The Effects of the Tax Credit on the Used Electric Vehicle Market

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Abstract

In the past few years, tax credits have become the fundamental policy instrument to incentivize the adoption of electric vehicles (EVs) in the United States. However, contemporary research primarily focuses on new EVs, while the impact of tax credits on the used EV market remains obscure. This research aims to enhance the knowledge of EV adoption by examining the potential effects of Used Clean Vehicle Credit, a federal program providing up to $4,000 credit to eligible consumers. We have collected sales data of used cars from 245 Carmax locations in the U.S. between 2021 and 2023 to assess the change in prices of EVs before and after implementing the tax credit. The results suggest eligible EV prices increased by $1,521, about 4.74%, once the policy was implemented. Relative to pre-owned non-EVs, EV prices have increased by $2,214, indicating that car dealers have captured a more significant portion of the subsidy amount. We also observe a continually growing trend in EV sale quantities.

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Electric vehicles (EVs) have attracted remarkable attention in the recent decade because of their potential to reduce greenhouse gas emissions and lessen the dependence on fossil fuels, aiming for more fuel-efficient solutions. Despite the prime advantages of EVs in terms of environmental and societal benefits, widespread usage of those vehicles has been a challenge due to high production costs and lack of infrastructure. Hence, governments worldwide, including the United States, have promoted the adoption of electric vehicles by implementing tax credits and incentives in both the demand and supply sides of the market. Particularly, EV tax credits have become a prominent policy instrument in many countries, primarily incentivizing consumers to purchase electric vehicles. The tremendous amount of research on EV subsidies has proven the effectiveness of tax credits in stimulating the EV market.

Nevertheless, the current tax credit in the United States is still inefficient and inequitable compared to other incentives. Individuals with AGI exceeding $75,000 have received approximately 90% of federal EV tax credits (Borenstein & Davis, 2016). In other words, most individuals could afford to purchase an EV without the implementation of tax credits. EV adoption is still confined to upper-income households, and lower-income individuals are underrepresented in the share of tax credit benefits, making this policy somewhat regressive.

Realizing the disadvantages of current tax credits, the U.S. government has implemented a new policy to tackle the inequitable issue and to increase demand for used EVs, particularly among low-income individuals who might be unable to purchase a new electric vehicle. On January 1st, 2023, Congress passed the Used Clean Vehicle Credit bill, a tax credit for purchasing a previously owned, qualified electric, plug-in EV, or fuel cell vehicle (FCV). Starting from the implementation date, a purchase of a pre-owned EV made in and after 2023 from a licensed dealer for $25,000 or less may qualify for this tax credit. The credit equals 30% of the sale price and can be up to a maximum credit of $4,000. Another requirement is that the model year of a qualified vehicle must be at least two years older than the year when purchasing. For example, the vehicle purchased in 2023 would need a model year of 2021 or earlier. Besides restricting vehicle qualification, the U.S. government also sets a qualification for who is qualified for the used clean vehicle credit. Specifically, the credit is qualified for individuals whose modified adjusted gross income (AGI) does not exceed $150,000 for married filing jointly or a surviving spouse, $112,500 for heads of households, or $75,000 for all other filers. However, taxpayers can claim the used clean vehicle credit using their AGI from the year of the purchase or the previous year, depending on which year is less and below the threshold.

The EV market is currently competitive. With the implementation of the new tax credit, we predict that the demand for the EV market, primarily used plug-in EVs and FCVs, will increase since it will offset the price. Subsequently, the quantities and price of used EVs would escalate compared to the prior Used Clean Vehicle Credit adoption period based on the supply-demand model. However, it may not necessarily be accurate for this subsidy. The price of the used EV market may stagnate at $25,000 since it is the qualification for the tax credits. The quantities may also be limited because the suppliers, the original owners of EVs, may not respond to the policy.

