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Political Ideology and U.S. Electric Vehicle Adoption

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Abstract

The prospect for electric vehicles (EVs) as a climate change solution hinges on their widespread adoption across the political spectrum. In this paper, we use detailed county-level data on new vehicle registrations from 2012-2022 to measure the degree to which EV adoption is concentrated in the most left-leaning U.S. counties, and how this concentration has changed over time. The results point to a strong and enduring correlation between political ideology and U.S. EV adoption. During our time period about half of all EVs went to the 10% most Democratic counties, and about one-third went to the top 5%. There is relatively little evidence that this correlation has decreased over time, and even some specifications that point to *increasing* correlation. The results suggests that it may be harder than previously believed to reach high levels of U.S. EV adoption.

JEL: D12, H23, Q48, Q50

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1 Introduction

The prospect for electric vehicles (EVs) as a climate change solution hinges on their widespread adoption by households across the political spectrum. Policymakers envision EVs reaching two-thirds of U.S. new vehicle sales by 2032, so even ubiquitous adoption in left-leaning areas like Cambridge, Massachusetts will simply not be enough.[1]

In this paper, we examine the correlation between political ideology and U.S. EV adoption. Using detailed county-level data on new vehicle registrations for the entire United States from 2012-2022, we measure the degree to which EV adoption is concentrated in the most left-leaning counties, and how this concentration has changed over time.

The results point to a remarkably strong correlation. During our time period about half of all new EVs in the United States went to the 10% most Democratic counties, and about one-third went to the top 5%. Counties with affluent left-leaning cities like Cambridge MA, San Francisco CA, and Seattle WA, play a disproportionately large role in driving the entire national increase in EV adoption.

Surprisingly, we find little evidence that the correlation between political ideology and EV adoption has decreased over time. As late as 2022, about half of all new EVs still went to the 10% most Democratic counties, and about one-third still went to the top 5%. Looking year-by-year, the correlation between political ideology and

[1] "Biden Plans an Electric Vehicle Revolution. Now the Hard Part." *New York Times*, Coral Davenport and Neal E. Boudette, April 13, 2023.

EV adoption goes up and down but with no clear negative trend. There are even some specifications that point to *increasing* correlation. The overall scale of the EV market expands dramatically over our sample period, yet we find that, at least through 2022, new registrations continue to be overwhelmingly concentrated in the most left-leaning counties.

These findings have significant policy implications. Probably most importantly, the enduring role of political ideology suggests that it may be harder than previously believed to achieve widespread U.S. EV adoption. Proposed U.S. fuel economy rules, for example, are designed to ensure that EVs are two-thirds of new vehicle sales by 2032, but such an aggressive increase would require adoption patterns to change dramatically.[2]

Our paper contributes to a small literature in economics on political ideology and "green" vehicle adoption. In one of the first papers on this topic, Kahn (2007) finds that Census tracts in Los Angeles county with more registered Green Party voters are more likely to have hybrid vehicles. Kahn and Vaughn (2009) shows that zip codes in California with more registered Green Party voters are more likely to have hybrid vehicles, controlling for income and other household characteristics. Sexton and Sexton (2014) finds that zip codes in Colorado and Washington with more Democratic voters are more likely to have the Toyota Prius relative to less conspicuous hybrids like the Toyota Camry hybrid, consistent with what they call "conspicuous conservation".

[2] "E.P.A. Is Said to Propose Rules Meant to Drive Up Electric Car Sales Tenfold" *New York Times*, Coral Davenport, April 8, 2023

Our study is also related to a broader literature in economics on EVs. Previous work has shown that charging stations (Li et al., 2017; Springel, 2021; Li, 2023), subsidies (Muehlegger and Rapson, 2022), household income (Borenstein and Davis, 2016), gasoline prices (Bushnell et al., 2022), and peer effects (Tebbe, 2023) all matter for EV adoption.[3] Our results show that political ideology also plays a central role and that the effect of political ideology remains strong and statistically-significant even after controlling for household income, population density, and gasoline prices.

The paper proceeds as follows. Section 2 discusses data sources. Section 3 describes the correlation between political ideology and U.S. EV adoption, and how this correlation has changed over time. Section 4 considers alternative explanations, testing to see how the correlation changes after controlling for household income and other factors. Section 5 takes a preliminary step toward understanding mechanisms, following Sexton and Sexton (2014) in comparing patterns for "conspicuous" versus "inconspicuous" EVs. Section 6 concludes.

2 Data

The core dataset for this analysis is the Experian Auto Registration Database. See `https://www.experian.com/automotive/auto-vehicle-data`. This proprietary dataset was compiled by Experian using data from state department of motor vehicle

[3]There is also an analogous literature examining how many of these same factors drove adoption of conventional hybrid vehicles. See, e.g, Grinblatt et al. (2008); Gallagher and Muehlegger (2011); Sallee (2011); Heutel and Muehlegger (2015). Farther afield, there are also papers about what an EV replaces (Xing et al., 2021), how much EVs are driven (Burlig et al., 2021), and the environmental impact of EVs (Holland et al., 2016, 2020).

offices and other sources, and describes the universe of U.S. new vehicle registrations. Our primary measure of EV adoption is the "EV Share", which is the share of all new vehicle registrations that are EVs. We define EVs as including both battery EVs (like all Tesla models) as well as plug-in hybrid EVs (like the Prius Plug-In Hybrid). We observe shares at both the state- and county-level over the period 2012 to 2022. See Appendix Table 1 for descriptive statistics for our county-level dataset.

A valuable feature of the Experian data is that they include both sales and leases. Vehicle leasing is common in the United States, and the percentage of new vehicles that are leased varied widely during our sample period, increasing from 21% in 2012 to 30% in 2016, and then decreasing again to 27% in 2020, and to below 20% in 2022.[4] The Experian data provide a record of all new vehicles as they become initially registered, regardless of whether they are purchased or leased.

Our primary measure of political ideology is Democrat vote share. We use state and county voting records from the 2012 U.S. presidential election. We use 2012 because this is the beginning of our sample period. We also show that results are similar when we use instead 2016 or 2020. See the appendix for details. In the 2012 election, there were 26 states plus Washington DC won by the Democratic party, and 24 states won by the Republican party. Less than 2% of voters selected the Libertarian or other third parties. We obtain state and county voting records from the MIT Election Lab data. County-level voting records are not available for Alaska for 2012, so Alaska is

[4]See "Car Buyers Shun Leases as Deals and Vehicles Dwindle" Nora Eckert, *Wall Street Journal* March 24, 2022, and "Car Leasing Plummeted During Pandemic, Could Take Years to Recover," Ryan Felton, *Wall Street Journal* January 28, 2023.

dropped in all county-level analyses.[5]

In some specifications we control for median household income. EVs have historically been more expensive than their conventional counterparts, making them more accessible to higher-income households. Prior work has shown that higher-income households have been more likely to adopt EVs. See, e.g. Borenstein and Davis (2016); Gillingham et al. (2023). We use county-level median household income estimates for 2012 from the U.S. Census Bureau Small Area Income and Poverty Estimates (SAIPE) Program. See `https://www.census.gov/programs-surveys/saipe/data/datasets.html` for details.

In some specifications we also control for population density. Densely populated urban areas tend to have more robust charging infrastructure which in turn can encourage more EV adoption in higher population density areas. In addition, shorter driving trips, partly due to smaller commuting distances, and more frequent stop-and-go travel patterns make EVs a practical and cost-efficient choice for households in more densely populated environments. We define population density as county-level population divided by total county land area. We obtain county-level population estimates for 2012 from the U.S. Census Bureau Population Estimates Program while information on land area for 2012 comes from the U.S. Census Bureau TIGER/Line Shapefiles. See `https://www.census.gov/programs-surveys/popest/data/tables.html` and `https://www.census.gov/programs-surveys/geography.html` for more detail.

[5] County voting records for Kalawao, Hawaii were obtained separately, from `https://en.wikipedia.org/wiki/2012_United_States_presidential_election_in_Hawaii` as these records are not included in the MIT Election Lab data.

We also control for gasoline prices in some specifications. Previous research has shown that vehicle buyers are attentive to gasoline prices in choosing which gasoline-powered vehicle to purchase. See, e.g. Busse et al. (2013); Allcott and Wozny (2014); Sallee et al. (2016). So it would make sense that gasoline prices would also matter for buyers choosing between gasoline-powered vehicles and EVs (Bushnell et al., 2022). We use state-by-year average gasoline prices from 2012 to 2021 from the U.S. Department of Energy, Energy Information Administration, *State Energy Data System* (SEDS). See `https://www.eia.gov/state/seds/` for details.

3 Main Results

This section describes the correlation between political ideology and U.S. EV adoption, and how this correlation has changed over time. We start in Section 3.1 looking at the more aggregated state-level, before diving into county-level data in Sections 3.2, 3.3, and 3.4.

3.1 State-Level Scatterplots

Figure 1 is a scatterplot showing the relationship between EV adoption and political ideology. There are 51 observations, one for each state plus Washington DC. The x-axis is the Democrat vote share, ranging from near 25% in Utah and Wyoming to more than 65% in Vermont, Hawaii, and Washington DC. The y-axis is EVs as a share of all new vehicles 2012-2022. EV adoption was highest in California, with EVs representing over 6% of all new vehicles registered.

There is a clear positive correlation between EV adoption and Democrat vote share. The three West coast states (CA, WA, and OR) all have high Democrat vote shares and high EV adoption. But even if one were to exclude those three states there is still a clear positive correlation with households in majority Democrat states (in blue) about twice as likely on average to adopt an EV than households in majority Republican states (in red).

Figure 2 is the same as the previous figure, except rather than a single scatterplot, we include eleven separate scatterplots, one for each year 2012 to 2022. In each case, the y-axis is EVs as a share of new vehicles registered during that year, and we use the same the y-axis range throughout to facilitate comparison across years.

The figure reveals explosive growth in EV adoption during our sample period. In the early years of the sample, EV shares are near 0% in most states, and below 5% everywhere. Adoption increases sharply year-after-year with particularly notable growth in 2018, 2021, and 2022. By the end of the sample period, EVs represent more than 5% of the market in most Democratic states, while still less than 5% in most Republican states.

These state-level scatterplots show a strong and enduring relationship between EV adoption and political ideology. It is hard to say from looking at these figures whether political ideology matters more or less in 2022 than it did in 2012, but it clearly does matter throughout the sample period. In the next section we dig deeper by turning from state-level data to county-level data. The state-level patterns provide an intuitive starting point for the analysis but they also obscure rich variation within states that can shed additional light on this relationship.

3.2 Top U.S. Counties for EVs

Table 1 reports the top 20 U.S. counties for EVs. For the purposes of this table, but not the analyses which follow, we restrict the list to counties with population higher than 750,000. For each county we report EVs as a percentage of all new registered vehicles during out sample period 2012-2022.

Most of these counties are urban, high-income, and in Democratic states. California features prominently in the list with nine of the top ten counties. Strikingly, the top four counties are all in California's Bay Area, one of the primary "green" clusters shown by Kahn and Vaughn (2009) to have a disproportionate number of conventional hybrid vehicles, and this pattern clearly continues with EVs. Counties from outside California mostly include urban left-leaning cities. Washington's King County, for example, is home to the city of Seattle. Other examples include Multnomah County, OR (Portland), Middlesex County, MA (Cambridge), and Travis County, TX (Austin).

