Political Partisanship and Electric Vehicle Adoption in the US

Peter Shi

March 2023

Introduction

Background. Electric Vehicles (EVs) are a key technology for the decarbonization of transportation. Recent literature has identified a wide array of factors affecting consumer adoption of EVs but the effect direction and magnitude of certain factors are poorly understood and require further investigation.

Main Question. How does political partisanship affect EV adoption?

Hypothesis. Negative relationships between county Republican vote share and EV adoption.

Motivation

EV adoption has been steadily rising over the past few years, why bother with partisanship and EVs?

1. Light vehicles account for a significant share of Greenhouse Gas emissions (15% of total GHG in 2020 in the US)
   - Internal Combustion Engines also emit other pollutants (Particulate Matter, NOX, Carbon Monoxide) that are linked to adverse public health outcomes
2. Knowing the relationship between partisanship and EV adoption can help forecast adoption patterns more accurately
3. Despite political rhetoric, climate change is inherently bipartisan. Further investigation could inform better political decision-making
   - ex. Targeted subsidies, Tax rebates, or Infrastructure spending

Meta-Analyses of EV adoption factors

Coffman et al. (2016) and Anastasiadou and Gavanas (2022)
Factors:

- Acquisition and Ownership Costs
- Vehicle Range
- Vehicle Charging Time
- Fuel/Electricity Prices
- **Consumer Characteristics**
- Distances Travelled
- Infrastructure
- Policy Mechanisms

Literature Review

- Hayashida et al. (2021): governors and state legislatures were not significant for state EV subsidies but significant for household charger subsidies. Panel OLS model with state and year fixed effects.
- Sintov et al. (2020): democrats were more likely to adopt EVs compared to republicans. Biased survey with a small sample ($N = 545$).
- Adua and Clark (2020): significant relationship between governorship and congressional delegation on state-level electric utility efficiency. 4SLS OLS model with clustered errors. But EV adoption occurs in a much more decentralized manner compared to electrical infrastructure.

Literature Review (Economics)

- Beresteanu and Li (2011): Strong positive effect of fuel prices on Hybrid EV sales.
- Gallagher and Muehlegger (2011): Significant effect of Tax Incentives and Fuel prices on EV purchases, insignificant effect of HOV lane access.
- Bushnell et al. (2022): Gasoline prices have a larger effect on demand for EVs than electricity prices (4x-6x the effect size).
- Archsmith et al. (2021): Projects future scenarios of EV adoption. Does mention partisan bias and preference for sedans versus trucks but effect sizes were not estimated.

Methodology

- Units: US Counties
- Dependent Variable: EV Share of Total Vehicles Registered in County
- Independent Variable: Republican vote share in counties in the 2016 federal election, Δ in 2020 federal election
- Control Variables: State Partisanship (Governor, Legislature), County Demographics (Income, Education, Population, Poverty), Charging Infrastructure, fuel price

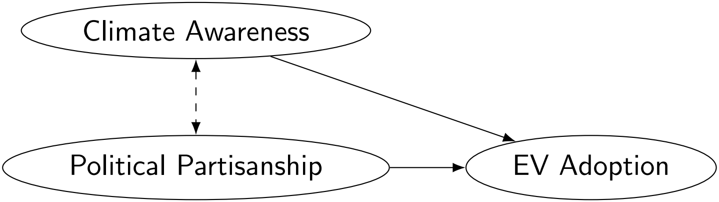
Methodology

Proposed Model: Panel OLS with Controls and Fixed effects

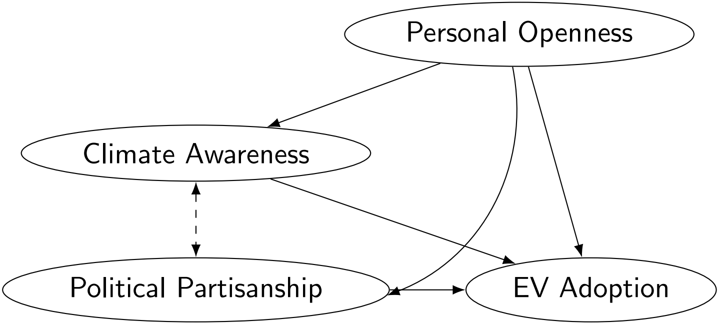
$$EVProportion_{t,c} = \alpha + \beta_1 fedpol_{2016,c} + \beta_2 \Delta fedpol_{2020,c} + \theta STATEPOL_{t,s} + \delta DEMOG_c + \kappa infra_{t,c} + \omega fuelprice_t + \gamma_t + \tau_s + \epsilon$$

