. Duration of EV Policies by State, 2011-2018

Vehicle Purchase Incentive (Subsidy or Sales Tax Exemption)		Home Charger Subsidy	Reduced Vehicle License Tax or Registration Fee		Emission Inspection Exemption		HOV Lane Exemption		Annual EV Fee	
BEV	PHEV		BEV	PHEV	BEV	PHEV	BEV	PHEV	BEV	PHEV
CA 11.1-18.2	CA 11.1-18.2	AZ 11.1-17.1	AZ 11.1-18.2	CT 13.1-18.2	AZ 11.1-18.2	MD 11.1-12.2	AZ 11.1-18.2	AZ 14.1-15.1	CO 14.1-18.2	CO 14.1-18.2
CO 12.1-18.2	CO 12.1-18.2	DE 15.2-18.2	CT 13.1-18.2	IL 11.1-18.2	CT 11.1-18.2	NV 11.1-18.2	CA 11.1-18.2	CA 11.1-18.2	GA 15.2-18.2	GA 15.2-18.2
CT 15.1-18.2	CT 15.1-18.2	HI 11.1-12.1	IA 11.1-14.1		MD 11.1-18.2		FL 11.1-18.2	FL 11.1-18.2	ID 15.1-18.2	ID 15.1-18.2
DE 15.2-18.2	DE 15.2-18.2	IL 13.2-15.1	IL 11.1-18.2		NC 11.1-18.2		GA 15.2-18.2	GA 15.2-18.2	IN 18.1-18.2	IN 18.1-18.2
GA 11.1-15.1	HI 11.1-12.1	LA 11.1-17.1			NH 11.1-18.2		HI 11.1-18.2	HI 11.1-18.2	MI 17.1-18.2	MI 17.1-18.2
HI 11.1-12.1	IL 11.1-15.1	MD 11.2-18.2			NM 12.1-18.2		MD 11.1-18.2	MD 11.1-18.2	MN 18.1-18.2	MO 18.1-18.2
IL 11.1-15.1	MA 14.1-18.2	MO 15.1-18.1			NV 11.1-18.2		NC 11.1-18.2	NC 11.1-18.2	MO 11.1-18.2	MS 18.2
LA 11.1-18.2	MD 11.1-18.2	NY 13.1-17.2			NY 11.1-18.2		NY 11.1-18.2	NY 11.1-18.2	MS 18.2	SC 18.1-18.2
MA 14.1-18.2	NH 18.1-18.2	OR 11.1-17.2			OR 11.1-18.2		TN 11.1-18.2	TN 11.1-18.2	NC 14.1-18.2	VA 12.2-13.1
MD 11.1-18.2	OR 11.1-11.2; 18.1-18.2				PA 11.1-18.2		UT 11.1-18.2	UT 11.1-18.2	NE 11.1-18.2	WI 18.1-18.2
NH 18.1-18.2	PA 11.1-18.2				TX 11.1-18.2		VA 11.1-18.2		SC 18.1-18.2	WV 17.2-18.2
NJ 11.1-18.2	RI 16.1-17.1								TN 17.2-18.2	WY 15.2-18.2
OK 11.1-18.2	SC 12.1-16.2								VA 12.2-18.2	
OR 11.1-11.2; 18.1-18.2	TN 11.1-13.1; 15.1-16.1								WA 13.1-18.2	
PA 11.1-18.2	TX 14.1-15.2; 17.2-18.2								WI 18.1-18.2	
RI 16.1-17.1	UT 11.1-17.2								WV 17.2-18.2	

SC 12.1-16.2 TN 11.1-13.1; 15.1-16.1 TX 14.1-15.2; 17.2-18.2 UT 11.1-17.2 VT 14.1 WA 11.1-18.1	VT 14.1 WA 15.2-18.1								WY 15.2-18.2	

Appendix Table 2. State Policy Variable Descriptions, Summary Statistics, and Data Sources: 2011 - 2018.

Variable	Description	Mean	S.D.	Min.	Max.	Source
EV Policies						
BEV purchase incentive	Dollar value of vehicle purchase incentive (in the form of a rebate, subsidy, income tax credit, excise tax credit, or sales tax exemption) in state *s* in half-year *t*	902	1,428	0	6,000	AFDC, 2019; govt websites; phone calls and email correspondences.
PHEV purchase incentive		481	1,043	0	6,000	AFDC, 2019; govt websites; phone calls and email correspondences.
Home charger subsidy	Dollar value of home charge subsidy for hardware and/or installation in state *s* in half-year *t*	45	180	0	1,500	AFDC, 2019; govt websites; phone calls and email correspondences.
BEV reduced VLT or registration fee	Present value savings from reduced VLT or registration fee in state *s* over six-year vehicle ownership based on the applicable fee in the purchase period and frequency assessed	58	265	0	1,599	AFDC, 2019; govt websites; phone calls and email correspondences.
PHEV reduced VLT or registration fee		17	89	0	528	AFDC, 2019; govt websites; phone calls and email correspondences.
BEV emissions inspection fee exemption	Present value savings from emissions inspection fee exemption in state *s* over six-year vehicle ownership based on the applicable fee in the	20	44	0	184	AFDC, 2019; govt websites; phone calls and email correspondences.