To discover the actual changes in the used EV market, our research aims to capture whether prices and quantities in the electric vehicle market respond to the availability of electric vehicle tax credits like the supply-demand model suggested. More specifically, this research aims to investigate the potential effects of this program on the price of used EVs. We hypothesize that the sale price and quantities of used EVs would increase. This is because this subsidy changes the price that buyers pay such that the actual price a buyer pays is the sale price minus whatever credit they receive. Thus, it shifts the demand curve outward, resulting in an escalation in price and quantity. Knowing the price changes will tell us how much the subsidy is split.

To conduct this research, we collected used car sales data from 245 Carmax locations in the U.S. between 2021 and 2023 for descriptive summary results and data between 2022 and 2023 for the regression result. The sample is also restricted to analyzing vehicles with a sale price of less than $40,000 and have a model year of 2021 and earlier. The difference-in-difference estimation strategy is applied to estimate the price change in EVs between 2022 and 2023 due to the tax credit program. To be precise, we compare the average prices of EVs and non-EVs before and after the implementation of the tax credit in January 2023. Consistent with the hypothesis, the results demonstrate a positive growth in sale prices and quantities of EVs after the tax credit was enforced. Compared to pre-owned non-EVs, EV prices have increased by $2,214, indicating that car dealers have captured a more significant portion of the subsidy amount.

Literature Review

In their study of EV subsidies in California, Muehlegger and Rapson observed that the demand for EVs is price-elastic with a value of −2.1 (2022). On the other hand, Li et al. (2017) found that the price elasticity of EV is −1.288. Overall, the price elasticities of EVs have ranged from −3.97 to −2.37, with an average of −2.67 and a standard deviation of 0.21 (Xing et al., 2021). However, Springel (2021) proposed that the mean of EV's own-price elasticity of demand ranged from −1.5 to −2.1, less elastic than Xing et al. (2021) suggested. Although the price elasticity of demand varies from research to research, EV prices are concluded to be consistently elastic. The general results from previous studies have indicated that the elastic demand would increase the number of EV purchasers when the incentive programs are implemented. In addition to elastic demand, EVs have a high subsidy pass-through rate. Approximately 70 to 80% of subsidies are captured by consumers, and consumers have also caught a higher share of benefits through tax incentives compared to direct consumer subsidies (Barwick et al., 2023; Muehlegger & Rapson, 2022). Therefore, subsidy policies, especially tax credits, effectively incentivize EV transportation adoption and contribute to increasing EV sales.

Various research studies have also found that the federal income tax credit policy directly increases the sales of EVs. For instance, a 29% increase in EV sales in the U.S. is due to federal tax credits (Xing et al., 2021), or the policy even contributed to 40% of EV sales during 2011–2013 (Li et al., 2017). Similarly, Tal and Nicolas (2016) reported that federal tax credit has contributed to more than 30% of plug-in electric vehicle (PEV) sales using an online survey of households that purchased PEVs in 11 states. The authors also concluded that the tax incentives actively motivated high-income consumers to purchase PEVs. Not only in the U.S., based on the vehicle registry data from Norway, Springel (2021) highlighted that a subsidy of KR10,000 (US$1,239) per vehicle in registration tax exemptions is associated with a 2.5% increase in EV sales.

Besides tax credits, other incentives have also contributed to the widespread adoption of EVs in the U.S., and consumers have responded diversely to different types of incentives. In their findings on the effect of financial incentive programs on EV adoption, Clinton and Steinberg (2019) analyzed that direct purchase rebates are associated with an 8−11% increase in battery electric vehicles (BEVs) registrations per $1000s subsidy across the United States. The argument of whether the subsidy for electric cars would be more effective on the demand side or the supply side is still inconclusive. Subsidies on the supply side, such as charging infrastructure subsidies, HOV lane access, and local presence of production facilities, were strongly associated with the increase in EV sales and adoption (Jenn et al., 2018; Springel, 2021; Li et al., 2017; Sierzchula et al., 2014). Many studies have indicated that supply-side subsidies, especially charging infrastructure, would substantially affect EV adoption and be more cost-effective. On the other hand, Li et al. (2017) that subsidies in charging station installations could be two times more effective in encouraging the adoption of EVs than the equal amount of spending on other subsidies. However, the authors also found a more substantial indirect network effect on the demand side of the EV market, meaning that the value of EVs increases as more people purchase this type of vehicle. This elevates the effectiveness of tax credit policy in promoting the adoption of EVs.