Problem: Endogeneity between voting patterns and EV adoption

Methodology



Methodology



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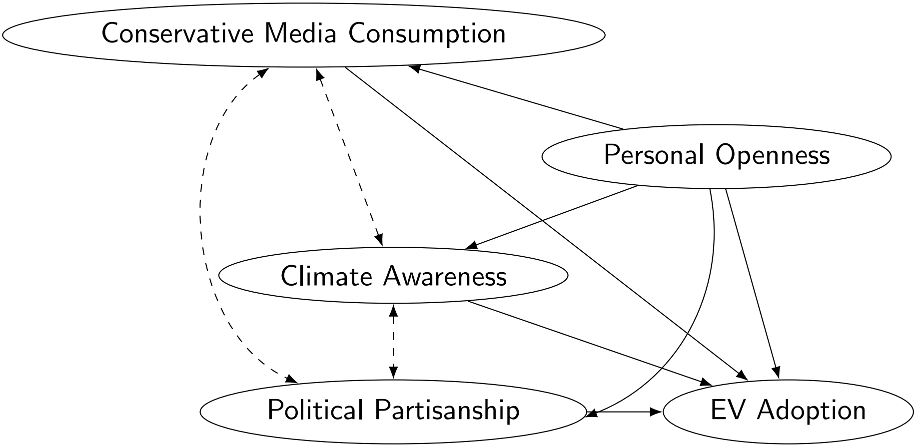

Methodology

A Brief Aside:

I don't think how a particular county votes **in isolation** has any causal relationship with EV adoption. It's just a proxy metric for American Republican ideology which encompasses all the aforementioned confounders.

My Point

A proxy metric needs Endogeneity to be a good proxy. But at what point does Endogeneity become a problem?

Methodology

Possible Remedies:

- Find an Instrument (Difficult)

  AND/OR

- Specify a different question/regression with the same dataset

Open to suggestions

Data

- County Partisanship: Election returns in the 2016 and 2020 federal elections. Published by the MIT Election Data Lab
- State Partisanship: Governor and Legislature partisanship. Scraped from the National Governors Association and Ballotpedia respectively
- EV Population: Monthly county-level vehicle population grouped by vehicle class (passenger vs truck) and drivetrain (electric, hybrid, non-electric). Published by State of Washington Department of Licensing

Data

- Demographics: County-level Population, Education, Unemployment, and Poverty from census data. Published by the Economic Research Service of the US Department of Agriculture
- Fuel Price: Monthly US mean gasoline price ($/gallon). Published by the Federal Highway Administration of the US Department of Transportation
- Charging Station: County-level station count. Published by the Alternative Fuels Data Center of the US Department of Energy

Merged and Processed with Python (Pandas)

Spatial Merging (ZIP-code to County) done with U.S. Department of Housing and Urban Development's Crosswalk Files