As a group, these twenty counties were responsible for 40% of all U.S. EV adoption over the period 2012-2022, while representing only 12% of all U.S. vehicle registrations.

Table 2 reports the *bottom* 20 U.S. counties for EVs. We continue to restrict the list to counties with population higher than 750,000. Interestingly, of the 79 U.S. counties with population higher than 750,000, 66 are Democrat and only 13 are

Republican. So this list by construction includes many Democratic counties. But the list nonetheless looks quite different from the previous table, with multiple counties from Texas, Michigan, New York, and Florida appearing on the list.

In the following section we continue to examine the concentration of EVs, but with a more explicit focus on political ideology.

3.3 Quantifying the Concentration of EVs

Figure 3 describes the pattern of U.S. EV adoption across counties with regard to political ideology, and how this has changed over time. The x-axis is the percentile shares of counties based on Democrat vote shares, from highest to lowest. The y-axis is the share of all registered EVs. For each year, the figure plots the cumulative distribution function (CDF) for EV adoption.

The figure shows that EV adoption is highly concentrated in the counties with the highest Democrat vote share. The CDF starts out very steep, indicating high concentration of EVs in the counties with the very highest Democrat vote shares. About 50% of all new EVs went to the 10% most-Democratic counties, about 70% to the top 25%, and about 90% in the top 50%.

There is no clear pattern across years. The CDFs for 2012 and 2022 are quite close together, showing essentially the same level of concentration. Relative to 2012, the pattern becomes somewhat more concentrated in 2015 and 2018, and then somewhat less concentrated in 2022.

Table 3 presents the same information but as a table rather than as a figure, for the top 10%, 5%, and 1% of counties with the highest Democrat vote share, as well as for all counties with a Democrat majority. In addition to reporting EV shares for each year, the table also reports the slope for each statistic across years, to show whether the statistic is going up or down.

Overall, there is little change in the concentration of EV shares across years. The slopes are negative, indicating lower concentration, but small in magnitude and mostly not statistically significant. Moreover the pattern fluctuates across years, tending to increase during the first half of the sample, and then decrease during the second half.

3.4 Binned Scatterplots and Correlations

Figure 4 shows the correlation between EV adoption and political ideology. Whereas we began by looking at the state-level correlation, this binned scatterplot uses counties as the underlying level of analysis, taking advantage of the rich within-state variation in political ideology. We use a binned scatterplot because with over 3,100 counties there are otherwise so many observations that it obscures the underlying relationship. For this figure, we used the entire sample period 2012-2022.

The figure confirms the strong positive correlation. EVs average less than 0.5% (i.e. half of 1%) in states with less than 40% Democrat vote share. EV shares then increase sharply between 40% and 60% Democrat vote share. Finally, EV shares continue to increase above 60% Democrat vote share, with shares between 1% and 2%. The relationship is nonlinear and convex, increasing faster than would be predicted with a linear model.

Figure 5 repeats this exercise separately for each year 2012 to 2022. The overall level of EV adoption increases dramatically during this time period. Notice that the y-axis grows from 0 to 0.4 in 2012, to 0 to 6 in 2022. Yet the basic pattern remains quite similar, with a strong positive correlation in all years.

Table 4 reports the correlation for each year. The slope across years is positive (0.15) and statistically significant, implying a total increase of .165 over the 11-year period.[6] Thus, this evidence points to an *increasing* correlation between EV adoption and political ideology.

4 Alternative Explanations

The most Democratic counties in the U.S. tend to have high household incomes, high population densities, and high gasoline taxes. As we mentioned in the introduction, all three of these factors have been shown in previous studies to matter for EV adoption. Thus one might reasonably ask whether the patterns in the previous section reflect these other factors – rather than political ideology itself.

In this section we continue to examine the correlation between EV adoption and political ideology – while controlling for one or more of these other factors. Overall, the correlation between EV adoption and political ideology remains strong and statistically significant even after controlling for these other factors. While we cannot rule

[6] Appendix Table 2 shows similar results when correlations are examined at the state-level. In that case, the slope across years is somewhat larger (0.17) but not statistically significant (p-value .059.)

out that there are additional omitted variables, the evidence in this section shows that neither household income, nor population density, nor gasoline taxes are driving the results in the previous section.

4.1 Graphical Evidence

We start with household income. Figure 6 shows the correlation between EV adoption and political ideology, after controlling for county-level median household income. The pronounced positive correlation remains even after controlling for household income. We have also examined binned scatterplots for this same relationship year-by-year, and the pronounced positive correlation remains in all years, with no visually discernible evidence of weakening correlation in later years. See Appendix Figure 2.

We next look at population density. Figure 7 is a scatterplot constructed by restricting the sample to counties above the 90th percentile for population density. Elsewhere we prefer binned scatterplots for presenting county-level information, but the regular scatterplot works well here because the sample is restricted to only 10% of all counties. For these figures we also return to using red and blue for indicating counties with majority vote Republican and Democrat, respectively.

A strong positive correlation remains even after restricting the sample to high population density counties. Among Republican majority counties, EV adoption tends to range between 0 and 2.5%, whereas among Democratic majority counties, EV adoption tends to range from 0% to 10%, with some outlier counties with adoption above 10%.

Figure 8 presents separate scatterplots by year. Continuing to restrict the sample to high population density counties, the figure shows the dramatic growth in EV adoption in Democratic counties. During the first half of the sample period, adoption tends to be below 10% almost everywhere, but there are clear bursts in EV adoption in Democratic counties in 2018, 2021, and 2022. The difference in adoption between Democratic and Republican counties remains pronounced throughout the sample period.

Appendix Figures 3 and 4 present analogous evidence from low-population density counties. Restricting the sample to counties below the 10th percentile for population density, the overall level of EV adoption is much lower. There continues to be an apparent positive correlation between EV adoption and political ideology, but it is less clear than in the high population density counties.

4.2 Regression Evidence

We now turn to regressive evidence. Table 5 reports estimates from four separate least squares regressions, adding control variables progressively. These regressions are estimated using county-by-year data from 2012 to 2022, and standard errors are clustered by state.

The effect of political ideology on EV adoption remains even after adding controls. In column (1) without any controls, a one percentage point increase in Democrat vote share (e.g. going from 45% to 46%) is associated with a .024 percentage point increase in EV adoption (e.g. from 0.500 percent to 0.524 percent). Mean EV share is less than 1 percent, so this is a large effect. The coefficient attenuates with controls in columns (2), (3), and (4), but remains large in magnitude and strongly statistically significant.

See the appendix for additional results and alternative specifications. Appendix Table 6 provides the full set of regression estimates, including coefficients corresponding to control variables. Appendix Table 7 reports results from an alternative specification which weights observations using the population of the county. Appendix Table 8 reports results from an alternative specification which includes year fixed effects. Results are quite similar in these alternative specifications.

Combined with the previous evidence, this table illustrates that the correlation between EV adoption and political ideology remains strong even after controlling for household income, population density, and gasoline taxes. These other factors matter. But these other factors are not driving the correlations described in Section 3. Overall, the role of political ideology appears to be separate and distinct, above-and-beyond the roles played by income, population density and gasoline taxes.

5 Mechanisms

The previous sections document a strong and enduring positive correlation between EV adoption and political ideology (Section 3), and show that these correlations are not driven by household income, population density, or gasoline prices (Section 4). In this section we turn to mechanisms, and begin to think about the behavior underlying these patterns.

The main idea in this section is to compare patterns for "inconspicuous" EVs versus "conspicuous" EVs, in an effort to shed light on EV buyers' intrinsic versus extrinsic motivations. As we emphasize throughout, the evidence in this section is more suggestive than definitive, but, overall, the evidence seems to point to extrinsic motivations playing a particularly strong role in the most Democratic counties.

5.1 Intrinsic versus Extrinsic Motivations

Following the broader economics literature on "pro-social" behavior we focus on two main mechanisms, which we will refer to as "intrinsic" versus "extrinsic" motivations. For the intrinsic mechanism we have in mind the idea of "warm glow" (Andreoni, 1989, 1990).[7] That is, households derive utility from "doing their part", regardless of whether the action is observed by others.

For the extrinsic mechanism we have in mind signaling to others. Economists for decades have hypothesized that signaling to others plays an important role in motivating charitable giving and other pro-social behaviors. See, e.g., Glazer and Konrad (1996) and Bénabou and Tirole (2006). With the extrinsic mechanism, a household does not derive utility from the action itself. Instead, the utility is derived from *being*

[7] Andreoni (1989) and Andreoni (1990) make a distinction between pure altruism and warm glow. With pure altruism an individual might value improvements to the global environment, for example, regardless of how that improvement comes about. With "warm glow", however, it is particularly important to the individual that these improvements come from actions taken by the individual themselves. With warm glow, EV adoption by others would not be a perfect substitute for EV adoption by oneself. For our purposes, we describe both of these as part of the "instrinsic" mechanism.

seen taking this action by others.

Both intrinsic and extrinsic motivations are potentially modulated by political ideology. From an intrinsic perspective, Democrats and Republicans may not agree on what it means to "do ones part". From an extrinsic perspective, the value of signaling may depend on the political ideology of the community. For example, an EV adopter might derive utility from signaling to Democrats, but not derive utility from signaling to Republicans.

Our thinking is also informed by the small existing literature on political ideology and "green" vehicle adoption that we described earlier. Most closely related to our analysis in this section, Sexton and Sexton (2014) tests whether communities with more Democratic voters are more likely to have the "conspicuous" Toyota Prius relative to "less conspicuous" hybrids like the Toyota Camry hybrid. In this paper as well as previous work by Matt Kahn and coauthors (Kahn, 2007; Kahn and Vaughn, 2009), households derive utility by signaling their "greenness" to others, and more utility is derived from signaling in a "greener" community.

5.2 "Conspicuous" Versus "Inconspicuous" EVs

We are planning to conduct a U.S. nationally representative survey, showing respondents images of different EV and non-EV models, and asking them whether or not each vehicle is an EV. If 90% of respondents can identify a particular EV model as an EV, we would call this "conspicuous", whereas if only 10% can identify it as an EV, we would call this "inconspicuous". It will also be interesting to test whether responses differ for Democrats and Republicans.

In the meantime, we hypothesize that Tesla vehicles are perhaps the most well-known EVs to a U.S. audience. We postulate that from a signaling perspective, Tesla is particularly effective because it will be widely understood to be an EV by other drivers. We also examine the Nissan Leaf, which is another EV with a very distinctive profile. For now, we include all other EVs in an "other" category which, includes many vehicle models that we hypothesize to be much less conspicuous. The Volvo XC90 plug-in hybrid, for example, looks almost identical to the internal combustion engine version of the XC90.

Table 6 reports the correlation between EV shares and political ideology, for different categories of vehicles and years. The construction of the table is very similar to Table 4 except rather than looking at the EV share for all types of EVs, the share includes only, Tesla, for example. See also Appendix Tables 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, and 19, for separate results by year and vehicle model.

