Wealth and Electric Vehicle Adoption:

Examining Effects of Gross Domestic Product Per Capita as an Indicator of Wealth on Electric Vehicle Registration Rates

By

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Abstract

This paper investigates the effects of GDP per capita as an indicator of wealth on Electric Vehicle (EV) registration rates. Following Baptiste et al.'s 2017 paper examining the relationship between GDP and EV adoption rates in Europe, my paper expands on that by focusing on the GDP per capita of the counties within the state of California from 2015-2020. I utilized panel data consisting of unemployment rates, educational attainment, electricity prices, urban vs rural, as well as time and county specific fixed effects in my multilinear regressions. My findings indicate that GDP per capita as an indicator of wealth had a negative and statistically insignificant effect on EV (Electric Vehicle) registration rates. However, by including *urbanization* as a control, my results show that GDP per capita as an indicator of wealth had a negative and significant effect on EV registration in urban counties only. Furthermore, my analysis suggests that urbanization plays an imperative role in determininghow GDP per capita and other county specific differences affect EV registration rates.

Introduction:

At the turn of the 21st century, we have seen a significant increase in the importance of resource-efficient modes of transportation. Electric vehicle adoption rates in the U.S. alone have grown by more than 300% over the past 6 years (Desilver 2021). With that in mind, many governments worldwide have introduced incentives and tariff-based policies to ease and motivate the transition into a green-transportation economy. As a result, electrification of the mass automotive industry enabled electric cars to occupy 4.6% of the global vehicle market sales (IEA 2021). In the United States, federal and state-level initiatives have taken place to lower the overall cost of transitioning from conventional vehicles (ICEs) to electric/electricity-powered vehicles (EVs). Furthermore, the Biden administration in 2022 alone announced a federal objective that states that EVs must make up at least 50% of the national vehicle market share by 2030. In efforts to achieve such a goal, the White House announced a multi-billion infrastructure project via the Bipartisan Infrastructure Law, allocating $7.5 billion of the national budget towards constructing 500,000 EV charging stations, north of $7 billion towards battery manufacturing resource security and another $10 billion towards green public transportation and green school buses (The White House 2022).

Seeing as not only the market share of EVs has grown staggeringly in the past couple of years, but multi-billion-dollar projects by both private and public entities have been initiated, it is only fair to investigate how GDP, an indicator of wealth, affects EV (Electric vehicle) adoption rates. We understand from previous literature that wealth plays a big role in a household's decision to transition from ICEs to EVs (Rapson et al.,2022). To add, we also recognize that GDP is highly correlated with EV adoption, such as in Europe where "ECV market share of above 3.5% only occurs in countries with a GDP per capita of more than

€42,000," while "countries with an ECV market share of less than 1% have a GDP below €29,000" (ACEA 2019).

This paper aims to investigate the relationship between GDP and EV adoption, by looking at annual per capita changes in both aforementioned variables. To properly capture the effects of GDP growth on EV adoption, I will be looking at the 58 counties of California and observe the changes in the variables of interest throughout a 6-year period (2015-2020). I chose the 58 counties of California not only because it has the highest number of EV registration[1] in the US, but also because I want to reflect a diverse range of data, rather than an aggregated state or country-level dataset. By capturing the diversity within these counties, I am hoping to secure a better understanding of the difference between urban and rural areas when it comes to EV adoption. Consequently, I will be able to capture industrial areas with higher GDP per capita, metropolitan areas with high population density and lower GDP per capita, and rural areas with low population density and low GDP per capita.

When transitioning from conventional vehicles to EVs, many factors must be considered from the consumer's perspective. According to one consumer survey conducted by Statista, "76 percent of American commuters use their own car to move between home and work" (Richter 2022). However, even with personal vehicles being the most dominant and traditional mode of transportation, only 5 percent of the US vehicle market share is attributed to EVs (International Energy Agency, 2021). Future market prediction conducted by the Edison Electric Institute reports that the "number of EVs on U.S. roads is projected to reach 26.4 million in 2030," and "will make up nearly 10 percent of the 259 million light-duty vehicles…expected to be on U.S. roads in 2030" (Orlando, 2022).

[1] Figure 1 in the Appendix

Previous literature has noted that policymakers still struggle to grasp the true estimates of electric vehicle use, due to data limitations (Burlig et al., 2021). Therefore, the motivation behind this research is to find the importance of GDP growth in the world where transitioning towards a greener future is dependent in a large way on green modes of transport such as EVs. Although other literature argue that GDP growth is tightly linked to greenhouse gas emissions (Sun et al., 2022), my argument is that GDP is also closely linked to zero-emissions policies and especially to EV adoption. With an assumption that GDP is an indicator of wealth, and that wealth is positively correlated with EV registration (Rapson et al.,2022), we can see how GDP per capita would be positively correlated with EV adoption. On the macro-level, GDP can also indicate development and infrastructure (Hanžič et al., 2019), and thus, "GDP growth impacts the effectiveness of EV policies for the individual and household market to business adoption of EFs (electric fleets)" (Alali et al., 2022).

