Do Used Car Buyers Benefit from Electronic Vehicle Credits?
A Study of the New U.S. Federal Tax Credit

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Abstract

This paper studies who (buyers or sellers) benefits from the U.S. federal tax credit on used Hybrid Electric Vehicles (HEV). The US government introduced a tax credit on used HEVs for the first time in 2023. We build an empirical model to estimate the impact of the credit on the price of used Hybrid Electric Vehicles (HEV). Interestingly, our results suggest the credit on used HEV has a negative impact on the seller prices. Further, our estimates suggest that a $1 increase in tax credit decreases the seller price by around $0.07 to $0.17; thus, the buyers of used HEVs capture more than the amount of subsidy, which illustrates over-shifting. The result may be interpreted in various ways. We conclude that the tax subsidy on used HEVs may be only beneficial for buyers but not sellers.

I. Introduction

This paper studies the impact of the introduction of a federal tax credit for used hybrid electric vehicles (HEVs) in 2023 on the price of HEVs. The goal is to determine whether buyers or sellers of used HEVs capture the benefit of subsidies. Economic theory suggests that the gross of credit price received by sellers should increase and the net of credit price to buyers should decrease. While the incidence of tax credits for new HEVs has been previously studied, our study is the first analysis, as we are aware of, that focuses on the tax subsidy and its incidence for "used" HEVs.

With rising concerns about the consequences of petroleum consumption, governments have been enacting various policies to stimulate the consumption of fuel-efficient vehicles. The U.S. federal government first enacted the Energy Policy Act in 2005 which gives certain amount of tax credit to new hybrid vehicle purchasers. The policy on fuel-efficient vehicles undergoes several changes since then. In 2009, the federal government expanded the Energy Policy Act to adjust the tax credit limit and some qualification on purchasing new fuel-efficient vehicles. In 2023, the Energy Policy Act was further expanded to provide tax credit on purchase of used HEVs. The history of tax policy changes under the Energy Policy Act will be further discussed in Section III.

Previous literature has devoted much attention to the impact of the federal tax credit on new HEVs purchases and prices (e.g., Sallee, 2011; Boyle and Matheson, 2009; Gulati et al. 2017). Not surprisingly, we could not find any papers focusing on the impact of the new federal tax credit on used HEVs. The results from previous literature point to contrary conclusions. While Sallee (2011) conducts empirical analysis on Toyota Prius suggests that consumers take most of the benefit from tax credit, Boyle and Matheson (2009) find that the dealers capture the bigger proportion of the credit, about 75%. Hence, the impact of tax credit on HEVs market and study about its incidence require closer analysis.

We collect data on prices of four different vehicle models by different makers before and after the enactment of the credit policy in 2023. Each model has both an electric powered and a gasoline powered model. We picked these four models based on their credit eligibility introduced in IRS website[1]. We obtained the vehicles market price data from CarGurus. They provide market price trend data of each model every day. The price data is market price of used vehicles listed by sellers(dealers).

Our empirical analysis suggests a few novel results. Our regression analysis with diff-in-diff methods shows that the enaction of tax credit on used HEVs has a negative impact on used HEV market price. Also, our result from second regression analysis shows that a $1 increase in credit decreases seller price by about $0.0.7 to $0.17. This result suggests that the incidence of the subsidy is over-shifted; thus, the purchasers capture more than the amount of subsidy and the sellers lose from the subsidy.

Our paper also contributes to a more specific growing body of research on subsidies for energy efficient automobiles (Gulati et al., (2017), Barwick and Kwon et al., (2023), Kaul et al., (2016)). The purpose of tax credit policy is to stimulate usage of HEVs to prevent environmental concerns and reduce the overall CO_2 emission level. Many data demonstrate that the sales of used vehicles are almost three times of sales of new vehicles.[2] Therefore, this considerable size of used vehicle market require further study to test the efficiency of the tax policy.

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[1] https://fueleconomy.gov/feg/taxused.shtml
[2] https://www.statista.com/statistics/183713/value-of-us-passenger-cas-sales-and-leases-since-1990/

The paper proceeds as follows. Section II discusses previous literature related to tax credit program on energy efficient vehicles and tax incidence. In Section III, we show the background of Energy Policy Act (2005) which provide subsidy to HEVs. We also introduce the theory of tax incidence in Section III. Furthermore, in section IV, we explain about our data and samples. We discuss our assumption about the market price and seller price to utilize our data to calculate subsidy incidence. The section V discusses estimation strategy and regression models. Section VI shows the results of regressions. We provide the interpretation of our interesting result in section VII. The final section concludes.