Summary Statistics

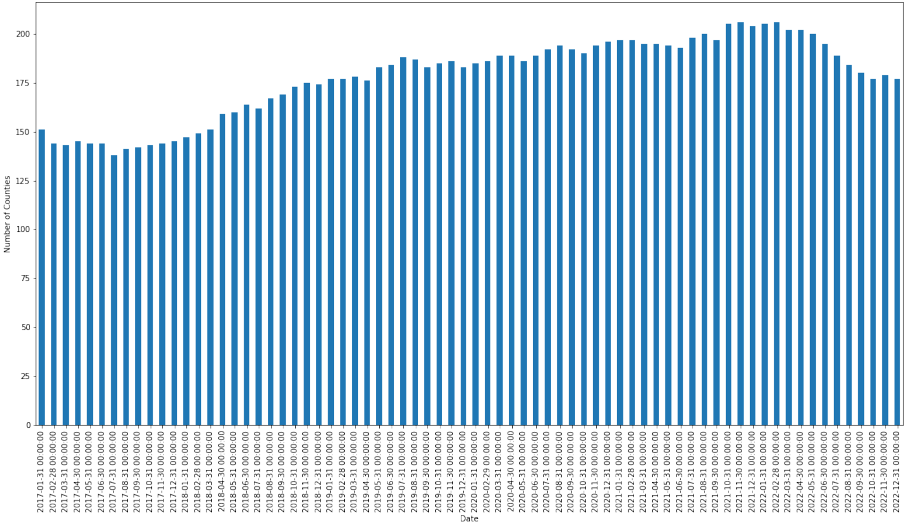

Figure: Number of Counties counted

Summary Statistics

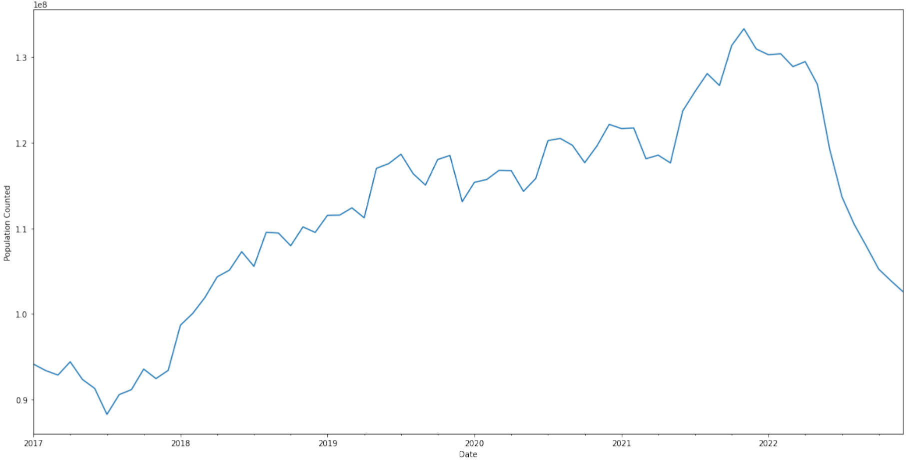

Figure: Population Counted

Summary Statistics

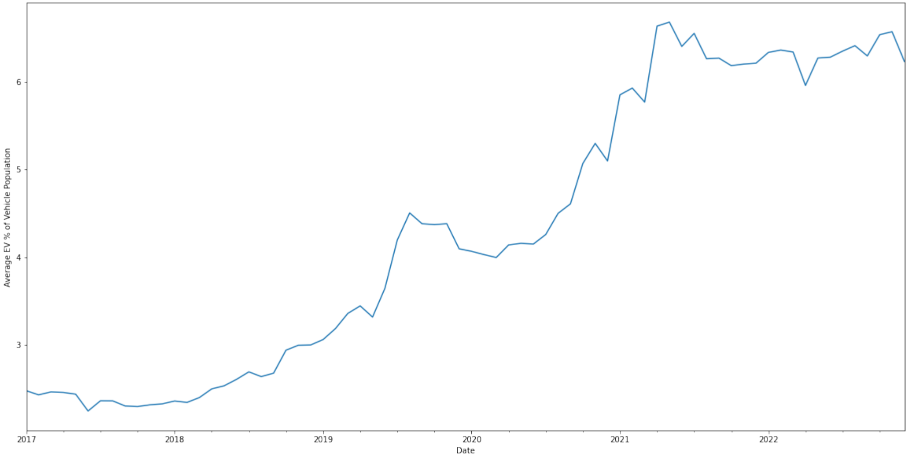

Figure: Average EV population as a % of total vehicle population

Summary Statistics

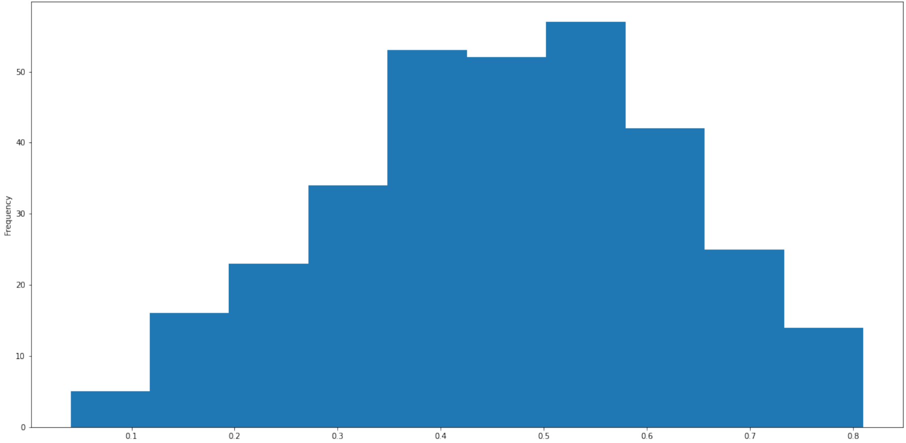

Figure: Histogram of County Republican Vote Share in 2016 US Federal Election

Summary Statistics

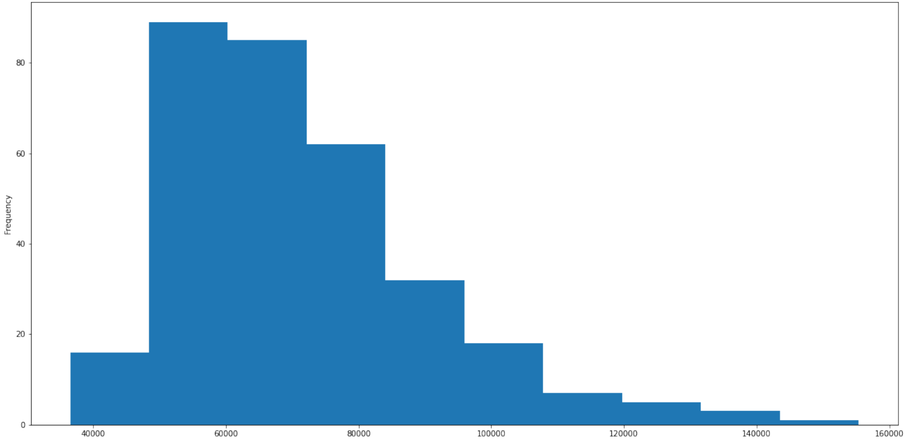

Figure: Histogram of County Median 2020 income

Preliminary OLS Results

All regressions run with linearmodels.PanelOLS

Base Case Regression:

	Parameter	Std. Err.	T-stat	P-value
const	4184.5	369.88	11.313	0.0000
percent_rep	-4193.5	399.51	-10.497	0.0000
percentchange	-1932.5	192.25	-10.052	0.0000

F-test for Poolability: 110.71
P-value: 0.0000
Distribution: F(51,12635)

Included effects: State, Year

Preliminary OLS Results

Regression with demographic controls:

	Parameter	Std. Err.	T-stat	P-value
const	2109.4	228.19	9.2443	0.0000
percent_rep	-3387.7	221.09	-15.322	0.0000
percentchange	-2211.2	234.93	-9.4120	0.0000
Median_HH_Income	0.0349	0.0033	10.604	0.0000
Percent w/ a bachelor	-19.207	1.8533	-10.363	0.0000
Population 2021	0.0004	4.524e-05	8.6449	0.0000
PCTPOVALL_2020	-14.712	5.7036	-2.5794	0.0099

F-test for Poolability: 117.54
P-value: 0.0000
Distribution: F(51,12631)

Included effects: State, Year

Preliminary OLS Results

	Parameter	Std. Err.	T-stat	P-value