Previous research studies have also suggested that buyers in disadvantaged communities tend to buy used plug-in electric vehicles (PEVs) rather than new PEVs (Canpena & Hardman, 2019). Middle and low-income consumers are also more sensitive to EV prices than the income class. The own-price elasticity of demand estimate for EVs for those with income less than \$100,00 is −3.13, compared to the overall average elasticity of −2.76 (Xing et al., 2021). These results have implied that low and middle-income consumers are more price-elastic to EVs than higher-income purchasers. The authors also suggested that incentive programs subsidizing lower-income households could potentially be more cost-effective. Consequently, based on the preliminary literature on the EV market and different income groups, this newly implemented tax credit would attract more consumers from low and middle-income groups, allocating equity in the EV market.

Model

Table 1: Variables, definition, and expected signs.

Variables	Definition	Expected Signs
Dependent Variable		
saleprice	The sale price of the vehicle	None
lnsaleprice	Natural log of the sale price of the vehicle	None
Independent Variables		
EV	1 if the vehicle is eligible for the Used Clean Vehicle Credit	Positive
EV_post	The effect of tax credit, average price change between EVs and non-EVs before and after the tax credit	Positive
mile	Number of miles	Negative
car_age	The age of the vehicle at the time it was purchased	Negative
color	The color of the vehicle	Negative

Table 1 defines several variables affecting the sale price of a vehicle, which are whether the car is eligible for the tax credit, the effect of the tax credit, the number of miles, the age of the vehicle at the time it was purchased, and the color of the car. The sales data from 245 Carmax locations are used to analyze this data. In general, data between 2021 and 2023 is used for descriptive summary results, and data between 2022 and 2023 is applied for the regression results. It is expected that used EVs and the effect of the tax credit will have a positive relationship with the sale price. This is because this subsidy changes the price that buyers pay on a used EV such that the actual price a buyer pays is the sale price minus whatever credit they receive. Thus, it shifts the demand curve of used EVs outward, resulting in an escalation in price and quantity. It might also have a slight substitution effect of non-EVs toward EVs, resulting in a higher price than non-EVs. However, the number of miles and the vehicle's age are expected to affect its sale price negatively. As the number of miles increases, the vehicle's sale price tends to decrease. Buyers often associate lower mileage and newer cars with better overall condition and reliability. A vehicle with lower mileage and relatively new may be perceived as being in better shape, having less wear and tear, and potentially needing fewer repairs in the near future. The relationship between car color and its sales price is not straightforward. Certain colors may have higher demand in the used car market, leading to slightly higher sale prices. For example, popular colors like black, white, and silver are often in demand due to their versatility and broader appeal across different consumer demographics. Therefore, most colors may be negatively correlated to the price, and the car color generally has a negative effect on its sale price. However, this effect is usually modest compared to other factors influencing sale price.

Data and descriptive summary results

Table 2: Descriptive statistics results.

Variables	**All** Mean (Standard Deviation)	**EV** Mean (Standard Deviation)	**Non-EV** Mean (Standard Deviation)
saleprice	24681.44 (7136.666)	25557.74 (7978.204)	24672.53 (7127.047)
lnsaleprice	10.07006 (.3011697)	10.09583 (.3340722)	10.06979 (.3008054)
EV	.0100671 (.0998287)		
miles	47699.35 (28409.8)	36263.69 (19960.37)	47815.64 (28459.26)
car_age	4.649372 (2.501726)	4.035879 (1.966441)	4.655611 (2.505811)
price_first	25270.66 (7437.792)	26469.88 (8892.284)	25258.46 (7420.544)
diff_in_price	-589.2218 (1174.324)	-912.1367 (2392.101)	-585.9379 (1154.903)