The data that I will be using is publicly published on the data portals of U.S. government entities or are sourced from them. My unit of observation will be all 58 counties of the state of California, from the years 2015-2020. Since I am interested in the effect of GDP per capita on EV adoption, my key independent variable will be GDP per capita, and my key dependent variable will be EV registration per capita.

Baptista et al. (2017) previously investigated the relationship between GDP and EV adoption in Europe. I build upon that by digging deeper not only by differentiating between urban and rural areas, but also by focusing the effects of GDP on EV adoption through county-level data rather than aggregated country-level data and looking at GDP and EV registration per capita to capture per-capita level effects. Additionally, I consider education, unemployment and electricity prices as factors that may affect the relationship of interest.

Literary Review:

The question this paper aims to answer is one that has piqued the interest in much of previous literature. Some literature look at GDP as a measure of development (Hanžič et al., 2019), and others view GDP as the enemy of zero-emissions policies (Sun et al.,2022). These papers argue for the positive relationship between GDP and greenhouse gas emissions, finding that urbanization and development contribute greatly to the reduction of quality air due to the positive feedback rooted at the increased urbanization and increased demand for fossil fuels (Zhang et al.,2017). Literature has also found a positive correlation between GDP growth and greenhouse gas emissions, stating that productivity growth necessitates the utilization of coal, oil and other fossil fuels (Sun et al.,2022).

Using panel data, Rapson et al. (2022) finds that adoption of EVs differs among different census block groups, highlighting the correlation between demographic, wealth, income and electric vehicle adoption. Research has found that EV adoption is positively associated with high-income households and areas with lower population density (Rapson et al.,2022). Additionally, literature has also found that demographics that are more invested in not only purchasing an EV but are more likely to install a separate charging unit or EV meter, tend to come from the wealthier demographic of households (Burlig et al., 2021).

My findings will contribute to the literature of GDP and CO2 emissions by (Sun et al., 2022), building on the foundation of Hanžič et al., (2019), and looking at GDP Per Capita as a representative of wealth. Unlike Sun et al. (2022) and Hanžič et al., (2019), my focus will be on GDP as an indicator of wealth, exploring its relationship with EV adoption. Although previous literature looks at GDP and development as burdens towards a greener future, my paper will look at the essentiality of GDP per capita in EV registration, and thus, in the zero-emissions future.

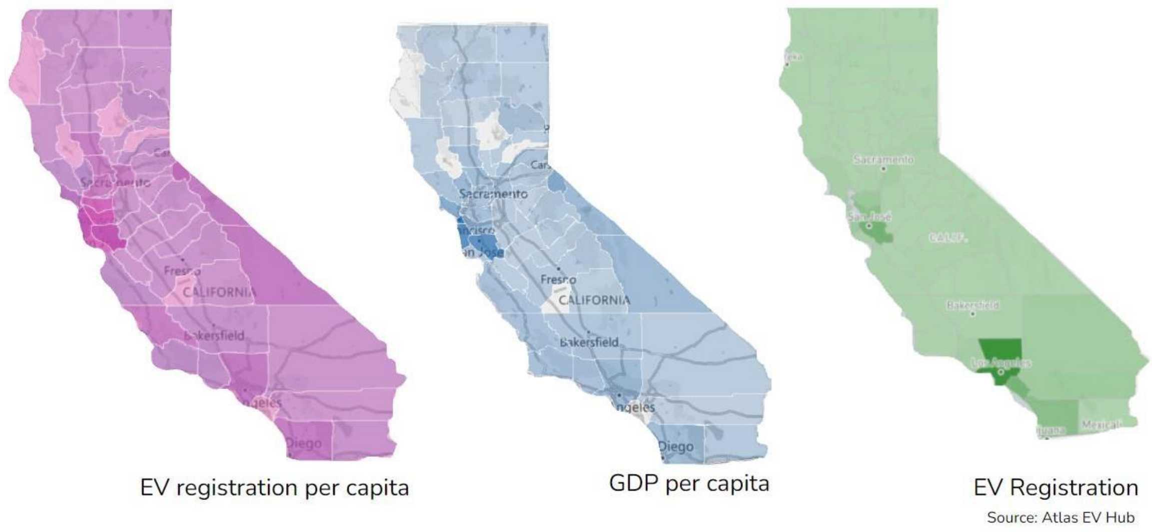
The most closely related literature to my analysis is Baptista et al. (2017) where the authors look at various determinants affecting EV adoption among 29 European countries. Like my study, Baptista et al. (2017) gathers data on GDP and electric vehicle (EV) to analyze a correlation between the two. However, unlike my analysis, this literature looks at macro-level factors. Baptista et al. (2017) utilizes country-scale indicators such total country-level GDP, net country-level EV sales etc. The data is then put through Exploratory Data Analysis and then similar to my study, it is analyzed through a multiple linear regression model. The results that Baptista et al. (2017) found were intriguing since some of it agreed with other literature and some did not. Through the cross-country analysis of 29 European countries, the paper found that the presence of EV was positively correlated with higher population density (different to Rapson et al.,2022) and higher income (similar to Rapson et al.,2022 and Burlig et al., 2021).