PHEV emissions inspection fee exemption	purchase period and frequency assessed	0.31	3.0	0	35	AFDC, 2019; govt websites; phone calls and email correspondences.
BEV HOV access value	Present value of HOV access value in state *s* over six-year vehicle ownership based on the initial purchase period value	590	1,021	0	3,493	AFDC, 2019; govt websites; phone calls and email correspondences; Texas A&M Transportation Institute, 1982-2017.
PHEV HOV access value		392	711	0	2,799	AFDC, 2019; govt websites; phone calls and email correspondences.
Annual BEV fee	Present value of the annual EV fee in state *s* over six-year vehicle ownership based on the initial purchase period value	95	238	0	1,139	AFDC, 2019; govt websites; phone calls and email correspondences.
Annual PHEV fee		36	151	0	1,139	AFDC, 2019; govt websites; phone calls and email correspondences.
BEV subsidies	Dollar value of vehicle purchase incentive, home charger subsidy, reduced registration fee/vehicle license tax, emissions fee abated, annual fee (-), and HOV access value weighted by population in state *s* at in half-year *t*	1,479	1,837	-1,066	6,000	AFDC, 2019; govt websites; phone calls and email correspondences.
PHEV subsidies		1,045	1,551	-533	6,000	AFDC, 2019; govt websites; phone calls and email correspondences.
BEV index (scalar 1-2)	Number of parking policy instruments (designated parking, and free parking) effective in state *s* in half-year *t*	0.16	0.37	0	1	AFDC, 2019; govt websites; phone calls and email correspondences.
PHEV index (scalar 1-2)		0.16	0.37	0	1	AFDC, 2019; govt websites; phone calls and email correspondences.

Appendix Table 3. Poisson Psuedomaximum Likelihood Regressions with *A4LAdjustedSmokePlumes*: BEV Sample

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Full Sample 2011-2018	Split Sample 2011-2014	Split Sample 2015-2018	Without California	With Above Median Sales	Population Interaction	Income Interaction	ZEV Interaction
A4LPM2.5	0.20943***	-0.11920	0.29343***	0.21621***	0.21701***	0.16091***	0.08496	0.24335***
	[0.035]	[0.106]	[0.051]	[0.036]	[0.037]	[0.035]	[0.154]	[0.040]
*A4LPM2.5 * Treatment*						0.00228**	0.35622	-0.09652
						[0.001]	[0.459]	[0.073]
A4LAdjustedSmokePlume	-0.02468**	0.01481	-0.05202**	-0.02753**	-0.02732**	-0.03512**	-0.01033	-0.02973**
	[0.012]	[0.022]	[0.022]	[0.012]	[0.013]	[0.014]	[0.082]	[0.014]
*A4LAdjustedSmoke Plume * Treatment*						0.00050**	-0.03910	0.01125
						[0.000]	[0.245]	[0.029]
BEV-Subsidies	0.00018	0.00010	0.00019	0.00019	0.00018	0.00018	0.00018	0.00018
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
PublicChargers	0.00004	-0.00022*	-0.00001	0.00130***	0.00004	0.00004	0.00003	0.00005
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Constant	4.08783***	6.61005***	3.81607***	3.26233***	4.14668***	3.97258***	4.06989***	4.06392***
	[0.415]	[1.016]	[0.554]	[0.295]	[0.435]	[0.404]	[0.456]	[0.401]
Obs	11,852	5,416	6,436	11,076	4,699	11,852	11,852	11,852
Metro-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Robust standard errors in brackets. *** p<0.01, ** p<0.05, * p<0.1

Appendix Table 4. Poisson Pseudomaximum Likelihood Regressions with *A4LAdjustedSmokePlumes*: PHEV Sample

	(1) Full Sample 2011-2018	(2) Split Sample 2011-2014	(3) Split Sample 2015-2018	(4) Without California	(5) With Above Median Sales	(6) Population Interaction	(7) Income Interaction	(8) ZEV Interaction
A4LPM2.5	-0.09803***	-0.25195***	-0.06788***	-0.12024***	-0.09630***	-0.08137***	-0.27513***	-0.11662***
	[0.022]	[0.051]	[0.022]	[0.014]	[0.024]	[0.022]	[0.068]	[0.014]
*A4LPM2.5 * Treatment*						-0.00073***	0.52166**	0.06280
						[0.000]	[0.208]	[0.042]
A4LAdjustedSmokePlume	0.01030	0.01525	0.01937***	0.00919	0.00426	0.00498	-0.03714	0.00396
	[0.013]	[0.036]	[0.005]	[0.015]	[0.013]	[0.014]	[0.048]	[0.016]
*A4LAdjustedSmokePlume * Treatment*						0.00022**	0.14538	0.02656
						[0.000]	[0.115]	[0.018]
PHEV-Subsidies	-0.00002	-0.00007	-0.00001	-0.00002	-0.00002	-0.00002	-0.00002	-0.00002
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
PublicChargers	-0.00006**	-0.00052***	-0.00001	-0.00024*	-0.00005*	-0.00006**	-0.00006**	-0.00006**
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Constant	6.79456***	8.05080***	6.67982***	6.80754***	6.98549***	6.83360***	6.75166***	6.80218***
	[0.174]	[0.466]	[0.151]	[0.110]	[0.188]	[0.182]	[0.133]	[0.137]
Obs	12,856	6,328	6,528	12,060	4,699	12,856	12,856	12,856
Metro-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: Robust standard errors in brackets. *** p<0.01, ** p<0.05, * p<0.1