II. Literature Review

The study of HEVs incentives has a rich history with technology development and government's tax policy changes. Many scholars study about the impact of tax subsidy on vehicles (Jenn et al., 2018; Gallagher et al., 2011; Münzel et al., 2019). Mersky et al., (2016) studied the impact of various factors to HEVs adoption concluding that the package of incentives on Norway has been effective in promoting electric vehicle adoption. As we are aware, Sallee (2011) was the first investigated about the incidence of tax subsidy provided under Energy Policy Act (2005). Sallee utilized empirical analysis to find that cash rebates for hybrid purchase during mid-2000s had no effect on the prices of U.S. Toyota Prius, so that consumers capture 100% of benefits from the tax subsidies. Boyle and Matheson (2009) investigated five different hybrid vehicle models to examine the incidence of subsidy provided to new hybrid purchasers under Energy Policy Act (2005). Their study concludes that for every dollar of tax credit provided, the price of hybrid vehicles rose by approximately $0.75, demonstrating that sellers capture higher subsidy than the buyers. Gulati et al., (2017) also studied the incidence of tax subsidy on new HEV purchase in Canada between 2004-2009, concluding that $1000 increases in subsidy raises seller received price by $575. Their result demonstrate that the seller takes about 57.5 percentage of the subsidy. Their paper emphasizes the impact of vehicle upgrading to price changes which estimated about two-thirds of the increase. Barwick and Kwon et al., (2023) investigated the pass-through of hybrid vehicle subsidies in a global level. It was demonstrated by examining the EV sales data between 2013 to 2020 from 13 countries. They concluded that the overall pass-through rate is between 70 – 80 percentage. Kaul et al., (2016) studied a similar tax credit program, "cash for clunkers program", in Germany. Their study demonstrates that the pass-through rates of tax subsidy provided by clunkers program is above 100% which showing an over-shift. They conclude that the price discrimination in market is the main driver of the over-shifting. Besley and Rosen (1999) also found over shift but from U.S. commodity market. They study the incidence of sales taxes on various commodities in different U.S cities. They found some commodities are over shifted which an increase in tax revenue of one dollar per unit increase the buyers' price by more than one dollar.

We contributed to this literature by investigating the impact of tax subsidy on price of used HEVs and the pass-through rate of the tax credit between dealers and buyers. Our analysis highlights the contrasting impact of tax subsidy on price of HEVs when it comes to used vehicle markets.

III. Institutional background and Theory

3.1 Policy Background

The tax credits for purchase of energy efficient vehicles were first introduced as part of the Energy Policy Act of 2005 to encourage the production and adoption of energy efficient vehicles.[3] The credit was first available for only hybrid vehicles and was capped at $3,400.[4] In 2009, the American Recovery and Reinvestment Act expanded the credit to include plug-in electric vehicles and increased the maximum credit to $7,500. Since then, the credit has undergone several changes, but the credit was still available for only new vehicle purchases. However, starting 2023, government further expand the Energy Policy Act and began to provide the tax credit on used HEV purchases. The tax policy changes are illustrated in Table 1.

Table 1- Policy History

Date Effective	Tax Credit for New vehicles	Tax Credit for Used vehicles
2005 - 2009	max $3,400	$0
2009 - 2023	max $7,500	$0
2023 - present	max $7,500	max $4,000

Note: this table shows the historical changes of Energy Policy Act of 2005. We see that the tax credit for used vehicles was only available from 2023.

3.2 The tax credit on used HEVs

It is not all used HEV purchases receive the credit, but there are many qualifications to be satisfied for the subsidy. IRS has shared the list of qualified vehicle models for the tax credits.[5] In addition to the type of vehicles, IRS demonstrate that purchasers are eligible for the tax subsidy only when transaction is done after Jan 1, 2023 at price lower than $25,000. Also, there exist Adjusted Gross Income (AGI) qualification -- $150,000 for married filing jointly or a surviving spouse, $112,500 for heads of households $75,000 for all other filers. Lastly, purchasers should satisfy following conditions to be eligible for tax credit; they should be an individual who bought the vehicle for use and not for resale, not be the original owner, not be claimed as a dependent on another person's tax return, not have claimed another used clean vehicle credit in the 3 years before the purchase date.