Compared to Baptista et al. (2017), my paper will look at different counties within California throughout the periods of 2015-2020. My paper will contribute the following: (1) it will look at different counties within a state to control for differences in adoption policies (2) it will look at GDP per capita growth and EV registration per capita growth between 2015-2020 (3) it will include variables such as education, urbanization, electricity prices and unemployment rates. I believe that these county-level factors will contribute greatly to literature because it enables a deeper and more comprehensive understanding of the relationship between GDP and EV adoption. Additionally, Baptista et al. (2017) does not look at the multiple periods, but rather a static correlation between the two. My introduction of annual per capita change, differentiation of metropolitan/urban vs rural, and the inclusion of variables such education and unemployment rates, will grasp a greater understanding of the determinants of EV adoption.

Data and Methods:

For the analysis I will be using public annual county data on GDP change, population growth, electric vehicle (EV) registration, unemployment rate, electricity prices and education. The database will range from the year 2015 to the year 2020, covering over a 6-year period of the counties (unit of observation) within the state of California. The data variables were sourced as follows: (1) GDP data was collected from the U.S. Department of Commerce/ Bureau of Economic Analysis (2) Population data was collected from the United States Census Bureau (3) Electric vehicle (EV) registration data was collected from the Atlas EV Hub, which cites the California Energy Commission as its source (4) Unemployment data was sourced from the U.S. Department of Agriculture (5) Electricity data was collected from the California Public Utilities Commission and (6) Education data was collected to Statistical Atlas.

Heat maps representing EV registration and GDP data for the state of California



As displayed above, upon organizing the data and comparing my heat maps with that available through the *Atlas EV Hub,* we can clearly see that although EV registration is highly dense in Los Angeles, registration per capita like GDP per capita, is much denser in the counties of San Francisco and San Jose. Thus, this highlights the importance of analysing the effects of GDP per capita on EV registration. Similarly, the density of EV registration in Los Angeles, highlights the existence of variables other than GDP per capita, that influences EV registration decisions.

In order to properly utilize the data to reflect the variables of interest, I had to clean, filter, and rearrange the data collected from multiple sources into a separate panel dataset form. I restricted the data to include only counties within the state of California through the periods of 2015-2020. Furthermore, I had to modify the GDP and EV registration data to reflect the per capita degree. To answer my research question, I organized my key variables as follows: Key X (Independent) variable is the county-level GDP per capita, Key Y variable (Dependent) is the county-level EV (electric vehicle) registration. Additionally, I will be controlling for changes in electricity prices and unemployment via control variables, while also controlling for county and time specific attributes using county and time fixed effects.

The variables included in my analysis are described as follows: (1) GDP and EV registration data for each county will be divided by their respective population, to transform them into per capita levels (2) Electricity prices will remain in dollar value (3) Educational attainment, which reflect the percentage of college graduates in each county, will be constructed as a binary, with 1 representing higher than state mean, and 0, the opposite (4) Urban vs Rural will also be defined into a binary, with 1 representing urban counties, and 0 representing rural counties (5) Unemployment rates are already in percentage form, and thus, will remain as is.

To properly analyze the relationship between GDP per capita and EV registration per capita, I will be constructing a multiple linear regression model. The regression will allow us to properly see to what extent changes in GDP per capita reflect in the changes of EV registration per capita. Furthermore, it is important to note that a panel dataset with inputs from across 58 counties and 6 periods, would have vast differences in terms of changes and levels of the variables. This means that GDP per capita and registration per capita would have highly skewed distributions due to vast idiosyncratic differences. Therefore, before running the regressions, I logged all of the non-binary variables, which will enable a more accurate regression analysis, by controlling for the skewness and normalizing the distribution.