The table indicates higher correlation for conspicuous vehicles. The correlation for Tesla is higher in both halves of the sample (0.176 and 0.205), than for other EVs (0.121 and 0.115). The correlation for Nissan Leaf is also higher (0.134 and 0.221) than for other EVs. There also continues to be little evidence of declining correlation over time. For Tesla and Nissan Leaf, in particular, the correlations are higher 2018-2022 than 2012-2017. These patterns are consistent with conspicuous EVs having higher (and perhaps increasing) signaling value in Democratic counties.

This evidence is interesting and suggestive, but should be interpreted cautiously.

Tesla and Nissan EVs are different from other EVs on the market, so there are multiple potential explanations for the higher correlations. Moreover, the EV market has also changed significantly over our sample period. Even individual EV models like the Nissan Leaf have changed significantly, for example, with significant increases in range. There are also changes over time in U.S. politics, which mean that Democratic vote share may be becoming a better (or worse) measure of the greenness of communities.

6 Conclusion

Many new technologies start off as niche products, appealing only to a relatively small subset of households. But it has now been 14 years since Nissan introduced the Leaf, and 16 years since Tesla introduced the original Roadster. Moreover, there are now over 100 different EV models for sale in the United States. Enough time has passed – one might have thought – for the U.S. EV market to have broadened considerably.

Yet we find a strong and enduring correlation between political ideology and U.S. EV adoption. About half of all EVs still go to the 10% most-Democratic counties, and despite dramatic growth in the overall size of the market, the correlation in 2022 is actually higher than the correlation in 2012. Thus, overall, we do not find evidence that the U.S. EV market is broadening across the political spectrum.

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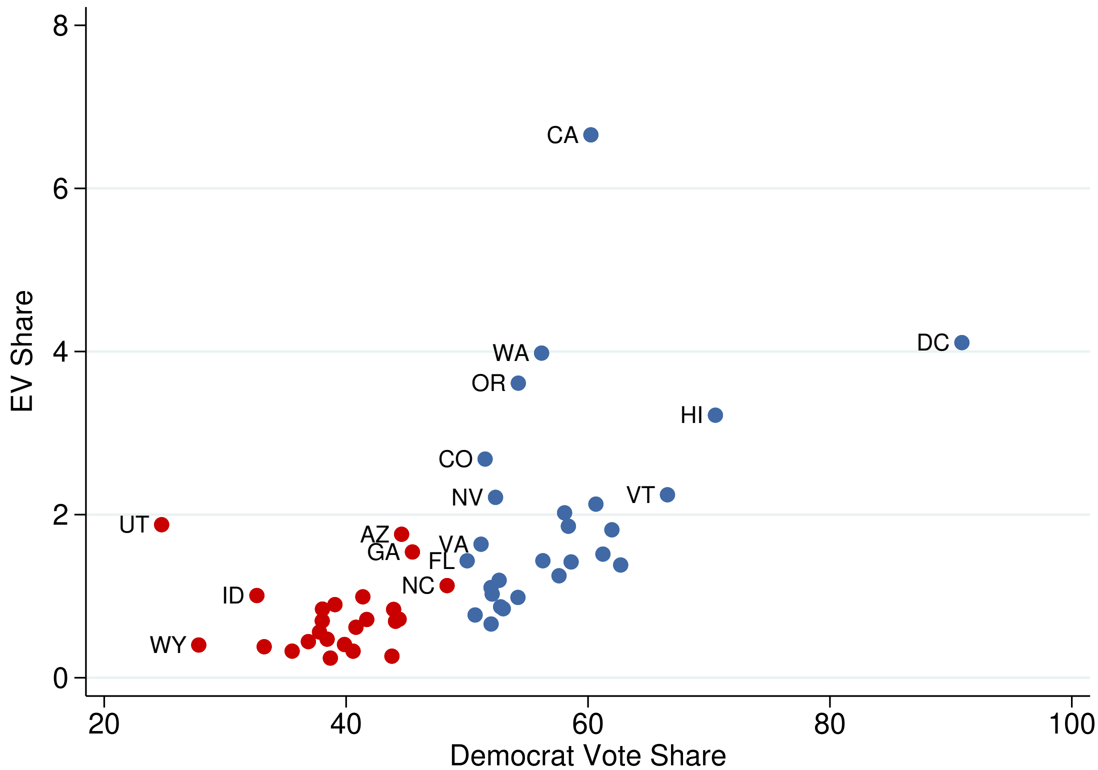
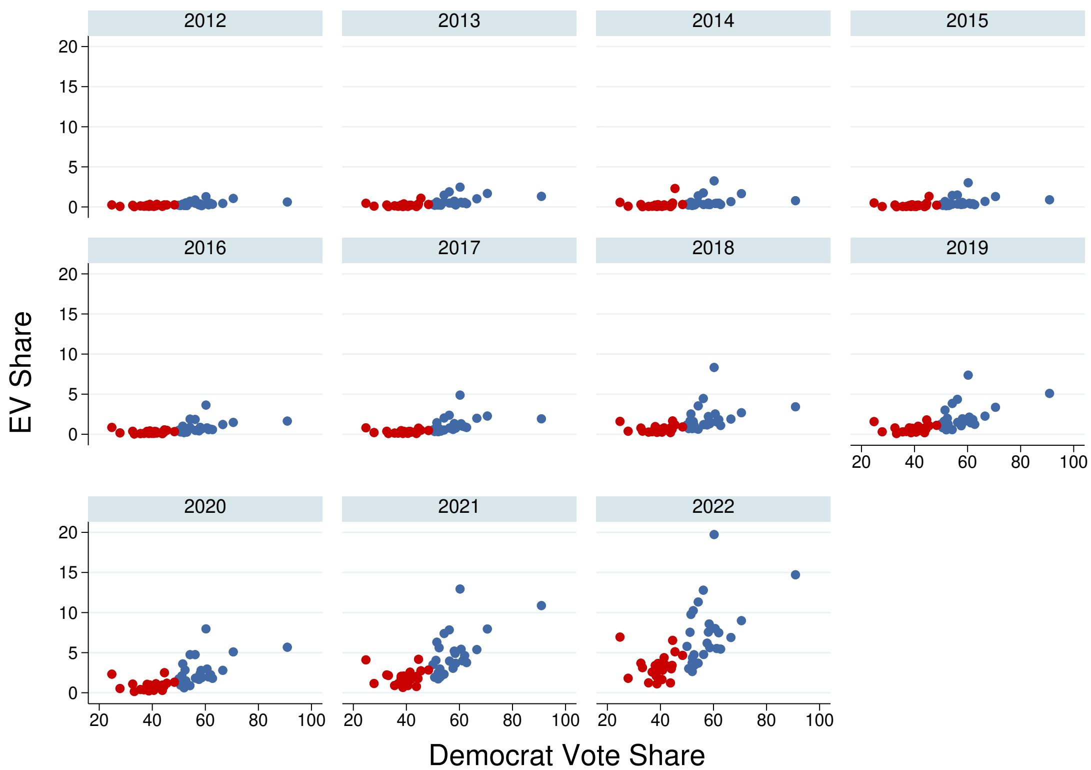
Figure 1: EV Adoption and Political Ideology



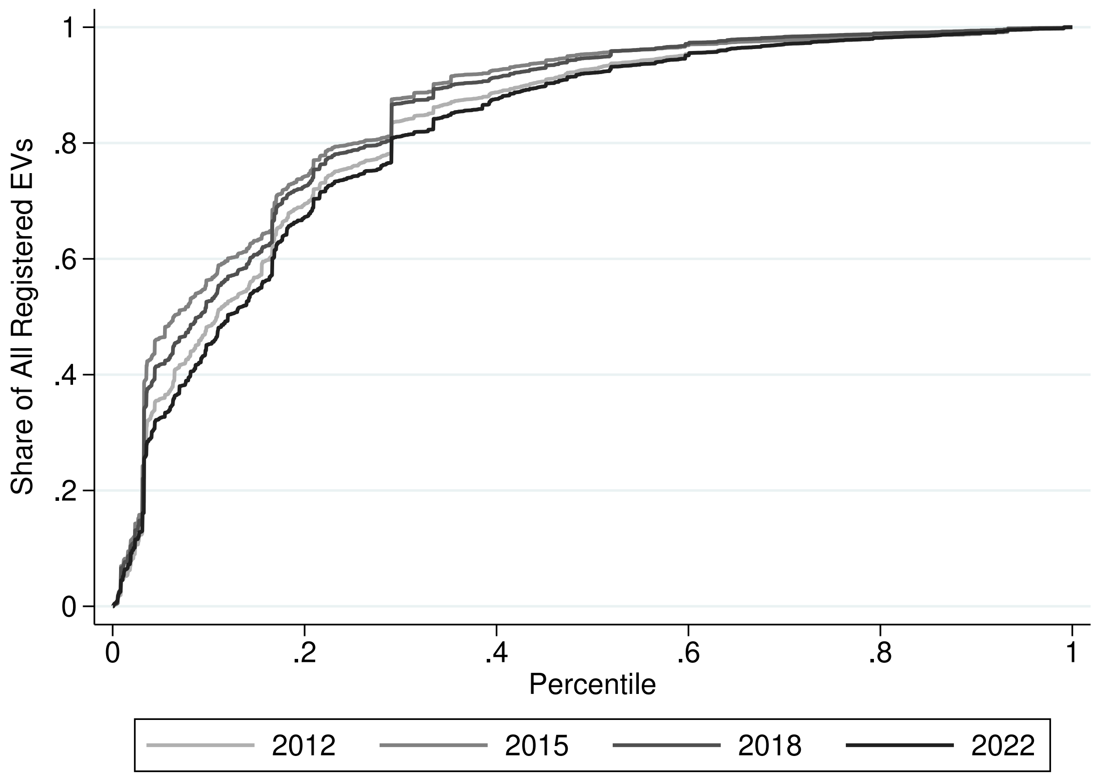
Notes: This scatterplot has 51 observations, one for each state and one for Washington, DC. The x-axis is the share of voters in the 2012 U.S. presidential election who voted for Barack Obama. The y-axis is EVs as a share of all new vehicles registered during the period 2012 to 2022. States with majority vote Democrat are in blue and states with majority vote Republican are in red.