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[3] https://www.cbo.gov/sites/default/files/112th-congress-2011-2012/reports/09-20-12-electricvehicles0.pdf

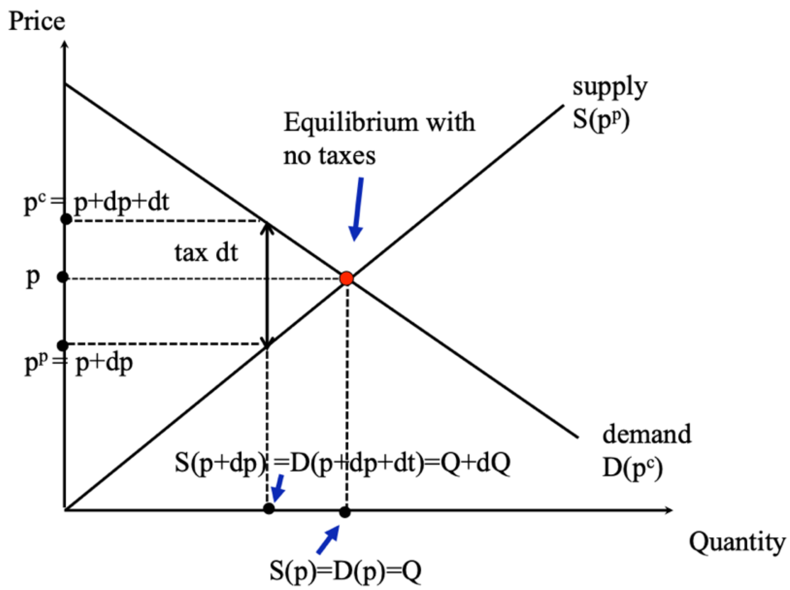
[4] https://www.irs.gov/credits-deductions/manufacturers-and-models-for-new-qualified-clean-vehicles-purchased-in-2022-and-before

[5] https://fueleconomy.gov/feg/taxused.shtml

3.3 Theory of Tax incidence

Although the tax credit is directly given to the clean vehicle purchasers, it does not necessarily mean the purchasers take 100% of the benefit. In public economics, who pays tax does not determine who bears the burden of the tax, and the same is true of subsidies. In other words, who claims the subsidy on their tax form may not be the party that benefited from the subsidy. The triangle on the left side of the equilibrium shows the total amount taxation, and this area of triangle is shared by buyers and sellers (Figure 2). The price P^c and P^p show the change of price from buyers and sellers due to taxation (subsidy). Our research goal is to find the incidence of tax credit between car sellers and consumers of used HEVs; therefore, our aim is to find the P^c and P^p (Figure 2).

Figure (3), (4) and (5) illustrate the changes in both sellers and buyers' price in different elasticity situation. Figure 3 and 4 show the case of perfect inelastic and elastic demand respectively. In Figure 3, the buyers originally pay the price P_1, but they pay at higher price P_2 after the tax. In Figure 4, the producers (sellers) originally receive \$1.50 before tax, but it shows they receive only \$1.00 after the taxation. Figure 5 illustrates similar graph but with elastic and inelastic supply. In this case, P_1 is the original price (before tax) which sellers receive, and P_2 is the price where the sellers receive after the taxation. More explanation of each graph will be given in their Notes. These graphs show that one side captures whole amount of taxation when demand or supply are perfectly elastic(inelastic) which meaning the market is imperfect. Tax subsidy works exactly same as the following Figures with taxation. The only difference is that with taxation, the sellers(buyers) receive(pay) at less(more) price, but in the case of subsidy, sellers(buyers) receive(pay) at more(less) price.