Planned Methodology:

Equation 1:

$$Y_{it} = \beta_0 + \beta 1 X_{it} + \beta 2 \lambda_{it} + \mathrm{B}3 \mu_{it} + \alpha_i + \delta_t + \varepsilon_{it}$$

- EV Registration per capita growth = **Y**
- **X** is the independent variable of interest (GDP per capita growth)
- λ_{it} Variable controls for difference in electricity prices
- μ_{it} Controls for difference in unemployment rates
- α_i Represents county-specific fixed effects
- δ_t Represents time-specific fixed effects (the year)

Equation 2:

$$Y_{it} = \beta_0 + \beta 1 X_{it} + \beta 2 \lambda_{it} + \beta 3 \mu_{it} + \beta 4 X_{it} * \sigma_i + \beta 5 \lambda_{it} * \sigma_i + \alpha_i + \delta_t + \varepsilon_{it}$$

- EV Registration per capita growth = Y
- **X** is the independent variable of interest (GDP per capita growth)
- λ_{it} Variable controls for difference in electricity prices
- μ_{it} Controls for difference in unemployment rates
- σ_i Controls for urban vs rural (Binary dummy, 1 = Urban, 0 = Rural)
- α_i Represents county-specific fixed effects
- δ_t Represents time-specific fixed effects (the year)

Equation 3:

$$Y_{it} = \beta_0 + \beta 1 X_{it} + \beta 2 \lambda_{it} + \beta 3 \mu_{it} + \beta 4 X_{it} * \theta_{it} + \beta 5 \lambda_{it} * \theta_{it} + \alpha_i + \delta_t + \varepsilon_{it}$$

- EV Registration per capita growth = **Y**
- **X** is the independent variable of interest (GDP per capita growth)
- λ_{it} Variable controls for difference in electricity prices
- μ_{it} Controls for difference in unemployment rates
- θ_{it} Represents Educational Attainment
  (Binary dummy, 1 = Higher than state average, 0 = Below state average)
- α_i Represents county-specific fixed effects
- δ_t Represents time-specific fixed effects (the year)

Regression Discussion:

The first equation represents my main and rudimentary form for my planned regression analysis. The regression will examine the effects of GDP per capita (Independent Variable) on EV registration (Dependent Variable), while also controlling for differences in electricity prices and unemployment rates. The reasoning behind the inclusion of these control variables is because we know from previous papers that electricity prices play a significant role in household decisions when deciding to purchase EVs. Additionally, the relationship is shown to be a negative one, claiming that an increase in household electricity prices would result in an adverse outcome in electric vehicle registration rates. Therefore, the inclusion of the control for electricity prices across counties and years is crucial when trying to isolate the effects of GDP per capita on EV registration.

Furthermore, the first equation controls for unemployment rates across counties and years. The intuition behind this is that areas with higher unemployment rates will result to lower average household income and wealth. By controlling for differences in unemployment rates, I will be controlling for differences in average household income and wealth, as a result of high unemployment rates. Lastly, my standard regression also includes time and county-specific fixed effects. The rationality behind this, is that across the 58 counties of California, and across 6 time periods, it is natural to find vast numbers of different trends and variables. Due to the vast number of variables that my panel data cannot capture as result of idiosyncratic characteristics, my data would be biased. This in-turn would result in an inaccurate representation of the relationship of interest. Therefore, for a more accurate understanding, including time and county specific fixed effects is imperative in averaging out the unobservable differences in the data and controlling for these omitted variables.

My next equation dives into a deeper understanding of the impact of urbanization on the effects of GDP per capita on EV registration, as well as the influence urbanization has on electricity prices. The rationality behind this is that urban areas are much more densely populated and have better infrastructure, when compared to rural areas. Infrastructure plays a big role in EV adoption decisions because they can signal how readily available charging stations are, how short commute durations can be due to the accessibility of amenities within small radiuses, as well as signal the necessity for personal modes of transportations due to the convenience of public transportation. Furthermore, in terms of electricity prices, we know that urban areas have higher standards of living, and thus, would have higher electricity prices. Therefore, by including urbanization as an interaction term with GDP per capita and electricity prices, we can examine how urbanization changes the effects of GDP per capita and electricity prices on EV adoption.

To add, the reason I did not include unemployment rates as an interaction is because I noticed upward sloping trends between electricity prices and registration rates, and not between unemployment rates and registration. Therefore, the purpose of the inclusion of electricity prices as an interaction with urbanization, is to remove the 'false' causal effect that may be misinterpreted between electricity prices and electric vehicle registration. Thus, highlighting the possibility that the reason for the positive correlation between electricity prices and EV registration, is due to the effects of urbanization.

Lastly, my third equation replaces the interaction terms above, for another interaction term utilizing educational attainment levels. The educational attainment variable represents the percentage of individuals within a county that have attained a bachelor's degree or higher. The reasoning behind this is to examine how educational attainment is linked to GDP per capita, and therefore, its affect on the relationship between GDP per capita and EV adoption. If we assume that the attainment of higher education would result to better working conditions, higher sources of income, and greater opportunity for wealth, then higher educational attainment would most likely affect GDP per capita, and thus, affect EV registration rates. Similarly, if we assume that educational attainment would affect income and wealth, then we can also assume that the level of educational attainment would impact the price sensitivity households have towards electricity prices. Therefore, this would give us an understanding on how educational attainment within a county could affect the utility prices individuals choose to pay, and in turn, affect EV registration rates.