From Table 1, Table 2 of descriptive statistics are created to analyze the relationships between the sale price, the natural log of the sale price, and some of the key information on the data of the used vehicle market, including whether the car is eligible for the tax credit, the number of miles, the age of the vehicle at the time it was purchased, first-listing price on the website, and the difference between first-listing and sale price. By constructing a descriptive summary in STATA, we can interpret the descriptive statistics of seven listed variables, including mean and standard deviation, for the whole sample data and EVs and non-EVs. From the general sample data, the average sale price of all used cars between 2021 and 2023 is $24681.44, with a standard deviation of $7136.666. We observe that the average natural log of sale price in Carmax is 10.07006, meaning that the average change in wage rate is 10.07%. The sample set also indicates that approximately 1% of all vehicles from Carmax are eligible for the Used Vehicle Tax Credit. The average miles driven by a used car is 47699.35 miles, and the mean age is 4.65 years. It is also noteworthy that all used cars had the average first-listing price on the website of $25270.66, but this price decreased by about $589.22 when it was sold.

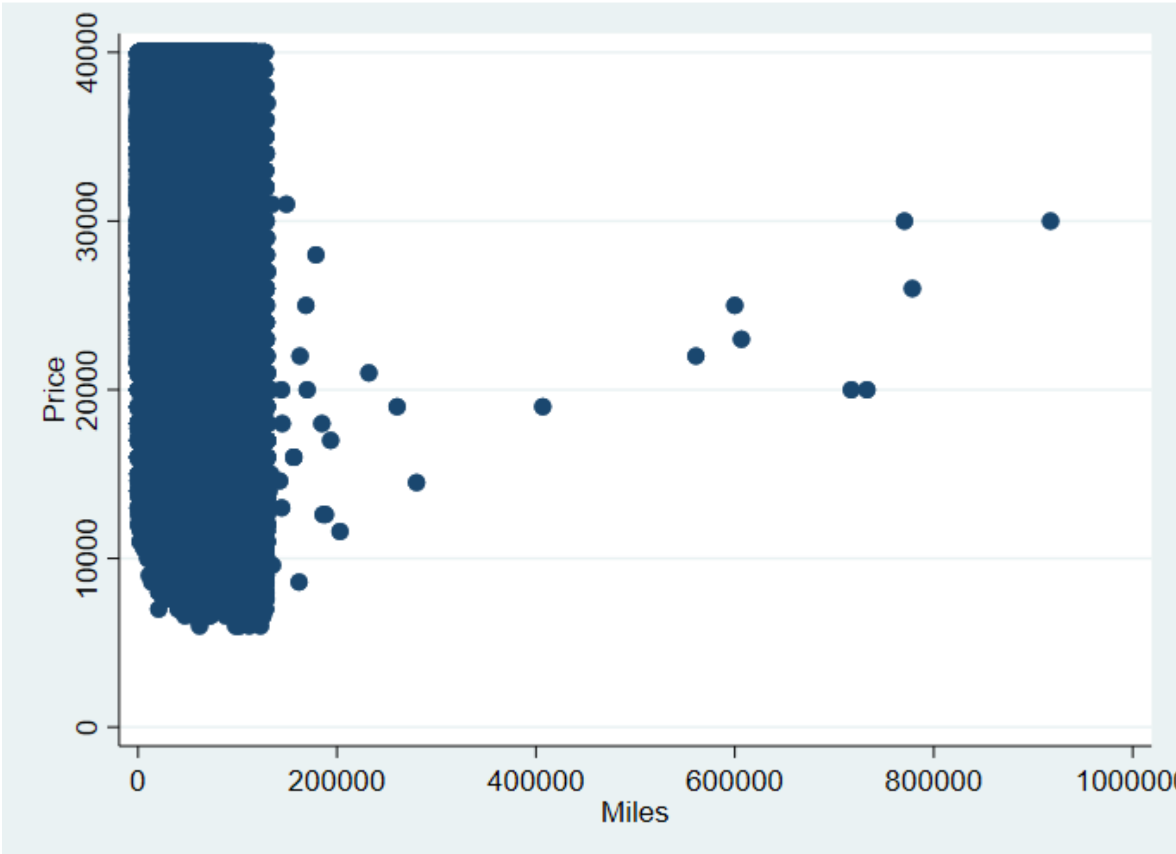
In addition to general data, we also observe the differences between EVs and non-EVs data. In general, used EVs have higher averages on the sale price, $25557.74 in EVs compared to $24672.53 in non-EV, slightly higher change in the sale price, 10.1% compared to 10.7%, and a higher fist-listing price on the website, $26469.88 compared to $25258.46. On the other hand, the results suggest that non-EVs have higher averages on miles and age, with 47815.64 in non-EVs compared to 36263.69 miles in EVs and 4.66 compared to 4.04 years, respectively. It is interesting to observe that, despite having higher prices, EVs have a more significant decrease from the first listing to the final price, -912.13 in EVs compared to -585.94 in non-EVs.