Figure 2: EV Adoption and Political Ideology, by Year



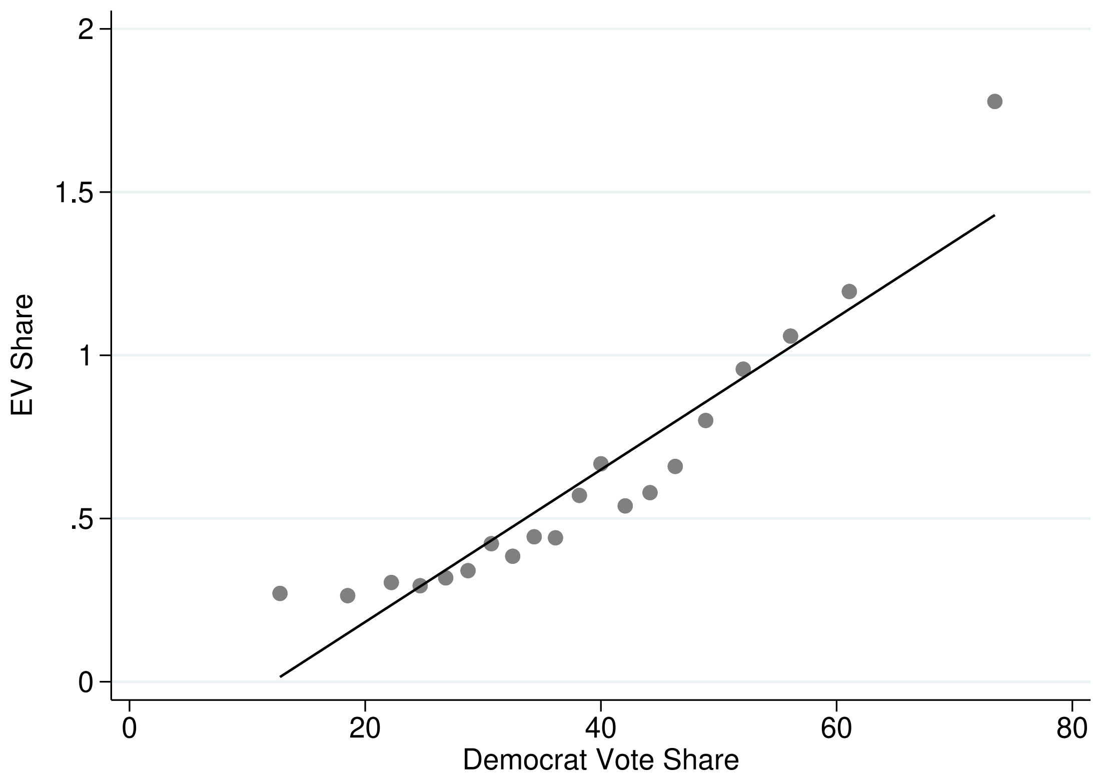
Notes: These scatterplots are identical to Figure 1, except we include a separate scatterplot for each year, 2012 to 2022. The x-axis in all years is the share of voters in the 2012 presidential election who voted for Barack Obama. The y-axis is EVs as a share of all new vehicles registered during that year. States with majority vote Democrat are in blue and states with majority vote Republican are in red.

Figure 3: EV Adoption and Political Ideology, Cumulative Distribution Function by Year



Notes: This figure describes the pattern of EV adoption across county percentiles based on Democrat vote share and how this has changed over time. For example, in all years about 80% of EV adoption occurred in the 30% most Democratic counties. The x-axis is the percentile shares of counties based on Democrat vote shares, from those with the highest Democrat vote shares to those with the lowest, divided into percentiles. The y-axis is the share of all registered EVs in the US during that year.

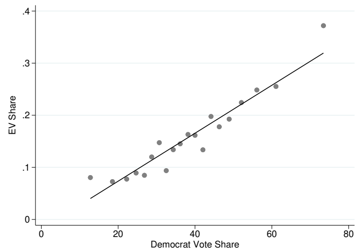
Figure 4: EV Adoption and Political Ideology, Binned Scatterplot



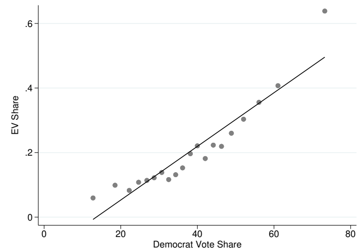
Notes: For this figure we group counties into twenty equal-sized "bins" on the basis of Democrat vote share, and then plot the mean EV share and Democrat vote share for each bin. We also plot a least squares linear regression line (in black). The x-axis is the share of voters in the 2012 presidential election who voted for Barack Obama. The y-axis is EVs as a share of all new vehicles registered during the period 2012 to 2022.

Figure 5: The Relationship Between EV Adoption and Political Ideology, by Year

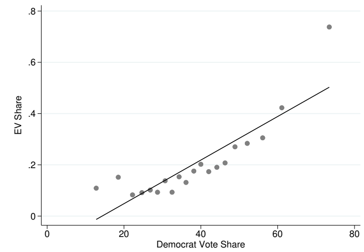
(a) 2012



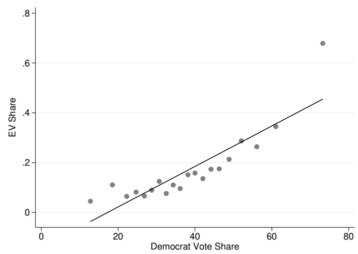
(b) 2013



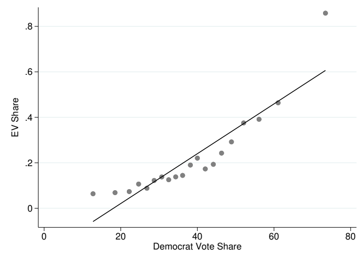
(c) 2014



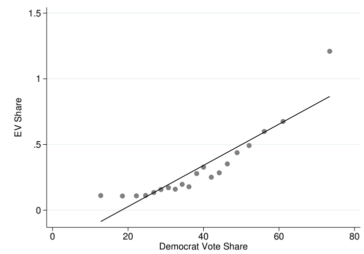
(d) 2015



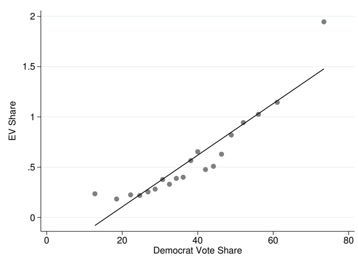
(e) 2016



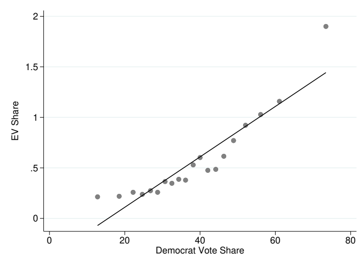
(f) 2017



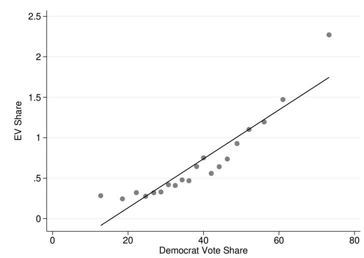
(g) 2018



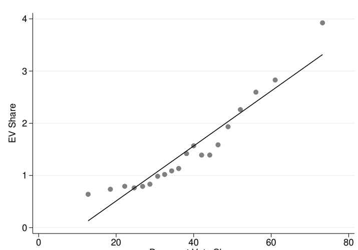
(h) 2019



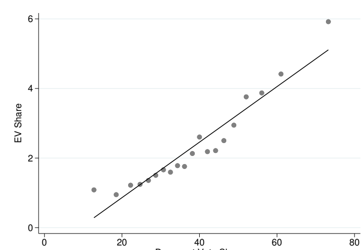
(i) 2020



(j) 2021

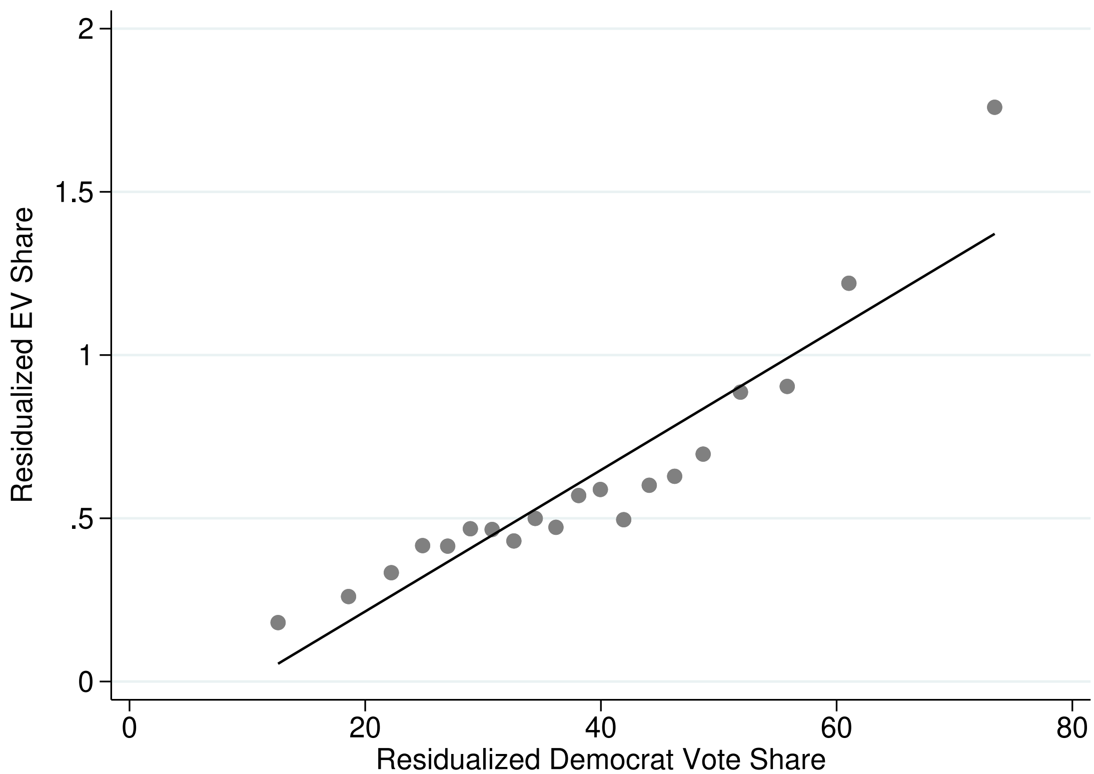


(k) 2022



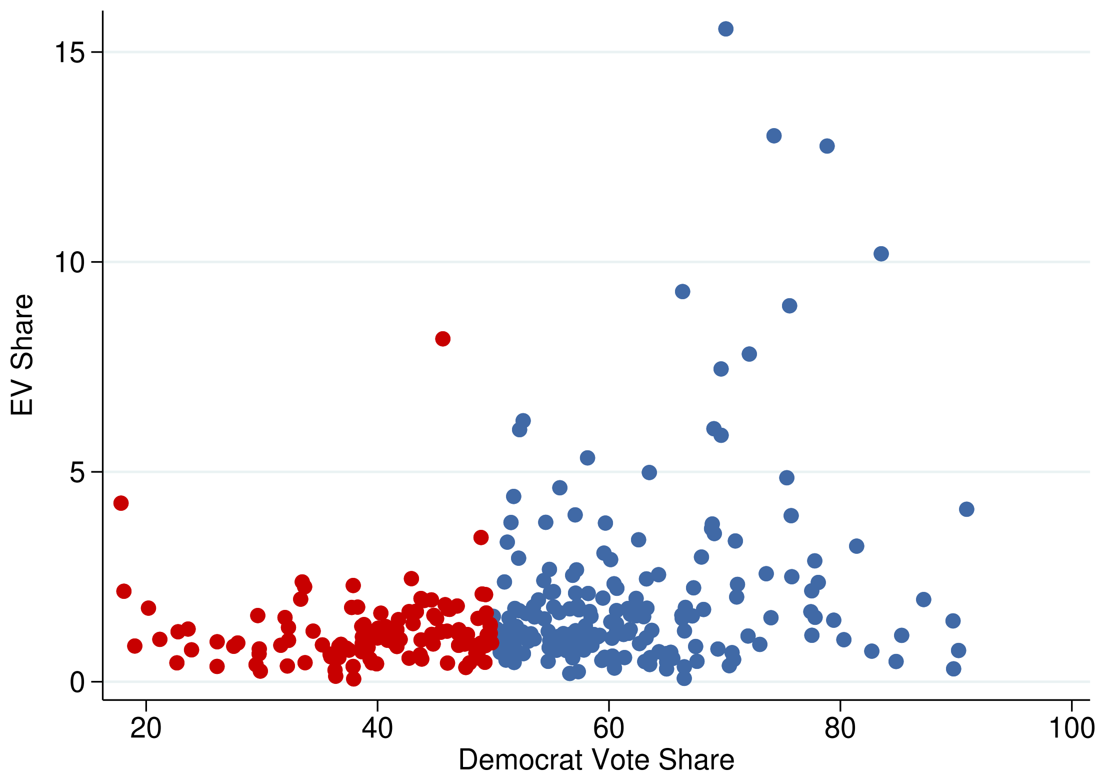
Notes: These binscatter plots are identical to Figure 4, except we include a separate scatterplot for each year, 2012 to 2022.