Results:

My initial intuition was to first examine the basic relationship between my independent and dependent variables. As discussed in previous literature, Graph 1[2] shows a positive relationship between GDP per capita and EV registration rates. This graph does not include any of the control variables that I wish to include in my regression.

Table 1

	(1) No Fixed Effects	(2) With Year Fixed Effects	(3) With County Fixed Effects
GDP Per Capita	0.980***	0.714***	-0.294
	(8.92)	(7.12)	(-1.23)
Unemployment Rate	-0.915***	-1.398***	-0.0448
	(-8.91)	(-12.60)	(-0.62)
Electricity Price	3.327***	1.955***	0.305
	(10.99)	(6.53)	(1.01)

t statistics in parentheses

="* $p<0.05$ ** $p<0.01$ *** $p<0.001$"

[2] Check Appendix for Graph 1

Next, I examined my regression with the control variables of unemployment rates and electricity prices. The results as shown in Table 1, yielded a positive relationship between GDP per capita and EV registration, showing that a 10% increase in GDP per capita would result in an approximately similar 9.8% increase in EV registration rates. On the other hand, the results also show a positive relationship between electricity prices and EV registration. However, this contradicts previous literature, because according to a recent study in California, a 1 cent increase in electricity prices resulted in a 0.4% decrease in EV sales (Bushnell et al., 2022). The possible explanation would be that due to California's overlapping utility service blocks/territories, counties with both median high and low GDP per capita, are averaged to pay similar prices. The overlapping of service territories for these utility companies, and the insensitivity of wealthier individuals may have resulted to a correlated but non-causal relationship. Additionally, unemployment rates is shown to have a negative relationship with EV registration. This is most probably due to differences in county wealth per capita, which is highly linked to county unemployment rates.

Column 3 reveals the proper regression with all the intended control and fixed effects variables. As can be inferred, Table 1 shows no statistical significance between GDP per capita and electric vehicle (EV) registration rates. All other variables also yield no statistical significance when examining its effects on EV registration. The likely rationality behind this is that there are other contributing factors/variables that play a greater role in EV registration other than GDP per capita. Another possible inference is that based on previous literature that show a strong positive relationship between wealth and EV registration (Rapson et al. 2020), GDP per capita may not be a suitable indicator of wealth at the county level data of California.

For further investigation, I decided to examine the effects of GDP per capita, unemployment and electricity prices in urban counties only. This differs from my analysis in equation 3, because instead of finding the impact of urbanization on the effect of GDP per capita and electricity prices on EV registration, I am now examining how differently the effects of GDP per capita, unemployment and electricity prices affects EV registration, when only enacted on urban counties. As we can see in Table 2, upon restricting all the variables to reflect urban counties only, GDP per capita can be observed to have statistical significance I EV registration. We can interpret the results and say that a 10% increase in GDP per capita would result in an 8.75% drop in EV registration. An assumption that can be made to explain this is that with the knowledge that wealthier individuals are more likely to purchase luxury vehicles, there may be an inflection point at play, affecting their registration decisions. This inflection point would suggest that when individuals witness an increase in wealth by a certain degree, they are more likely to purchase luxury cars, rather than EVs.

Additionally, Table 2 shows that that there is a statistically significant negative relationship between unemployment rates in urban counties and EV registration. To interpret this, we see that a doubling in unemployment rates in these urban counties would likely results to a 16.4 percent decrease in EV registration rates in urban counties. To better understand this, we can infer that on average, wealth is highly linked to unemployment rates, and the likelihood of less wealthy urban counties with high unemployment rates, having high rates on EV registration per capita is little. Furthermore, electricity prices show a negative but statistically insignificant relationship to EV registration.

Table 2

	(1)	(2)
	All Counties	Urban Counties Only
GDP Per Capita	-0.294	-0.875***
	(-1.23)	(-4.19)
Unemployment Rate	-0.0448	-0.165*
	(-0.62)	(-2.41)
Electricity Price	0.305	-0.329
	(1.01)	(-1.06)

t statistics in parentheses

="* p<0.05 ** p<0.01 *** p<0.001"

Diving into my next regression, I look at the impact of urbanization on the effects of GDP per capita and electricity prices on EV registration. As shown in column 1 of Table 3, when I included the interaction terms *GDP per capita * Urban* and *Electricity Prices * Urban,* with no fixed effects, I yielded no statistical significance for either of them. This, however, is not enough. We need fixed effects to make sure that we control for county and time varying trends and other omitted variables that might affect our results. Thus, in column 2, I included the time-specific fixed effect which will control for variables that might have changed with time, and are not GDP per capita. By doing so, both our interacted terms became statistically significant.