(Figure 2)

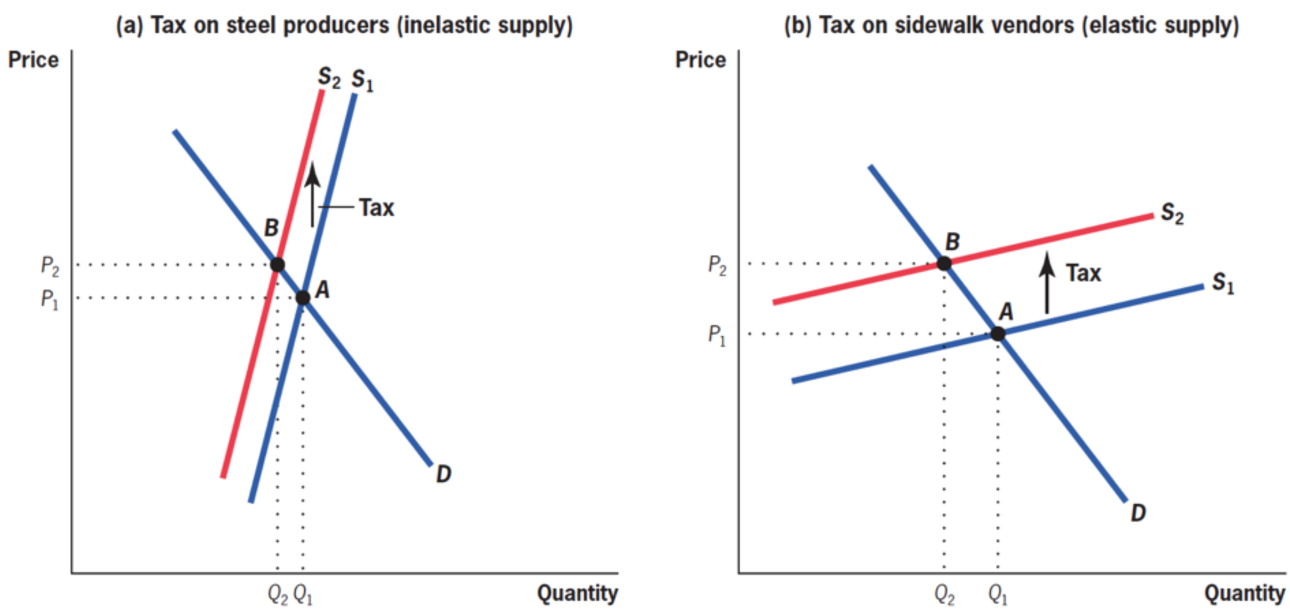
Note: this graph is from Stefanie Stantcheva's slides of "Tax Incidence and Efficiency Costs of Taxation" lecture. The red dot is the equilibrium price before the tax(subsidy) was introduced. The original price was P, but after the tax(subsidy) the price point changes to $P^c(P^p)$, how much buyers(sellers) pay(receive).

(Figure 3)

Note: This graph shows the case of perfect elastic demand. P_1 indicates the original price the consumers pay, and P_2 shows the after-tax ($0.50) price consumers pay. From this case, we see the consumers capture 100% of taxation. Thus, the consumers pay $2.00 ($1.50 + $0.50) instead of the original price $1.50.

(Figure 4)

Note: This graph shows the case of imperfect elastic demand. In this case, the producers/sellers capture all of the taxation. Thus, they receive only $1.00 instead of $1.50.



(Figure 5)

Note: Public Finance and Public Policy Jonathan Gruber Fourth Edition Copyright © 2012 Worth Publishers. It is similar to the previous two graphs. Graph (a) shows that the sellers(buyers) capture bigger(smaller) amount of burden, so the sellers(buyers) receive(pay) is (lower)(higher) price.

IV. Data and Method

4.1 Sample and data sources:

Based on credit eligibility, we identified eight different types from four different makers. The list of models is shown in Table 3. Since our aim for this paper is to estimate the impact of policy on their price and the incidence of tax credit, the historical price information for each vehicle is the most vital data. The price historical data for tax credit qualified vehicles are collected from CarGurus' Price Trends data set.[6] According to CarGurus, they track the market price of millions of used cars in the market. We collected the market price data of the four different types between the year 2022 and 2024. CarGurus' price data is the average market price of millions of used vehicles. We utilize this data for an alternative to the real transaction price. Thus, we assume that this market price represents the seller received price, P^p in Figure 2. This assumption could hold under two reasons. According to Huang (2010), many large used car dealerships do not adopt systematic negotiation. Thus, the transaction through large dealers such as CarGurus and Carmax tend to be done around dealer listed prices. Furthermore, the used vehicle market in the U.S. is very competitive, and with technological development, both dealers and buyers can get price information in much easier way. Therefore, it is becoming more common to purchase vehicles around the listed price. However, we still provide the results from regression analysis with the price adjusted by negotiation, and the result is in Appendix B.2. Among many different types of cars, we concluded that only these models best suit our research because these models have the price range which are eligible for the credit and have both gasoline and electric powered types. This is required for our regression analysis. For instance, we

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[6] https://www.cargurus.com/research/price-trends

are not able to use the price data of Tesla because it does not have gasoline powered types for DiD method.