Figure 6: The Relationship Between EV Adoption and Political Ideology After Controlling for Income



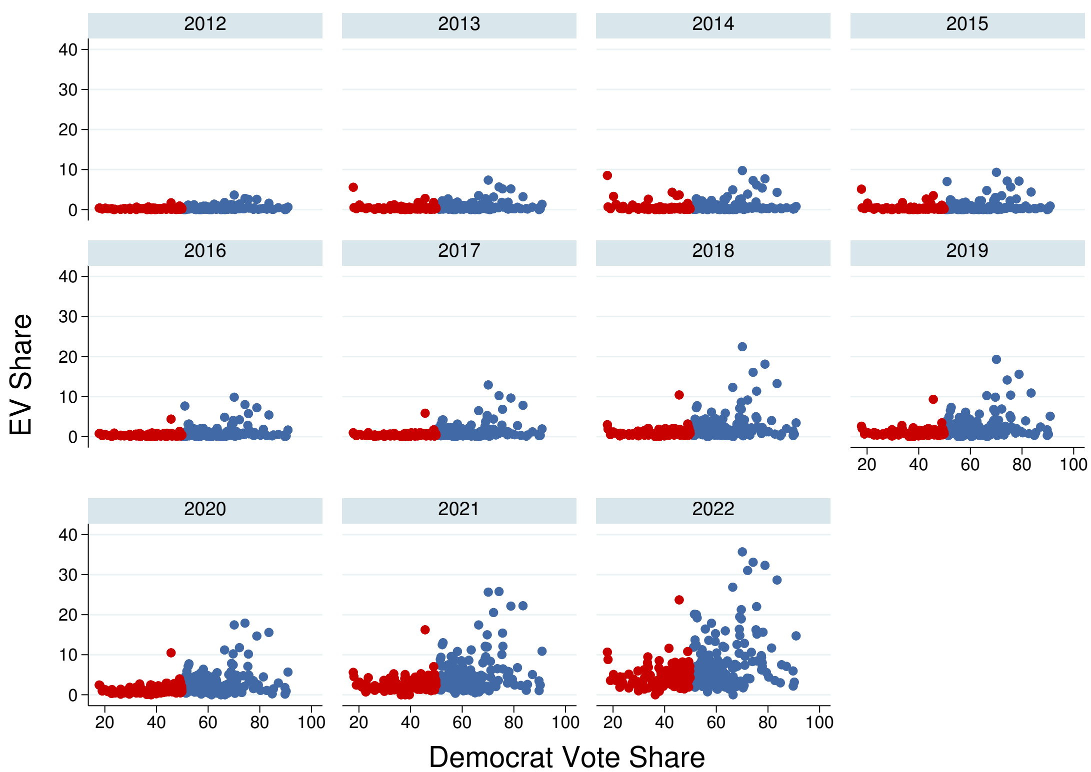
Notes: This binscatter plot shows the relationship between county-level residualized EV shares and residualized Democrat vote shares. The x-axis is the share of voters in the 2012 presidential election who voted for Barack Obama. The y-axis is EVs as a share of all new vehicles registered during the period 2012 to 2022. Both variables were residualized with respect to county-level median household income in 2012, and then the sample mean was added back.

Figure 7: EV Adoption in High Population Density Counties



Notes: This figure is a county-level scatterplot, restricted to high population density counties (above 90th percentile). The x-axis is the share of voters in the 2012 Presidential Election who voted for Barack Obama. The y-axis is EVs as a share of all new vehicles registered during the period 2012 to 2022. Population density is defined at the county level as population divided by land area. Counties with majority vote Democrat are in blue and counties with majority vote Republican are in red.

Figure 8: EV Adoption in High Population Density Counties, by Year



Notes: This figure is identical to Figure 7, except we include a separate scatterplot for each year, 2012 to 2022.

Table 1: Top 20 U.S. Counties with the Highest EV Adoption

County	EV Share (%)
Santa Clara, CA	15.6
Alameda, CA	12.8
San Francisco, CA	10.2
Contra Costa, CA	9.3
Orange, CA	8.2
San Diego, CA	6.2
King, WA	6.0
Ventura, CA	6.0
Los Angeles, CA	5.9
Sacramento, CA	5.3
Multnomah, OR	4.9
Riverside, CA	4.1
San Bernardino, CA	3.9
Fresno, CA	3.7
Honolulu, HI	3.6
Middlesex, MA	3.4
Montgomery, MD	3.4
New York, NY	3.2
Fairfax, VA	3.1
Travis, TX	2.9

Notes: This table reports the top 20 counties with the highest EV adoption during the period 2012 to 2022 from counties with population higher than 750,000. Cities represented here include San Jose (Santa Clara County), Oakland (Alameda County), Seattle (King County), Portland (Multnomah County), Cambridge (Middlesex County), and Austin (Travis County). Column (2) shows EVs as a share of all new vehicles registered during this period.

Table 2: Bottom 20 U.S. Counties with the Lowest EV Adoption

County	EV Share (%)
Hidalgo, TX	0.4
El Paso, TX	0.6
Macomb, MI	0.6
Bronx, NY	0.7
Cuyahoga, OH	0.8
Jefferson, KY	0.8
Milwaukee, WI	0.8
Wayne, MI	0.9
Shelby, TN	0.9
Tarrant, TX	0.9
Harris, TX	1.0
Baltimore, MD	1.0
Bexar, TX	1.0
Erie, NY	1.0
St. Louis County, MO	1.0
Marion, IN	1.0
Philadelphia, PA	1.1
Queens, NY	1.1
Duval, FL	1.1
Orange, FL	1.1

Notes: This table reports the bottom 20 counties with the lowest EV adoption during the period 2012 to 2022 from counties with population higher than 750,000.

Table 3: EV Adoption in the Most-Democratic Counties, by Year

Panel A: Share of All Registered EVs

Year	Top 10%	Top 5%	Top 1%	Democrat majority
2012	0.484	0.359	0.045	0.700
2013	0.523	0.410	0.053	0.729
2014	0.543	0.436	0.063	0.720
2015	0.564	0.464	0.070	0.748
2016	0.538	0.441	0.062	0.756
2017	0.545	0.448	0.066	0.750
2018	0.527	0.418	0.066	0.731
2019	0.510	0.396	0.063	0.722
2020	0.480	0.358	0.057	0.703
2021	0.450	0.324	0.048	0.677
2022	0.453	0.326	0.045	0.678

Panel B: Hypothesis Test

	Top 10%	Top 5%	Top 1%	Democrat majority
Slope	-0.007	-0.008	-0.000	-0.004
P-value	0.057	0.081	0.608	0.126

Notes: Panel (A) of this table presents EV adoption in counties with the highest Democrat vote shares in the 2012 presidential election. In particular, counties with the top 10% Democrat vote shares in Column (2), top 5% in Column (3) and top 1% in Column (4). Column (5) shows EV adoption in counties with majority Democrat vote. Panel (B) assesses for each statistic in Panel (A) whether it is going up or down over time. In each case, we run a regression using 11 observations, one for each year. We regress each statistic on a linear time trend, and report in Panel (B) the slope from this regression as well as a p-value from a test where the null hypothesis is that the slope is zero.

Table 4: Correlation Between County-level EV Shares and Democrat Vote Shares, by Year

Panel A: Correlation by Year		
Year	Correlation	P-value
2012	0.252	0.000
2013	0.289	0.000
2014	0.238	0.000
2015	0.253	0.000
2016	0.312	0.000
2017	0.338	0.000
2018	0.332	0.000
2019	0.342	0.000
2020	0.360	0.000
2021	0.379	0.000
2022	0.386	0.000
Panel B: Hypothesis Test		
Slope	0.015	0.000

Notes: Panel (A) of this table presents correlations by year between county-level EV shares and Democrat vote shares from the 2012 Presidential Elections. Panel (B) assesses whether this correlation is going up or down. We run a regression using 11 observations, one for each year. We regress the correlation on a linear time trend, and report in Panel (B) the slope from this regression as well as a p-value from a test where the null hypothesis is that the slope is zero.

Table 5: The Effect of Political Ideology on U.S. EV Adoption

	(1)	(2)	(3)	(4)
Democrat Vote Share	0.024**	0.023**	0.022**	0.017**
	(0.008)	(0.006)	(0.006)	(0.005)
County Median Household Income	No	Yes	Yes	Yes
County Population Density	No	No	Yes	Yes
State-Level Gasoline Prices	No	No	No	Yes
Observations	34,238	34,232	34,232	31,120
R-squared	0.061	0.160	0.162	0.185

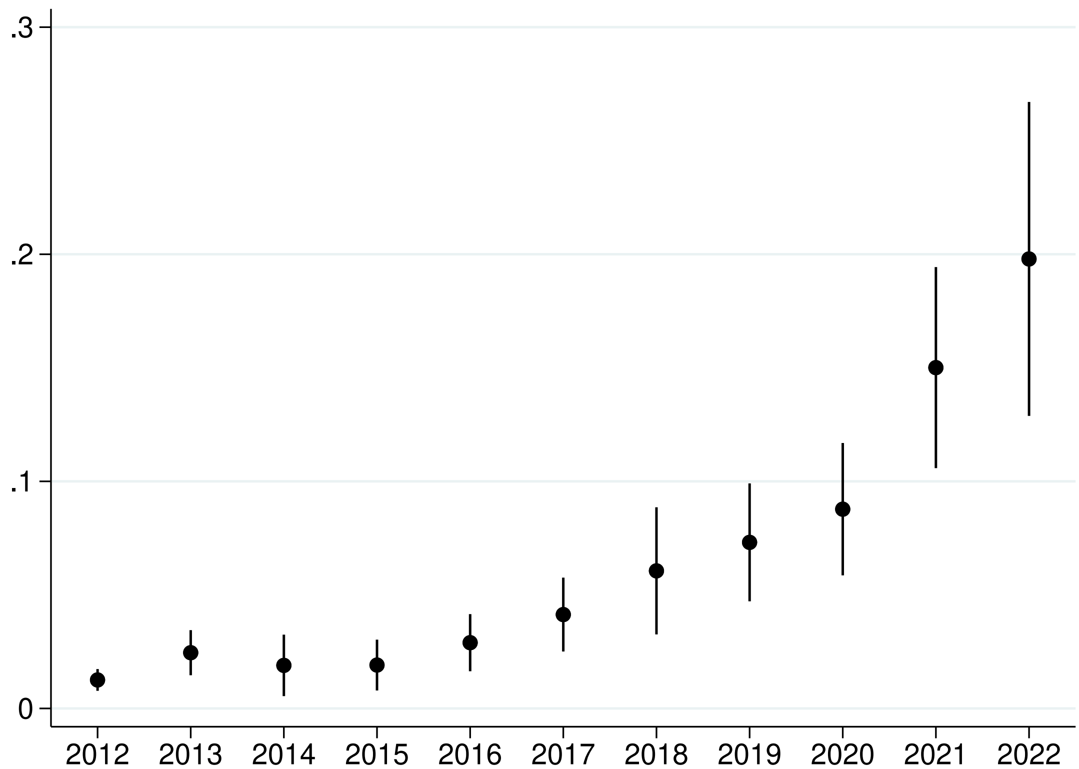
Notes: This table reports coefficient estimates and standard errors from four separate least square regressions. All regressions are estimated using county-by-year observations for 2012 to 2022. In all regressions the dependent variable is the share of all new registered vehicles that are EVs. There are no additional controls other than the controls listed in the row headings. Standard errors are clustered by state. ** Significant at the 1% level, *Significant at the 5% level.