Table 3: The matrix of correlation coefficients.

	saleprice	EV	miles	car_age
saleprice	1.0000			
EV	0.0124	1.0000		
miles	-0.4561	-0.0406	1.0000	
car_age	-0.4763	-0.0247	0.6831	1.0000

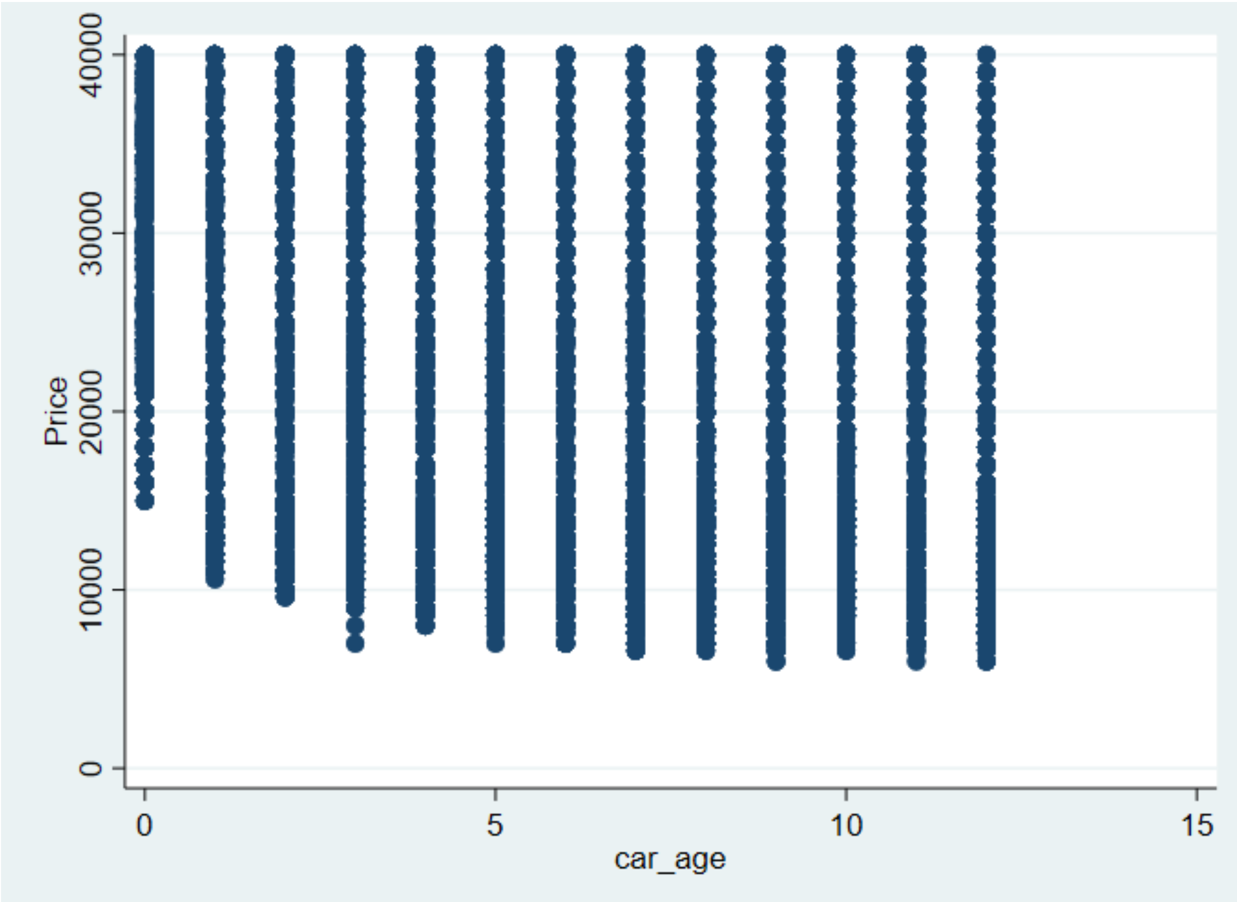
Table 3 is the matrix of correlation coefficients between sale prices, and some of the price determinants, consisting of whether the car is eligible for the tax credit, the number of miles, and the age of the vehicle at the time it was purchased. The correlation coefficient of the sale prices and being eligible for the tax credit is roughly 0.0124, which indicates a very weak, positive relationship. Hence, being eligible for the tax credit may not have a significant effect on the sample's sale prices. We can also observe a moderately strong negative relationship between sales prices and the number of miles and vehicle age with a correlation coefficient of -0.4561 and -0.4763 respectively. Thus, these variables may play an essential role in sales prices compared to being qualified for the tax credit. These findings are consistent with the rationale for the correlation between sale prices with the vehicle's characteristics.