Appendix Table 5. Poisson Pseudomaximum Likelihood Regressions with *AQI* Pollution: BEV Sample

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Full Sample 2011-2018	Split Sample 2011-2014	Split Sample 2015-2018	Without California	With Above Median Sales	Population Interaction	Income Interaction	ZEV Interaction
A4LAIQ	0.03206***	0.00430	0.04948***	0.02362**	0.03231***	0.02224**	0.02067	0.03012***
	[0.011]	[0.012]	[0.019]	[0.011]	[0.011]	[0.011]	[0.013]	[0.012]
A4LAIQ Treatment*						0.00386***	0.43880***	0.08258
						[0.001]	[0.133]	[0.074]
A4LSmoke Plume	-0.00794*	0.02019*	-0.02349***	0.00052	-0.00928**	-0.01106**	-0.00327	-0.00672
	[0.004]	[0.011]	[0.005]	[0.004]	[0.004]	[0.005]	[0.010]	[0.005]
*A4LSmoke Plume * Treatment*						0.00010	-0.07359	-0.01453
						[0.000]	[0.073]	[0.025]
BEV-Subsidies	0.00018	0.00007	0.00019	0.00020	0.00018	0.00018	0.00018	0.00019
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Public Chargers	0.00008**	-0.00026**	0.00006	0.00131***	0.00008**	0.00006*	0.00004	0.00007*
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Constant	4.12968***	5.35603***	3.59567***	3.84512***	4.22589***	3.75760***	3.46198***	4.00815***
	[0.364]	[0.765]	[1.011]	[0.423]	[0.371]	[0.425]	[0.480]	[0.378]
Obs	10,632	4,891	5,741	9,856	4,424	10,632	10,632	10,632
Metro-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: Robust standard errors in brackets. *** p<0.01, ** p<0.05, * p<0.1

Appendix Table 6. Poisson Pseudomaximum Likelihood Regressions with *AQI* Pollution: PHEV Sample

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Full Sample 2011-2018	Split Sample 2011-2014	Split Sample 2015-2018	Without California	With Above Median Sales	Population Interaction	Income Interaction	ZEV Interaction
A4LAQI	-0.02419***	-0.05576***	-0.00234	-0.02337**	-0.02569***	-0.02267**	-0.02023**	-0.02432***
	[0.008]	[0.012]	[0.003]	[0.011]	[0.009]	[0.009]	[0.008]	[0.009]
*A4LAQ*I Treatment*						-0.00122***	-0.11677	-0.00322
						[0.000]	[0.079]	[0.045]
A4LSmoke Plume	0.01631***	0.05475***	0.00510	0.01051***	0.01503***	0.01562***	0.02214***	0.01500***
	[0.004]	[0.009]	[0.004]	[0.002]	[0.004]	[0.005]	[0.005]	[0.004]
*A4LSmoke Plume * Treatment*						0.00017*	-0.04128	0.01500
						[0.000]	[0.041]	[0.010]
BEV-Subsidies	-0.00001	-0.00013	-0.00001	-0.00001	-0.00001	-0.00001	-0.00001	-0.00001
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Public Chargers	-0.00007**	-0.00050***	-0.00003	-0.00022	-0.00006**	-0.00007**	-0.00007**	-0.00008***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Constant	7.22249***	8.56347***	6.35172***	6.99109***	7.49905***	7.44709***	7.33966***	7.23935***
	[0.404]	[0.593]	[0.141]	[0.472]	[0.418]	[0.452]	[0.404]	[0.407]
Obs	11,436	5,628	5,808	10,640	4,424	11,436	11,436	11,436
Metro-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: Robust standard errors in brackets. *** p<0.01, ** p<0.05, * p<0.1

Highlights

- We analyze the effect of air pollution on EV adoption in 350 U.S. metro areas.
- Two measures of pollution, PM2.5 particles and wildfire smoke plumes, are specified.
- We use a Poisson pseudomaximum likelihood high definition fixed effect estimator.
- Increases in PM2.5 pollution result in more BEV and less PHEV adoptions.
- Increases in smoke plume pollution result in less BEV and more PHEV adoptions.