Table 6: Comparing Tesla and Nissan Leaf with Other EVs

	Correlation	P-value
Tesla 2012–2017	0.176	0.000
Nissan Leaf 2012–2017	0.134	0.000
Other EVs 2012–2017	0.121	0.000
Tesla 2018–2022	0.205	0.000
Nissan Leaf 2018–2022	0.221	0.000
Other EVs 2018–2022	0.115	0.000

Notes: This table reports the correlation between county-level EV shares and political ideology, for the vehicles and years indicated in the row headings. For each row, the table also reports the p-value corresponding to the null hypothesis that the correlation is zero.

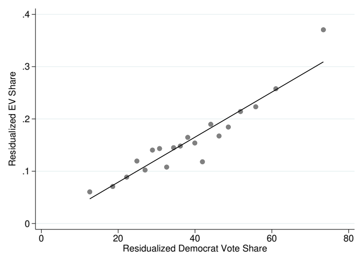
Appendix Figure 1: Slope by Year



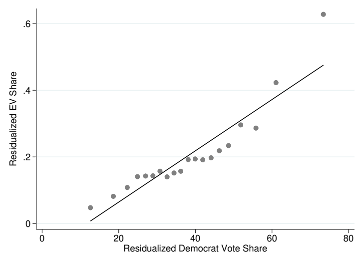
Notes: This figure shows the coefficient estimates with 95% confidence intervals from regressing EV shares on Democrat vote shares by year, without any additional control variables.

Appendix Figure 2: The Relationship Between EV Adoption and Political Ideology After Controlling for Income, by Year

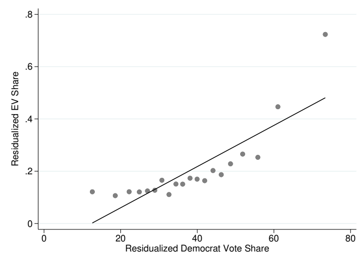
(a) 2012



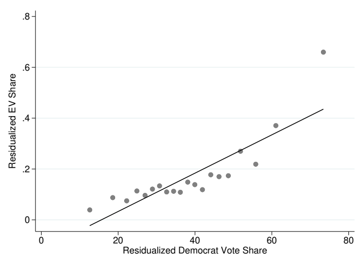
(b) 2013



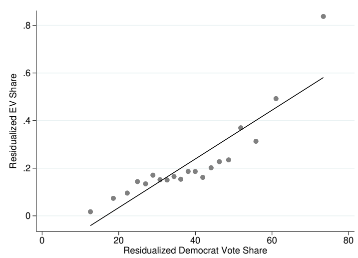
(c) 2014



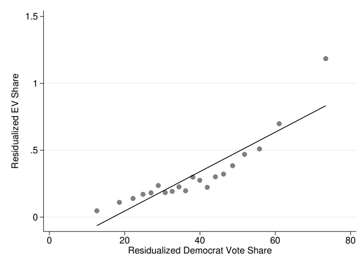
(d) 2015



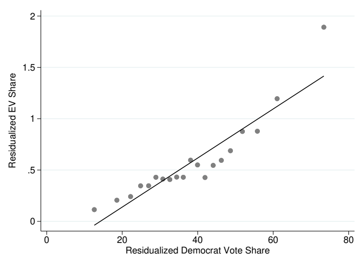
(e) 2016



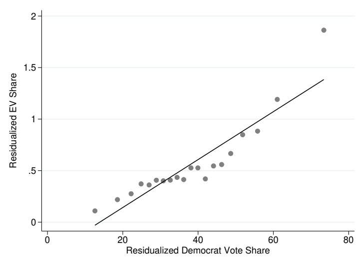
(f) 2017



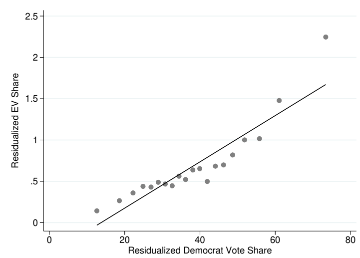
(g) 2018



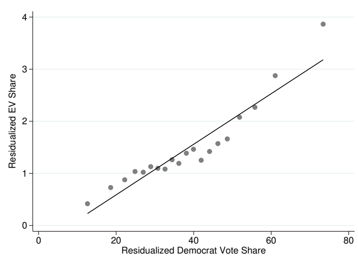
(h) 2019



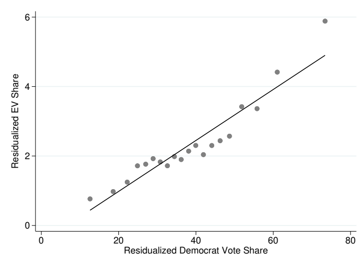
(i) 2020



(j) 2021

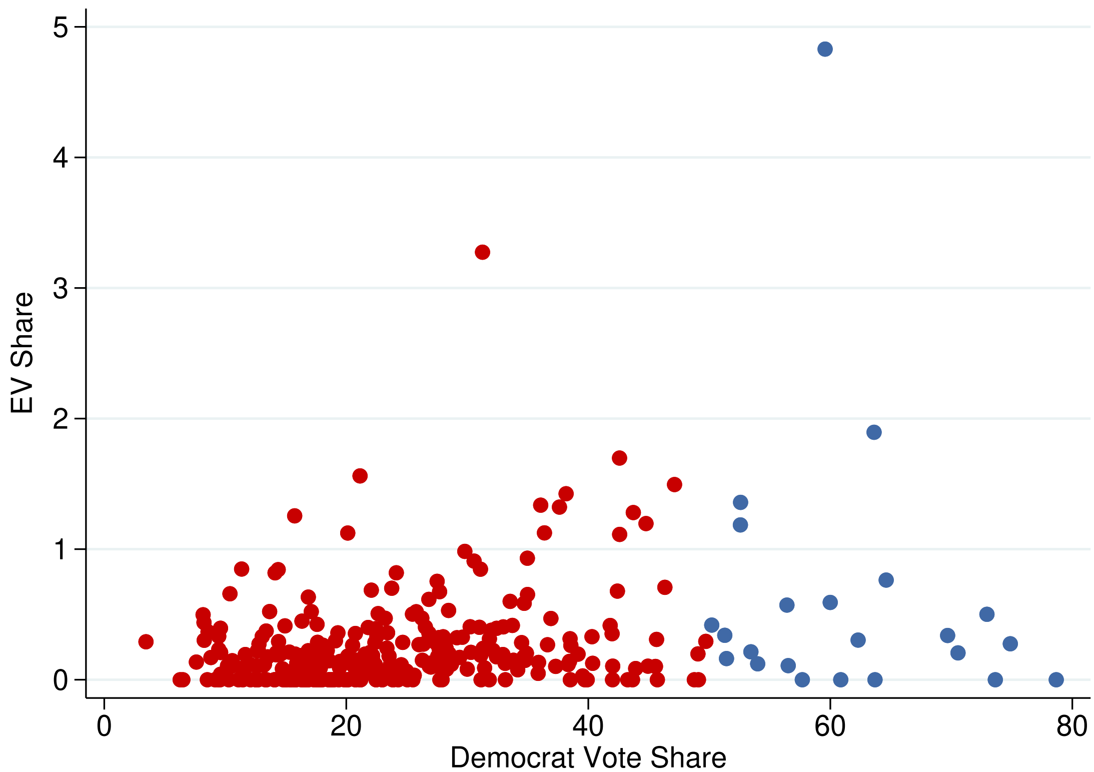


(k) 2022



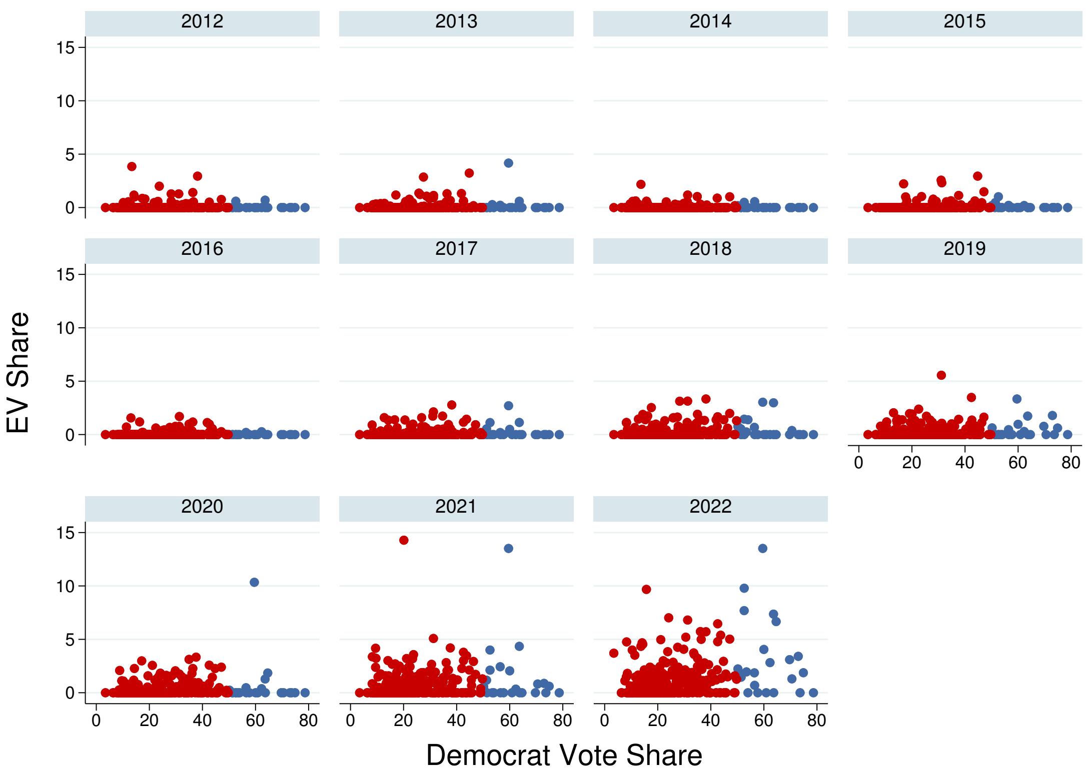
Notes: These binscatter plots are identical to Figure 6, except we include a separate scatterplot for each year, 2012 to 2022.