Furthermore, if we look at the difference between the interacted term of *Electricity Prices * Urban* and the variable for electricity prices, we can observe that upon placing the interaction term, the type of relationship/sign switched from positive to negative; which is the assumed type relationship. For the variable *Electricity Price*, we can understand this as a 10% increase in electricity prices would result to a 16.8% increase in EV registration. However, with the interaction term displaying the impact of urbanization on the effect of electricity prices on EV registration, we see a negative and significant relationship between the two. To describe this, we can say that 10% increase in electricity prices given that it is an urban county, would results to a 5.25% decrease in EV registration in that respective county. Therefore, by placing time fixed effected, not only were we able to shrink the coefficients, but our interaction term was able to show the negative relationship between electricity prices and EV registration. The shrinking in the coefficient value of electricity price, shows the importance of using fixed effects. That is, because we have controlled for omitted variables that vary with time, we were able to strip away coefficient values of omitted variables that could've been mistakenly associated with electricity prices. Moreover, the interaction term indicates that given that its an urban area, an increase in electricity prices will result to a drop in EV registration.

Additionally, when we look at the difference between the interacted term *GDP per capita * Urban* and the term of interest (GDP per capita), we see that the interacted term is statistically significant, while GDP per capita became insignificant. This would mean that urbanization had a great impact on the effects of GDP per capita on EV registration. To read this, we can say that given it is an urban county, a 10% increase in GDP per capita would result to a 5.92% increase in EV registration. Even though this concurs our understanding, it would be unwise to stop here. Now, we need to add county-specific fixed effects.

Finally, in column 3, we strip out the county varying trends and other county-specific omitted variables by including county fixed effects. By doing so, we are able to control for all year and county idiosyncratic variables, and isolate the effects of the included variables on EV registration. Here, we can see that GDP per capita, as well as the control and interacted terms, yield a statistically insignificant effect on EV registration. This comes back to my previous claim, where I indicate the existence of other omitted variables that play a much more influential role on EV registrations. As previously discussed, this can be environmental preferences, attitude towards EVs and finally, due to the scope of my data, can be policy and incentive variables; all which either cannot be quantitively captured or is unviable when looking at only 1 state.

Table 3

	(1) No Fixed Effects	(2) With Year Fixed Effects	(3) With County Fixed Effects
GDP Per Capita	0.486**	0.0470	-0.283
	(2.77)	(0.32)	(-0.96)
Unemployment Rate	-0.890***	-1.361***	-0.0485
	(-9.11)	(-13.94)	(-0.66)
Electricity Price	3.197***	1.688***	0.242
	(11.02)	(6.51)	(0.74)
GDPPC * Urban	0.396	0.592***	-0.0558
	(1.85)	(3.35)	(-0.15)
Electricity Price * Urban	-0.293	-0.525*	0.198
	(-1.02)	(-2.22)	(0.49)

t statistics in parentheses

="* p<0.05 ** p<0.01 *** p<0.001"

In my third regression we look at the effect of education levels on EV registration rates. At the state-level mean of 22.95 percent of Californians having any form of higher education, we find a negative relationship of marginal statistical significance in the impact of education on the effect of electricity prices on EV registration, as shown in Table 4. To better understand this, we can say that higher educational attainment has a marginal or a weak significant role in the likelihood of purchasing an Electric vehicle (EV). Another way to rationalize this, is that even if educational level of attainment has an importance, there are other more significant factors to EV registration, other than educational attainment.

Table 4

	(1) No Fixed Effects	(2) With Year Fixed Effects	(3) With County Fixed Effects
GDP Per Capita	0.368	-0.358	-0.244
	(1.38)	(-1.47)	(-0.74)
Unemployment Rate	-0.593***	-0.817***	0.0403
	(-5.35)	(-6.53)	(0.53)
Electricity Price	3.189***	1.931***	0.565
	(10.34)	(6.78)	(1.80)
GDPPC * Education	0.192	0.804**	0.157
	(0.66)	(3.03)	(0.42)
Electricity Price * Education	0.0168	-0.755*	-1.005*
	(0.04)	(-2.23)	(-2.45)

t statistics in parentheses

="* p<0.05 ** p<0.01 *** p<0.001"

Furthermore, the interaction term of electricity prices and educational attainment capture the effect of electricity prices given that the counties are educated. The results show that there is a negative relationship of low significance between electricity prices and EV registration, only if the level of educational attainment was held on average. A way to infer this is that an increase in electricity prices by 10 percent would result to a similar unit change of 10 percent reduction in EV registration. This is consistent with previous literature (Bushnell et al., 2022) showing a negative relationship between electricity prices and EV registration. However, the need for educational attainment to be on the median or higher would mean that the level educational attainment is significant in understanding electricity price elasticity on the complementary good (Electric vehicle). A probable explanation for this is that high levels of educational attainment is linked to a lower preference for EVs (or personal vehicles), which is probably true if higher educational attainment, would mean relocating to more urban areas.