Figure 1: The relationship between sale prices and miles.



This scatter plot represents a negative relationship between sale prices and miles. Although it is a little bit difficult to observe the magnitude and direction, we can still see the overall trend line moving from the top left upward to the bottom right, indicating a negative and weak relationship. Most of the observations are densely concentrated on the top left, and a few are spread toward the middle right. The result is consistent with the above correlation coefficient.

Figure 2: The relationship between sale prices and car age.



This scatter plot represents a negative relationship between sale prices and car age. There is a general trend line moving from the top left upward to the bottom right, indicating a negative and weak relationship. Most of the observations are densely concentrated on the top left and become denser on the bottom right. This result is consistent with the above correlation coefficient.

Empirical results

Table 4: Regression model results.

	EV saleprice	**EV** lnsaleprice	**All** saleprice	**All** lnsaleprice
EV_post	1521.3*** (14.75)	0.0474*** (12.23)	2214.2*** (20.11)	0.0758*** (17.62)
EV			-431.2*** (-4.63)	-0.0208*** (-5.71)
miles	-0.0670*** (-24.24)	-0.00000252*** (-24.22)	-0.0702*** (-314.76)	-0.00000302*** (-346.75)
car_age	-2252.3*** (-78.49)	-0.0950*** (-87.99)	-993.9*** (-378.65)	-0.0420*** (-409.49)
1. color_real (black)	-162.6 (-0.91)	-0.0121 (-1.80)	-1230.2*** (-65.74)	-0.0498*** (-68.02)
2. color_real (blue)	-1006.1 (-1.74)	-0.0401 (-1.85)	-115.3** (-2.59)	-0.00604*** (-3.47)
3. color_real (brown)	-1774.1** (-2.95)	-0.0639** (-2.82)	-1193.5*** (-21.03)	-0.0464*** (-20.91)
4. color_real (gold)	-644.1*** (-4.34)	-0.0234*** (-4.19)	-607.4*** (-39.50)	-0.0245*** (-40.71)
5. color_real (gray)	-2186.3*** (-4.17)	-0.0857*** (-4.34)	-407.2*** (-8.21)	-0.0228*** (-11.78)
6. Color_real (green)	-3891.9 (-1.58)	-0.152 (-1.64)	-458.2 (-1.32)	-0.0184 (-1.35)
7. color_real (orange)	-1049.3 (-1.15)	-0.0343 (-1.00)	-2162.3*** (-34.88)	-0.0838*** (-34.58)
8. color_real (purple)	-743.1 (-0.50)	-0.115* (-2.04)	-1660.2*** (-15.21)	-0.0706*** (-16.56)
9. color_real (red)	-71.58 (-0.37)	-0.00229 (-0.32)	-1260.2*** (-64.90)	-0.0513*** (-67.60)