Car prices change often, so we need frequent price data. Although we obtained daily vehicle price data, since our other data such as gas price and CPI data were only available by week. Therefore, we adopt weekly car price to match with them. We collected the year 2022 to 2024 weekly gas price data from the U.S. Energy Information Administration.[7] Both price of used vehicles and gasoline were adjusted by their own CPI level. The CPI information was collected from FRED.[8]

Figure 6 further provides outlook about the price trend of each vehicle type between year of 2022 and 2024. Some vehicles such as golf and optima show stronger price volatility for HEVs compared to gasoline powered vehicles or vice versa. We calculate their variance and standard deviation to check the price volatility of each model. We further calculate the difference in standard deviation between energy efficient and gasoline powered vehicles to check the price trend of both types for each model. Appendix A shows the variance and standard deviation of each model. In Appendix B.1, we show the regression results excluding these models determined based on their standard deviation. The purpose is to minimize the external factors impact price of HEVs and none HEVs differently. Lastly, we collected information about Energy Efficient Home Improvement Credit from IRS.[9] This data was collected because Energy Efficient Home Improvement Credit is our instrument variable for our 2SLS regression analysis.

[7] https://www.eia.gov/dnav/pet/hist/LeafHandler.ashx?n=PET&s=EMM_EPMR_PTE_NUS_DPG&f=W
[8] https://fred.stlouisfed.org
[9] https://www.irs.gov/credits-deductions/home-energy-tax-credits

Table 2 - Car Models

Models	Years	Purchase (Transaction) Date	# of Obs
Ford Fusion	2013-2020	Jan 1/2022 - Mar 31/2024	936
Ford Fusion Energi	2013-2020	Jan 1/2022 - Mar 31/2024	936
Volkswagen Golf	2015-2019	Jan 1/2022 - Mar 31/2024	585
Volkswagen e-Golf	2015-2019	Jan 1/2022 - Mar 31/2024	585
KIA Optima	2017-2020	Jan 1/2022 - Mar 31/2024	468
KIA Optima Hybrid	2017-2020	Jan 1/2022 - Mar 31/2024	468
Hyundai Sonata	2016-2019	Jan 1/2022 - Mar 31/2024	468
Hyundai Sonata Hybrid	2016-2019	Jan 1/2022 - Mar 31/2024	468
Total			4,914

Note: This table illustrates all vehicle models used for our study. They were chosen based on the qualification for tax credit.

Table 3 - Summary Statistics

Variable	# of Obs	Mean	Std. dev.	Min	Max
Used car price	4,914	16847.07	3851.01	8600.01	28682.2
Value of subsidy	4,914	1111.11	1791.80	0	4000
Gas price	4,914	3.47	.08	3.28	3.69
Age	4,914	2520.92	1416.36	104	4976
Presence of subsidy	4,914	.27	.44	0	1

Note: the “Used car price” and “Gas price” are adjusted for CPI level. “Age” is the age of each vehicle by weeks. “Presence of subsidy” is a dummy variable 1 if a vehicle “i” receives the subsidy at time “t”, 0 otherwise.

Figure 6: Price trend graph for each model between 1/1/2022 – 3/25/2024

Note: these graphs show the price trend of each vehicle model between 1/1/2022 to 3/25/2024. The level of variance and standard deviation of each car is illustrated in APPENDIX A.

V. Model & Estimation strategy

We use two regression models in our analysis. The first regression is to estimate the impact of the enactment of the credit policy on used HEV prices. We utilize difference in difference (DiD) method to estimate the impact of treatment. The second regression estimates the impact of changes in credit on vehicle price, thus the incidence of subsidy. We utilize 2SLS method to control the endogeneity problem with our model, and it will be further discussed in this section.