Appendix Figure 3: EV Adoption in Low Population Density Counties



Notes: This figure is a county-level scatterplot, restricted to low population density counties (below 10th percentile). The x-axis is the share of voters in the 2012 Presidential Election who voted for Barack Obama. The y-axis is EVs as a share of all new vehicles registered during the period 2012 to 2022. Population density is defined at the county level as population divided by land area. Counties with majority vote Democrat are in blue and counties with majority vote Republican are in red.

Appendix Figure 4: EV Adoption in Low Population Density Counties, by Year



Notes: This figure is identical to Figure 3, except we include a separate scatterplot for each year, 2012 to 2022.

Appendix Table 1: Descriptive Statistics

	Obs	Mean	Std dev.	Min	Max
EV Share	34,238	0.631	1.47	0	35.7
Democrat Vote Share	34,238	38.5	14.80	3.45	93.4
County Median Household Income ($1,000)	34,232	44.7	11.3	22.1	121
County Population (10,000 persons)	34,238	10.1	32.1	0.009	993
County Population Density (100 persons per square mile)	34,238	2.67	17.7	0.001	711
State-Level Gasoline Prices ($/gallon)	31,126	2.71	0.534	1.85	4.36

Notes: This table provides descriptive statistics for our county-level dataset. The unit of observation is county-by-year and the sample period covers 2012 to 2022. See Section 2 in the paper for a detailed description of data sources. EV share is the share of all new vehicles registered in a given county and year that are EVs. Democrat vote share is the share of voters in the 2012 presidential election who voted for Barack Obama. In 2012, Barack Obama received 51% of all votes (i.e. the popular vote), but the mean is lower here because these statistics are not weighted by population. County median annual household income is from 2012 and measured in thousands of dollars. County population is from 2012 and measured in ten thousands of people. Population density is measured at the county-level and measured in hundred persons per square mile. Gasoline prices are measured at the state-by-year level from 2012 to 2021, and measured in dollars per gallon.

Appendix Table 2: Correlation Between State-level EV Shares and Democrat Vote Shares

Panel A: Correlation by Year		
Year	Correlation	P-value
2012	0.601	0.000
2013	0.579	0.000
2014	0.373	0.007
2015	0.440	0.001
2016	0.552	0.000
2017	0.589	0.000
2018	0.528	0.000
2019	0.629	0.000
2020	0.654	0.000
2021	0.698	0.000
2022	0.635	0.000
Panel B: Hypothesis Test		
Slope	0.017	0.059

Notes: Panel (A) of this table presents correlations by year between state-level EV shares and Democrat vote shares from the 2012 Presidential Elections. Panel (B) assesses whether this correlation is going up or down. We run a regression using 11 observations, one for each year. We regress the correlation on a linear time trend, and report in Panel (B) the slope from this regression as well as a p-value from a test where the null hypothesis is that the slope is zero.

Appendix Table 3: Alternative Measures of Political Ideology

Year	2012 vote	2016 vote	2020 vote
2012	0.601	0.611	0.620
2013	0.579	0.623	0.634
2014	0.373	0.446	0.448
2015	0.440	0.509	0.517
2016	0.552	0.610	0.628
2017	0.589	0.636	0.655
2018	0.528	0.610	0.622
2019	0.629	0.700	0.713
2020	0.654	0.721	0.735
2021	0.698	0.766	0.780
2022	0.635	0.728	0.741

Notes: This table is identical to Appendix Table 2, but uses alternative measures of political ideology. Column (1) shows our baseline results using the share of voters in the 2012 Presidential Election who voted for Barack Obama. Columns (2) and (3) repeat the exercise, but using Democrat vote share from the 2016 and 2020 Presidential Elections, respectively.

Appendix Table 4: Population-weighted Correlation Between County-level EV Shares and Democrat Vote Shares, by Year

Year	Correlation	P-value
2012	0.332	0.000
2013	0.345	0.000
2014	0.304	0.000
2015	0.321	0.000
2016	0.363	0.000
2017	0.374	0.000
2018	0.360	0.000
2019	0.374	0.000
2020	0.425	0.000
2021	0.431	0.000
2022	0.456	0.000

Notes: This table presents population weighted correlations by year between county-level EV shares and Democrat vote shares from the 2012 Presidential Elections. County-level data excludes Alaska due to lack county-level information on the 2012 Presidential Election results.

Appendix Table 5: Correlation Between Residualized County-level EV Shares and Residualized Democrat Vote Shares, by Year

Year	Correlation	P-value
2012	0.247	0.000
2013	0.288	0.000
2014	0.233	0.000
2015	0.247	0.000
2016	0.315	0.000
2017	0.345	0.000
2018	0.342	0.000
2019	0.354	0.000
2020	0.377	0.000
2021	0.408	0.000
2022	0.421	0.000

Notes: This table presents correlations by year between residualized county-level EV shares and residualized Democrat vote shares from the 2012 Presidential Elections. Both were residualized with respect to county-level median household income in 2012. County-level data excludes Alaska due to lack county-level information on the 2012 Presidential Election results.

Appendix Table 6: The Effect of Political Ideology on U.S. EV Adoption, Full Regression Results

	(1)	(2)	(3)	(4)
Democrat Vote Share	0.024**	0.023**	0.022**	0.017**
	(0.008)	(0.006)	(0.006)	(0.005)
County Median Household Income		0.041**	0.040**	0.030**
		(0.008)	(0.008)	(0.007)
County Population Density			0.004	0.003
			(0.003)	(0.002)
State-Level Gasoline Prices				0.117
				(0.112)
Observations	34,238	34,232	34,232	31,120
R-squared	0.061	0.160	0.162	0.185

Notes: This table is exactly the same as Table 5 in the paper except we report coefficients for all variables. ** Significant at the 1% level, *Significant at the 5% level.

Appendix Table 7: The Effect of Political Ideology on U.S. EV Adoption, With Population Weights

	(1)	(2)	(3)	(4)
Democrat Vote Share	0.060*	0.052*	0.058*	0.042*
	(0.027)	(0.021)	(0.025)	(0.016)
County Median Household Income	No	Yes	Yes	Yes
County Population Density	No	No	Yes	Yes
State-Level Gasoline Prices	No	No	No	Yes
Observations	34,238	34,232	34,232	31,120
R-squared	0.076	0.159	0.163	0.220

Notes: This table is exactly the same as Table 5 in the paper except we use population weights in all regressions. In contrast, Table 5 in the paper uses no weights, so implicitly puts equal weight on all counties. ** Significant at the 1% level, *Significant at the 5% level.

Appendix Table 8: The Effect of Political Ideology on U.S. EV Adoption, With Year Fixed Effects

	(1)	(2)	(3)	(4)
Democrat Vote Share	0.024**	0.023**	0.022**	0.012**
	(0.008)	(0.006)	(0.006)	(0.003)
County Median Household Income	No	Yes	Yes	Yes
County Population Density	No	No	Yes	Yes
State-Level Gasoline Prices	No	No	No	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Observations	34,238	34,232	34,232	31,120
R-squared	0.259	0.358	0.360	0.418

Notes: This table is exactly the same as Table 5 in the paper except we add year fixed effects in all regressions. ** Significant at the 1% level, *Significant at the 5% level.

Appendix Table 9: County-level Correlation Between EV Model-level Shares and Democrat Vote Shares, 2012

Vehicle model	Correlation	EV Type
Ford C-MAX Energi	0.036	PHEV
Chevrolet Volt	0.134	PHEV
Tesla Model S	0.156	BEV
Nissan LEAF	0.182	BEV
Toyota Prius	0.200	PHEV

Appendix Table 10: County-level Correlation Between EV Model-level Shares and Democrat Vote Shares, 2013

Vehicle model	Correlation	EV Type
Mitsubishi i-MiEV	0.048	BEV
FIAT 500e	0.128	BEV
Ford Fusion	0.135	PHEV
Toyota RAV4 EV	0.138	BEV
Ford C-MAX Energi	0.141	PHEV
Nissan LEAF	0.152	BEV
Chevrolet Volt	0.167	PHEV
Ford Focus	0.168	BEV
Toyota Prius	0.228	PHEV
Tesla Model S	0.249	BEV

Appendix Table 11: County-level Correlation Between EV Model-level Shares and Democrat Vote Shares, 2014

Vehicle model	Correlation	EV Type
Toyota RAV4 EV	0.061	BEV
Cadillac ELR	0.071	PHEV
Nissan LEAF	0.106	BEV
BMW i3	0.116	PHEV
Chevrolet Spark EV	0.127	BEV
FIAT 500e	0.136	BEV
Ford Focus	0.155	BEV
BMW i3	0.161	BEV
Ford C-MAX Energi	0.161	PHEV
smart fortwo	0.170	BEV
Ford Fusion	0.174	PHEV
Chevrolet Volt	0.184	PHEV
Toyota Prius	0.189	PHEV
Tesla Model S	0.201	BEV

Appendix Table 12: County-level Correlation Between EV Model-level Shares and Democrat Vote Shares, 2015

Vehicle model	Correlation	EV Type
BMW i8	0.058	PHEV
Kia Soul	0.105	BEV
Nissan LEAF	0.106	BEV
Chevrolet Spark EV	0.128	BEV
Ford Focus	0.139	BEV
Toyota Prius	0.139	PHEV
Ford Fusion	0.144	PHEV
Ford C-MAX Energi	0.144	PHEV
FIAT 500e	0.148	BEV
smart fortwo	0.153	BEV
Mercedes-Benz B-Class	0.164	BEV
Tesla Model S	0.169	BEV
BMW i3	0.171	BEV
Volkswagen e-Golf	0.179	BEV
Chevrolet Volt	0.191	PHEV
BMW i3	0.240	PHEV

Appendix Table 13: County-level Correlation Between EV Model-level Shares and Democrat Vote Shares, 2016

Vehicle model	Correlation	EV Type
Porsche Cayenne	0.087	PHEV
FIAT 500e	0.094	BEV
BMW i8	0.110	PHEV
Toyota Mirai	0.111	FCV
Hyundai Sonata Plug-in Hybrid	0.122	PHEV
Chevrolet Spark EV	0.128	BEV
BMW i3	0.135	BEV
Kia Soul	0.149	BEV
Volvo XC90	0.152	PHEV
Volkswagen e-Golf	0.166	BEV
Toyota Prius Prime	0.166	PHEV
Tesla Model S	0.171	BEV
BMW X5	0.172	PHEV
Ford Fusion	0.172	PHEV
Nissan LEAF	0.196	BEV
Ford C-MAX Energi	0.199	PHEV
Audi A3 Sportback e-tron	0.205	PHEV
Tesla Model X	0.222	BEV
Chevrolet Volt	0.252	PHEV
BMW i3	0.255	PHEV

Appendix Table 14: County-level Correlation Between EV Model-level Shares and Democrat Vote Shares, 2017