const	4169.7	494.55	8.4311	0.0000
percent_rep	-3492.3	237.54	-14.702	0.0000
percentchange	-2409.5	268.92	-8.9599	0.0000
%_rep_house	-3949.4	630.23	-6.2666	0.0000
rep_maj_house	245.98	88.293	2.7859	0.0053
rep_supmaj_house	-107.74	91.382	-1.1790	0.2384
%_rep_sen	-229.63	575.62	-0.3989	0.6900
rep_maj_sen	213.41	80.822	2.6405	0.0083
rep_supmaj_sen	227.36	67.303	3.3782	0.0007
rep_gov	78.223	48.151	1.6245	0.1043
Median_HH_Income	0.0346	0.0032	10.721	0.0000
Percent w/ a bachelor	-22.111	1.8248	-12.117	0.0000
Population 2021	0.0002	3.29e-05	7.1229	0.0000
PCTPOVALL_2020	-14.251	5.7814	-2.4650	0.0137
n_charging_stations	1.5910	0.5004	3.1796	0.0015
Gas Prices ($/Gallon)	13.387	99.325	0.1348	0.8928

Preliminary Interpretations

- Economically and statistically significant negative effect size of county partisanship and Δ partisanship on EV registrations
- Negative effect for county education (Surprising)
- Positive effect for Republican state house majority, and Republican state senate majority and supermajority (Surprising)
- Insignificant effect size for Gasoline price, but the data I have isn't very good

Next Steps

- Collect + process more data (Vehicle Miles Travelled, Subsidies and other incentives, Better Gas Price Data)
- Consider finding an instrument
- Consider different questions with the same dataset
- Consider same regression but with different fixed effects (Month, County) - worried there is not enough data within each group
- Open to suggestions

Next Steps

Questions?