10. color_real (silver)	-1699.6*** (-9.87)	-0.0642*** (-9.91)	-1441.6*** (-83.52)	-0.0592*** (-87.66)
11. color_real (tan)	-153.1 (-0.22)	-0.00358 (-0.13)	-352.5*** (-5.29)	-0.0189*** (-7.26)
12. color_real (white)	-91.22 (-0.66)	-0.00955 (-1.84)	-189.1*** (-12.88)	-0.00780*** (-13.58)
13. color_real (yellow)			-677.6*** (-5.54)	-0.0341*** (-7.13)
_cons	40056.9*** (231.84)	10.71*** (1647.88)	35047.8*** (2234.88)	10.52*** (17152.58)
N	11949	11949	1238009	1238009
R-sq	0.5813	0.6210	0.3711	0.4118
F	999.4	1189.7	39267.6	46595.6

To construct the regression analysis and difference-in-different estimation strategy, the sales data of Carmax between 2022 and 2023 is applied. Findings based on coefficients and significance of the whole data from Table 4 suggest that EV_post, EV, miles, car age, and most car colors have statistically significant ($p < 0.05$) impacts on the sale price and the natural log of the sale price. It is also noteworthy to mention that being eligible for the Used Vehicle Tax Credit has a negative effect on prices. In general, interpreting the coefficients in a regression analysis involves understanding how a one-unit change in the independent variable affects the dependent variable, holding all other variables constant. In Table 4, the coefficient for the variable EV_post is 2214.2 in sale price with the corresponding value of 0.0758 in the natural log of the sale price for the whole data model. This means that the average price change in used EVs between 2022 and 2023 is $2214, which is approximately 7.58%. Therefore, being eligible for the tax credit has increased the value of the vehicle compared to those that are not, given other factors remain the same. However, when holding other variables constant and eliminating the tax credit effects, being a qualified used EV leads to a decrease of $431.2, which is about 4.08%, in the sale value. Moreover, as expected, miles and car age are negatively related to the sale prices. More specifically, for each additional mile that a car is driven, the sale price is expected to decrease by $0.0702, or 7 cents, all else being equal. Therefore, a used vehicle with more miles would typically have a lower sale price compared to a vehicle with lower miles, given other factors remain the same. Similarly, an additional year in car age contributes to a decrease of $993.9, about 4.2%, in its final sale price. The color of the car is the categorical variable, but each color code is assigned to dummy variables. In general, all colors have a negative impact on the sale price, but each color will have a different magnitude. For instance, a black car is associated with a decrease of $1230.2, about 4.98%, in price. The orange cars have the largest price decrease, which is -2162.3, while the blue cars have the smallest price effect, which is -115.3, ceteris paribus. The intercept of the regression line ("_cons") is large in each model and represents the price when all car characteristics and tax credit variables are absent. In this case, the original price of a used car is $35,047.8 when all other variables are equal.