Vehicle model	Correlation	EV Type
FIAT 500e	0.057	BEV
Porsche Cayenne	0.092	PHEV
Toyota Mirai	0.104	FCV
Ford Focus	0.113	BEV
Kia Optima	0.116	PHEV
BMW 5 Series	0.117	PHEV
Hyundai Sonata Plug-in Hybrid	0.120	PHEV
Volvo XC90	0.120	PHEV
BMW i3	0.125	BEV
Honda Clarity	0.126	BEV
Kia Soul	0.137	BEV
Tesla Model 3	0.145	BEV
Chrysler Pacifica	0.145	PHEV
Volkswagen e-Golf	0.156	BEV
Ford C-MAX Energi	0.160	PHEV
BMW X5	0.166	PHEV
Audi A3 Sportback e-tron	0.177	PHEV
Ford Fusion	0.188	PHEV
Chevrolet Volt	0.189	PHEV
BMW 3 Series	0.191	PHEV
Tesla Model X	0.195	BEV
Nissan LEAF	0.222	BEV
BMW i3	0.228	PHEV
Toyota Prius Prime	0.260	PHEV
Chevrolet Bolt EV	0.262	BEV
Tesla Model S	0.268	BEV

Appendix Table 15: County-level Correlation Between EV Model-level Shares and Democrat Vote Shares, 2018

Vehicle model	Correlation	EV Type
Chrysler Pacifica	0.099	PHEV
Hyundai IONIQ Plug-in Hybrid	0.100	PHEV
Porsche Panamera	0.105	PHEV
Toyota Mirai	0.110	FCV
smart fortwo	0.120	BEV
Volvo XC90	0.127	PHEV
Honda Clarity	0.133	BEV
Mercedes-Benz GLC	0.143	PHEV
BMW X5	0.148	PHEV
Volvo XC60	0.150	PHEV
Mitsubishi Outlander	0.155	PHEV
MINI Countryman Plug-in Hybrid	0.157	PHEV
BMW 3 Series	0.160	PHEV
Volkswagen e-Golf	0.166	BEV
Chevrolet Volt	0.173	PHEV
Ford Fusion	0.174	PHEV
Audi A3 Sportback e-tron	0.178	PHEV
Kia Soul	0.181	BEV
Kia Niro	0.183	PHEV
BMW 5 Series	0.184	PHEV
BMW i3	0.184	BEV
Nissan LEAF	0.199	BEV
Tesla Model X	0.203	BEV
BMW i3	0.220	PHEV
Toyota Prius Prime	0.228	PHEV
Tesla Model S	0.241	BEV
Honda Clarity	0.246	PHEV
Chevrolet Bolt EV	0.271	BEV
Tesla Model 3	0.294	BEV

Appendix Table 16: County-level Correlation Between EV Model-level Shares and Democrat Vote Shares, 2019

Vehicle model	Correlation	EV Type
Volvo XC90	0.020	PHEV
Volvo XC60	0.044	PHEV
Porsche Panamera	0.080	PHEV
BMW i8	0.096	PHEV
Toyota Mirai	0.104	FCV
Mercedes-Benz GLC	0.110	PHEV
Mitsubishi Outlander	0.115	PHEV
Jaguar I-PACE	0.121	BEV
Chevrolet Volt	0.124	PHEV
Chrysler Pacifica	0.127	PHEV
Kia Niro	0.129	BEV
Hyundai Kona Electric	0.131	BEV
Porsche Cayenne	0.140	PHEV
Ford Fusion	0.143	PHEV
BMW 5 Series	0.144	PHEV
Honda Clarity	0.144	PHEV
Subaru Crosstrek	0.149	PHEV
Hyundai IONIQ Plug-in Hybrid	0.183	PHEV
Audi e-tron	0.186	BEV
Hyundai IONIQ Electric	0.195	BEV
Volkswagen e-Golf	0.201	BEV
Tesla Model X	0.206	BEV
BMW i3	0.211	PHEV
BMW i3	0.214	BEV
Tesla Model S	0.215	BEV
Kia Niro	0.218	PHEV
Toyota Prius Prime	0.223	PHEV
Chevrolet Bolt EV	0.238	BEV
Nissan LEAF	0.240	BEV
Tesla Model 3	0.309	BEV

Appendix Table 17: County-level Correlation Between EV Model-level Shares and Democrat Vote Shares, 2020

Vehicle model	Correlation	EV Type
Lincoln Aviator	0.005	PHEV
Mitsubishi Outlander	0.089	PHEV
Chrysler Pacifica	0.097	PHEV
BMW 5 Series	0.116	PHEV
BMW X3	0.124	PHEV
Porsche Cayenne	0.125	PHEV
Kia Niro	0.130	BEV
Jaguar I-PACE	0.138	BEV
Volvo XC60	0.142	PHEV
Tesla Model S	0.148	BEV
Hyundai IONIQ Electric	0.155	BEV
Honda Clarity	0.166	PHEV
Porsche Taycan	0.166	BEV
MINI Hardtop 2 Door	0.174	BEV
Subaru Crosstrek	0.180	PHEV
Audi e-tron Sportback	0.181	BEV
Mercedes-Benz GLC	0.182	PHEV
Ford Fusion	0.184	PHEV
Kia Niro	0.189	PHEV
Audi Q5	0.190	PHEV
Hyundai IONIQ Plug-in Hybrid	0.200	PHEV
Hyundai Kona Electric	0.201	BEV
Nissan LEAF	0.203	BEV
Volvo XC90	0.205	PHEV
Tesla Model X	0.212	BEV
BMW X5	0.215	PHEV
Audi e-tron	0.215	BEV
Toyota RAV4 Prime	0.242	PHEV
Chevrolet Bolt EV	0.251	BEV
Toyota Prius Prime	0.263	PHEV
Tesla Model Y	0.301	BEV
Tesla Model 3	0.305	BEV

Appendix Table 18: County-level Correlation Between EV Model-level Shares and Democrat Vote Shares, 2021

(a) Lowest correlations, 2021

Vehicle model	Correlation	EV Type
Lincoln Aviator	-0.009	PHEV
Kia Sorento Plug-In Hybrid	0.053	PHEV
Chrysler Pacifica	0.082	PHEV
Polestar 2	0.084	BEV
Chevrolet Bolt EV	0.099	BEV
Chevrolet Bolt EUV	0.102	BEV
Mitsubishi Outlander	0.104	PHEV
BMW i3	0.105	BEV
Jaguar I-PACE	0.107	BEV
Porsche Cayenne	0.107	PHEV
Jeep Wrangler Unlimited	0.107	PHEV
Kia Niro	0.116	PHEV
Ford Escape	0.116	PHEV
Tesla Model X	0.118	BEV
Toyota Mirai	0.120	FCV
Hyundai IONIQ Plug-in Hybrid	0.126	PHEV
Volvo S60	0.131	PHEV
Tesla Model S	0.150	BEV
Porsche Taycan	0.160	BEV
BMW 5 Series	0.163	PHEV
Audi Q5	0.178	PHEV
Hyundai Santa Fe Plug-In Hybrid	0.185	PHEV

Appendix Table 18: County-level Correlation Between EV Model-level Shares and Democrat Vote Shares, 2021

(b) Highest correlations, 2021

Vehicle model	Correlation	EV Type
Audi e-tron Sportback	0.187	BEV
Kia Niro	0.194	BEV
Hyundai IONIQ Electric	0.198	BEV
Volvo XC90	0.198	PHEV
BMW X3	0.207	PHEV
Honda Clarity	0.213	PHEV
BMW 3 Series	0.219	PHEV
Subaru Crosstrek	0.227	PHEV
Nissan LEAF	0.227	BEV
MINI Hardtop 2 Door	0.230	BEV
Ford Mustang Mach-E	0.231	BEV
BMW X5	0.242	PHEV
Audi e-tron	0.245	BEV
Volvo XC40	0.250	BEV
Hyundai Kona Electric	0.257	BEV
Volvo XC60	0.262	PHEV
Toyota Prius Prime	0.267	PHEV
Toyota RAV4 Prime	0.273	PHEV
Volkswagen ID.4	0.301	BEV
Tesla Model 3	0.309	BEV
Tesla Model Y	0.316	BEV

Appendix Table 19: County-level Correlation Between EV Model-level Shares and Democrat Vote Shares, 2022

(a) Lowest correlations, 2022

Vehicle model	Correlation	EV Type
Lincoln Aviator	0.006	PHEV
Lincoln Corsair	0.017	PHEV
Kia Sportage Plug-In Hybrid	0.041	PHEV
Ford E-Transit 350	0.044	BEV
Lucid Air	0.044	BEV
Rivian EDV 700	0.050	BEV
Jeep Grand Cherokee	0.057	PHEV
Ford F-150	0.057	BEV
Kia Sorento Plug-In Hybrid	0.067	PHEV
Ford F-150 Lightning	0.071	BEV
Mitsubishi Outlander	0.079	PHEV
Lexus NX	0.098	PHEV
Polestar 2	0.102	BEV
Volvo S60	0.103	PHEV
Toyota Mirai	0.104	FCV
Audi e-tron GT	0.108	BEV
Mercedes-Benz EQB	0.108	BEV
Kia Niro	0.109	PHEV
Chrysler Pacifica	0.115	PHEV
Audi Q4 e-tron	0.132	BEV
Rivian R1S	0.133	BEV
Audi e-tron Sportback	0.137	BEV
Porsche Cayenne	0.144	PHEV
Genesis GV60	0.153	BEV
Audi Q5	0.154	PHEV
Jeep Wrangler Unlimited	0.156	PHEV
Ford Escape	0.156	PHEV
BMW iX	0.158	BEV
Volvo C40	0.160	BEV
Kia Niro	0.168	BEV

Appendix Table 19: County-level Correlation Between EV Model-level Shares and Democrat Vote Shares, 2022

(b) Highest correlations, 2022

Vehicle model	Correlation	EV Type
Volvo XC40	0.168	BEV
Toyota bZ4X	0.171	BEV
Rivian R1T	0.171	BEV
Chevrolet Bolt EV	0.175	BEV
Hyundai Santa Fe Plug-In Hybrid	0.179	PHEV
BMW 5 Series	0.181	PHEV
Mercedes-Benz EQS	0.192	BEV
Volvo XC90	0.193	PHEV
Kia EV6	0.193	BEV
Hyundai Kona Electric	0.202	BEV
Tesla Model S	0.206	BEV
Audi e-tron	0.206	BEV
Subaru Crosstrek	0.216	PHEV
Porsche Taycan	0.219	BEV
Chevrolet Bolt EUV	0.220	BEV
Hyundai Tucson Plug-in Hybrid	0.231	PHEV
BMW 3 Series	0.238	PHEV
Nissan LEAF	0.240	BEV
Volvo XC60	0.241	PHEV
Tesla Model X	0.250	BEV
MINI Hardtop 2 Door	0.254	BEV
BMW i4	0.259	BEV
Toyota Prius Prime	0.264	PHEV
Ford Mustang Mach-E	0.271	BEV
BMW X5	0.273	PHEV
Toyota RAV4 Prime	0.274	PHEV
Tesla Model 3	0.277	BEV
Hyundai IONIQ 5	0.287	BEV
Tesla Model Y	0.309	BEV
Volkswagen ID.4	0.313	BEV