Surprisingly, when we restrict for urbanization as we did in the first regression, we find the opposite of our previous findings. As shown in Table 5, we find that the effects of GDP per capita given that education is held the same across urban areas, to be significantly and negatively correlated by 120 percent. What this means is that if GDP per capita is doubled given that education is constant across urban areas, these individuals are a 120 percent less likely to purchase EVs. Thus, we can infer that in urban areas, the sensitivity in the level of wealth towards EV registration is higher in individuals with higher levels of education.

Table 5

	(1) All Counties	(2) Urban Counties Only
GDP Per Capita	-0.244	0.535
	(-0.74)	(1.47)
Unemployment Rate	0.0403	-0.0306
	(0.53)	(-0.44)
Education*GDP Per Capita	0.157	-1.209***
	(0.42)	(-3.45)
Electricity Prices*Education	-1.005*	-0.370
	(-2.45)	(-1.07)
Electricity Prices	0.565	0.0686
	(1.80)	(0.21)

t statistics in parentheses

="* p<0.05 ** p<0.01 *** p<0.001"

Conclusion:

Based on the results, we infer that GDP per capita is statistically insignificant when trying to understand the effects of wealth on EV per capita registration. This is likely true when we take into consideration differences in omitted variables such as preference and attitude towards EVs etc. Therefore, we can understand that when trying to investigate differences in economic behaviours, variables such as preference, level of infrastructure, political ideology and attitude towards EVs, are likely to play a bigger role. However, we can also infer that GDP per capita is only statistically significant in urban counties, as an indicator of wealth and its effects on EV registration. The results concur with other literature (Rapson et al.,2022) that GDP per capita affects EV registration decisions. However, it differs in that there seems to be a negative relationship (Table 2) between the two variables, when looking at urban counties. The best explanation for this is that although urban areas are linked with having higher GDP per capita, they are also linked to having higher infrastructure, more densely populated areas and more close and readily available resources/amenities. Consequently, this plays a role in the need and convenience of owning personal vehicles, which is highly unlikely in urban areas when compared to rural areas.

Furthermore, we can conclude that unemployment plays a significant role in electric vehicle adoption in urban counties. Unemployment in urban counties is shown to have a negative relationship with EV registration (Table 2). To be exact, we find that doubling unemployment rates in urban counties would likely result to a decrease of 16.4 percent in EV registration. Building upon our previous findings, examining this would lead us to believe that urban counties with densely populated areas are less likely to purchase electric vehicles, which is especially true if those areas are likely to have higher rates of unemployment. Thus, we can understand that the effects of urbanization on the need for EVs as personal vehicles is more probable to be negative, especially when taking into consideration the state of wealth and employment. On further studies, this can be cross-checked with the traditional ICE (Internal Combustion Engines) vehicles, to see if the same holds true for ICEs, which will also give us a better understanding on the whether EVs are a good substitute to the traditional ICE vehicles.

Taking educational attainment levels into consideration, we found that any form of higher education had a marginally significant and negative relationship. What this means is that the level of educational attainment plays weak role in EV registration. On the other hand, the fact that it is marginally significant, gives us a clearer picture on the significance of educational attainment when compared to other variables. Therefore, we can infer that other variables are much more significant, which is more likely. Additionally, we were able to prove this after the addition of the interaction term *Electricity * Education.* By adding the interaction term, our marginally significant role of the level of educational attainment was fully absorbed by the effects of electricity prices. Thus, we found that electricity prices are negatively correlated with EV registration, given that the level of educational attainment was constant across counties. Now, we found that electricity prices were significantly and negatively correlated unitarily. This means that an increase of electricity prices yielded an opposite unit change in EV registration, only if educational attainment was constant across the counties. Consequently, this leads us to believe that higher levels of education are associated with a lesser desire for EVs, which is presumably true given that achieving higher levels of education would require relocating to more urban regions with higher costs of electricity. Lastly, after restricting our regression to urban counties only, the opposite was true. Now, we found that a 10% increase in individuals with college degrees is associated with a 12% decrease in EV registration in urban areas, suggesting that those with higher levels of education are more sensitive to changes in wealth.