Firstly, we use the regression model similar to Boyle and Matheson (2009), but we adjusted the model to fit our study. For instance, instead of TMV (true market value) as a dependent variable, we use CarGurus price trend data to navigate the market value of used vehicles. Also, for accuracy, we adjusted the price of cars with monthly used car CPI.

$$price_{it} = \beta_1 post2023_t * HEV_i + \beta_2 HEV_i + \beta_3 post2023_t + \beta_4 X_{it} + \lambda_t + \lambda_i + \varepsilon_{it} \quad (1)$$

The subscript t represents the time in week and i represents the car type. Our dependent variable is the CPI adjusted price of car type i in week t. The price is the market price listed by sellers. For our study, it ultimately represents the seller received price as we discussed in section IV.

We have an interaction term with dummy variable *HEV* and *post2023*. *HEV* is a dummy 1 if the vehicle is hybrid or electric powered, 0 otherwise. *Post2023* is a dummy 1 if the time is year of 2023 or 2024 which indicates after the time of credit policy enaction, and 0 otherwise. Variable *age* represents the ages of the used cars in weeks. λ_t, λ_i represent time fixed and entity fixed effects respectively, and ε_{it} is the error term. The variable of interest is the coefficient of the interaction term β_1. The coefficient shows the change of HEV price before and after the credit is provided to used HEVs. Thus, the coefficient β_1 estimates the impact of tax credit policy on price of used HEVs. From this regression, the treatment is the tax credit policy, and treatment group is the HEVs after year of 2023. Our control group is all vehicles purchased prior to 2022 and all non-HEVs.

Secondly, we utilize the OLS regression model (2) to estimate the incidence of tax subsidy - how the $1 change in credit increase or decrease the seller received price of used HEVs. This regression model is similar to previous literature which analyze the incidence of tax credit for vehicles (Barwich et al (2023); Gulati et al (2017)).

$$price_{it} = \beta_1 subsidy_{it} + \beta_2 gasprice_t + \beta_3 age_{it} + \lambda_t + \lambda_i + \varepsilon_{it} \quad (2)$$

The definition of variables is identical to the regression model (1) except the variable of *subsidy*. The variable *subsidy* represents the amount of credit the purchasers can receive by buying certain vehicle. However, as we mentioned in Section III, the amount of subsidy depends on the price of vehicles. The equation (3) shows how the subsidy for vehicles are calculated.

$$Subsidy = max(4000, 0.3P), where\ p < 25{,}000 \quad (3)$$

Thus, we are expecting our variable to be endogenous due to simultaneous causality. We address this problem by utilizing 2 SLS regression method. When there is reverse causality problem, 2 SLS regression method solves the endogeneity problem by substituting endogenous variable to instrument variable. We determine the amount of "Energy Efficient Home Improvement Credit" as an instrument variable. There are two important conditions for determining instrument variable: relevance and exogeneity. First, the instrument variable should directly be correlated with the endogenous variable. Secondly, the instrument variable should be exogenous, meaning they are not correlated with the error term in the main equation. This ensures that the instrumental variables are not affected by any omitted variables or endogeneity issues in the main equation. Energy Efficient Home Improvement Credit is in a package of Clean Energy and Vehicle Credits with the used HEV subsidy program. Thus, when IRS adjusts Energy Efficient

Home Improvement Credit, clean vehicle credit is directly impacted. Further, Energy Efficient Home Improvement Credit is provided to purchase of equipment such as exterior doors, windows, skylights and insulation materials, central air conditioners, water heaters, furnaces, boilers, and heat pumps etc. Hence, we assume the credit program does not directly impact the price of used vehicles; thus, there is no correlation between our instrument variable and the original equation. The equation (4) is the regression model with instrument variable.

$$price_{it} = \beta_1 HomeImprovementcredit_t + \beta_2 gasprice_t + \beta_3 age_{it} + \lambda_t + \lambda_i + \varepsilon_{it} \quad (4)$$

VI. Regression analysis and results

The results in Table 4 show that there is significantly negative relationship between the enaction of credit policy and used HEV price. Column (1), (2), (3) are the results from using same control variables but different fixed effects. Column (4) is done with only the interaction term *post2023 * HEV*. Column (5) is run with only one control variable *age*. Interestingly, the coefficient of interaction variable post2023* HEV indicate identical value, negative 752, regardless of changes in variables and fixed effects. All columns demonstrate that the treatment effect, the enaction of credit policy, has a significantly negative impact on the seller received price for used HEVs. The coefficients can be interpreted as after the 2023, the price of HEVs received by sellers decreased by about $750.