Results from the EV data indicate that the effect of tax credit remains variable with the highest positive impact on the sale price and the natural log of price. As the tax credit is available, the average price of used EVs increases by $1521.3, approximately 4.74%. Other findings also share similar trends with whole data that miles, car age, and a few colors have a statistically significant, negative impact on the price of used EVs. More specifically, an additional mile decreases about 6 cents in the car value, and an increase in one year of age is associated with a decrease of $2252.3, about 9.5%, in price. It is noteworthy that the car age has a more significant decrease in EV prices compared to the whole data. The results also show that only the colors of brown, gold, gray, and silver have a statistically significant effect on sale price, with -1774.1, -644.1, -2186.3, and -1699.6, respectively. In summary, interpreting coefficients involves understanding the direction and magnitude of the impact of each independent variable on the dependent variable, while considering the effects of other variables in the regression model.

Furthermore, the signs of the coefficients in Table 4 are consistent with the expected signs mentioned in Table 1 and the correlation matrix in Table 3. For instance, the coefficient for miles is negative, indicating that as the mile increases, the sale price is expected to increase, which aligns with the expected negative sign in Table 1. Similarly, the coefficient for ages is negative, indicating that higher levels of car age are associated with lower sale prices, which is consistent with the expected sign in Table 1. However, the sign in the EV variable from the regression model contradicts the expected sign. It is anticipated that the qualified EVs will be associated with higher prices, but the regression model shows otherwise. However, the negative coefficient in the EV variable is still reasonable if eliminates the tax credit. In other words, the Used Vehicle Tax Credit has significantly contributed to the increase in the value of qualified used EVs.

In general, the overall model significance results are all statistically significant for the whole data with F-statistics of 39267.6 in the sale price and F-statistics of 46595.6 in the natural log of sale price models, along with the p-values of 0.0000***. The EV data has the F-statistics of 999.4 in the sale price and F-statistics of 1189.7 in the natural log of the sale price, along with the p-values of 0.0000***. These results suggest that whether the car is eligible for the tax credit, the effect of the tax credit, the number of miles, the age of the vehicle at the time it was purchased, and the color of the car have significant effects on the sale price for the whole data and EV data, with some variations. Moreover, R-squared results indicate that 37.11% of the variation in the sale price model and 41.18% of the variation in the natural log of the sale price model are explained by all determinants from the whole data. All determinants explain 58.13% of the variation in the sale price model and 62.1% of the variation in the natural log of the sale price model from the EV data. The overall model for each group is statistically significant, indicating that the included variables collectively explain a significant portion of the variance in the sale price of the used vehicle market.

Conclusion

In conclusion, this paper examines the elements affecting the sale prices of used vehicles in the United States. The analysis considers variables associated with the effect of the Used Clean Vehicle Tax Credit and vehicle characteristics. The effects display that sale prices have a positive relationship with the effect of tax credit and vehicles that are eligible for the tax credit. Conversely, there is a negative relationship between sale prices and the number of miles, the age of the vehicle at the time it was purchased, and all color spectra. The descriptive data and correlation coefficients contribute to enhancing the understanding of the used vehicle market and predict the regression results. The empirical effects from regression models verify the tremendous effect of those variables on the used car values. Overall, this study provides insights into the factors influencing used prices and the effect of the Used Clean Vehicle Tax Credit on the used vehicle market in the United States. The research concludes a positive growth in sale prices of EVs after the tax credit was enforced. The increase in sale prices implies that the subsidy is economically split between the buyers and sellers, and sellers benefit more from the program. When comparing the difference in average EV price and the change in EV prices, relative to non-EVs, from the difference-in-difference estimation, the data indicates that the tax credit might have a negative effect on used non-EVs, and there might be a slight substitution effect. However, this effect is still undetermined because of the huge difference in the market sizes of EVs and non-EVs.

Nevertheless, it is necessary to investigate more on whether the new tax credit actually increases the adoption rate of EVs to the target income groups. To answer this question, it is essential to precisely analyze the number of sales by using the difference-in-difference model. We also plan to measure the proportion of the population eligible for the tax credits in future research so that we can investigate whether the price and quantity changes are related to the fraction of residents who are eligible for credit. Then, we will be able to estimate the size and magnitude of the shift in the demand curve. It is so important to collect and analyze more data from other car dealerships to capture the used vehicle market more accurately and comprehensively.

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