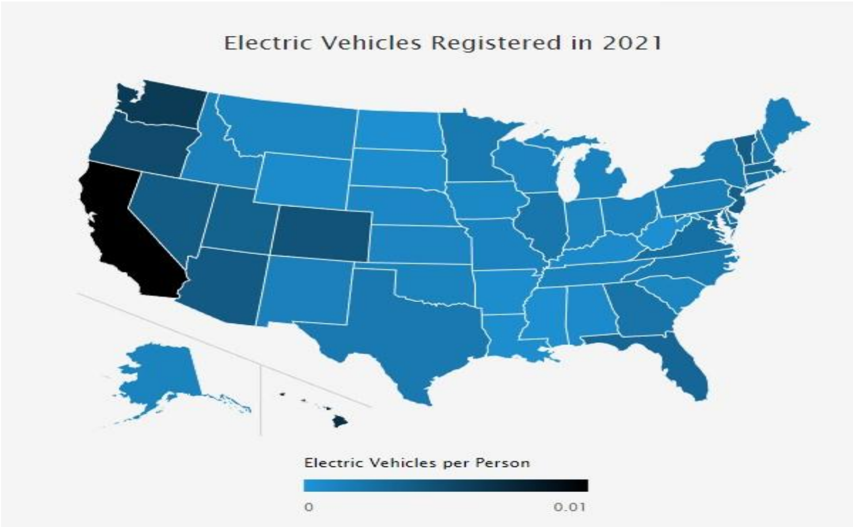
Overall, by including electricity prices, educational attainment and unemployment, we can concur with previous literature that wealth and electricity prices play a big role in in EV adoption, only in urban areas. Additionally, by my addition of the education and unemployment rates as variables, we can conclude that these variables are negatively correlated with EV adoption, only in urban areas. As to why that is the case, a further detailed study is needed. For now, we can say that urbanization plays a role in the direction and importance of economic behaviour, which is likely due to factors that differ urban from rural areas, such as the availability of public transportation, the population density of areas, and the availability of resources and amenities within small radiuses; all inversely affecting the preference and need for a personal mode of transportation.

Limitations:

Throughout the study, there are some important limitations that were highlighted and need to be addressed. Firstly, time and sample bias are limitations worth discussing. It is imperative to note that my sample was collected solely from the counties within the state of California. This would mean that my sample size is small and would not reflect an accurate understanding on the effects of GDP per capita on electric vehicle registrations. Additionally, California holds the rank as the highest GDP Per Capita in the United States, and failure to cross analyse the effects with other states, would deem my results unfit for generalization. Furthermore, my data was collected within a period of 6 years, which is a relatively small period of time when performing an econometric analysis of such depth. Finally, it is most imperative to realize the presence of other variables that may have been omitted in my analysis, such as preferences and range anxiety which are significantly valid, but difficult to collect and include in this analysis.

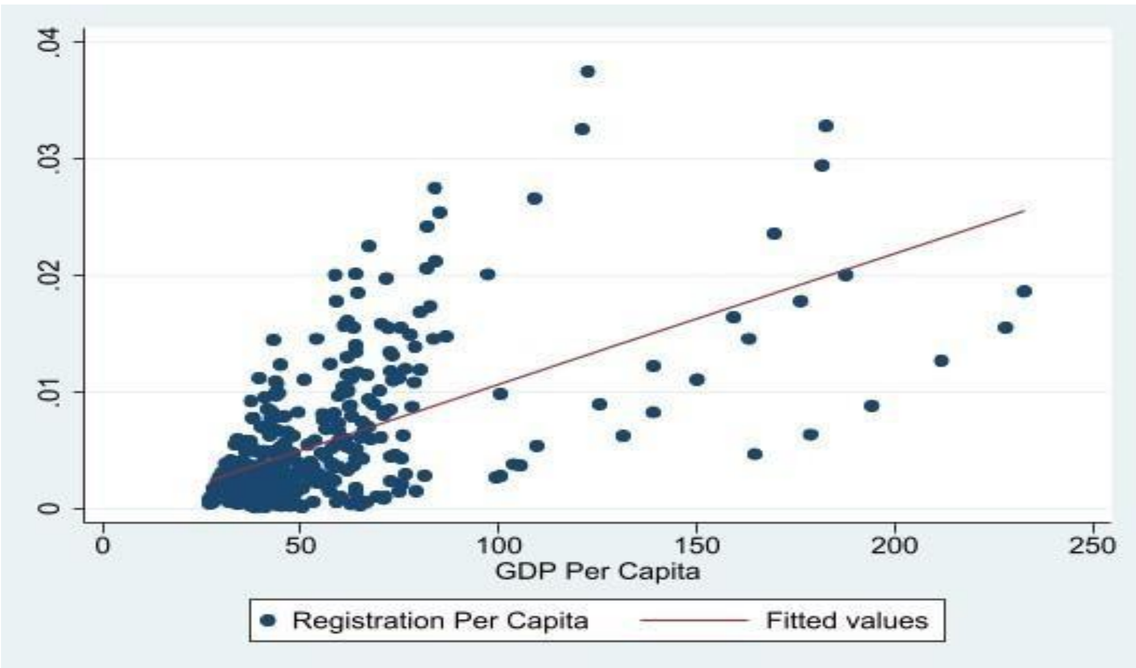
Appendix

Figure 1



Source EV Atlas Hub

Graph 1



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