Table 4: DiD Regression with all cars

Dependent variable: CPI adjusted price				
VARIABLES	(1)	(2)	(3)	(4)
METHOD	XTREG	XTREG	XTREG	DiD with STATA
post2023 * HEV	-752.154***	-752.154***	-752.153***	-752.155***
	(204.842)	(204.974)	(206.728)	(207.638)
HEV	2487.589***			
	(160.290)			
post_2023	-149.810	24.797	9236.572***	
	(210.031)	(100.394)	(2827.217)	
age	-.6463244 ***	-.720***	-2.553***	
	(.071)	(.038)	(.618)	
gas_price	298.4365	126.1884	1378.289**	
	(674.197)	(143.247)	(603.692)	
Constant	16490.06***	18419.32***	-518545.9***	17405.38***
	(2374.922)	(521.761)	(164286.7)	(103.662)
Observations	4,914	4,914	4,914	4,914
Number of i	42	42	42	42
R-squared	0.1646	0.6748	0.8249	0.8246
time FE	NO	NO	YES	YES
entity FE	NO	YES	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: Column (1) (2) (3) was run with same variables and same samples but with different fixed effects. We utilized STATA's DID command for column (4).

Table 5 demonstrates the results of 2SLS regression. The coefficient of *subsidy* in all columns indicates negative sign which means that the subsidy decreases the price received by sellers. This negative sign from result generally corresponds to the result from first regression in Table 4. The coefficient of *subsidy* in all columns show the value around negative 0.18 to 0.20. Since the value with 2SLS regression is only valid for our study, we interpret as one dollar increase in subsidy decreases the seller received price by about $0.18.

We further run regression with sample excluding the car models which have strong price volatility or those have different price trend between electric and gasoline powered. By doing this, we minimize the external factors would impact the price of HEVs and non-HEVs differently. We determine 11 different models by comparing their price trend graphs in Figure 6 and their standard deviation in APPENDIX A.1. The Table 6 demonstrate the result of this regression. The results show that the coefficient of subsidy increases by excluding vehicles have strong volatility. In particular, the coefficient on subsidy is higher at negative 0.074 compared to negative 0.18. However, the result still significantly indicates the over-shifting of subsidy. Results conclude that the adoption of subsidy policy on used HEVs lower the seller received price; in particular, $1 increases in subsidy decreases the market price of HEVs by about $0.10 to $0.18. This over-shifting corresponds with the result from Kaul et al (2016).

Table 5: Regression on Subsidy (2SLS)

Dependent Variable: CPI adjusted price			
	(1)	(2)	(3)
VARIABLES	Regular	Credit based 2022	2SLS
subsidy	-.201***	-.188***	-.175***
	(.050)	(.009)	(.023)
age	-2.481***	-2.553***	-.724***
	(.634)	(.877)	(.017)
gas_price	149442.2***	154955.8**	126.41
	(48620.58)	(68685.37)	(156.869)
constant	-499471.1**	-518545.9**	18422.9***
	(236415.6)	(237630.5)	(552.310)
Observations	4,914	4,914	4,914
Number of i	42	42	42
R-squared	0.827	0.8249	0.675
time FE	YES	YES	YES
entity FE	YES	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: column (1) shows the regression with endogenous variable (*subsidy*). Column 2 is the regression result with the endogenous variable (*subsidy*) calculated with car price in year 2022. Column (3) shows the result of 2SLS method. We run the 2SLS method with STATA's xtivreg command.

Table 6: Regression on subsidy with excluding stronger price volatility

	Dependent Variable: CPI adjusted price				
	(1)	(2)	(3)	(4)	(5)
VARIABLES	All Price	P < 25000	All Price	P < 25000	2 SLS
subsidy	-.089***	-.051			-.074***
	(.008)	(.050)			(.023)
post_2023_HEV			-322.071 *	-173.658	
			(185.921)	(201.031)	
age	-2.415***	-3.225***	-2.440***	-3.226***	-.736***
	(.772)	(.753)	(.613)	(.763)	(.016)
gas_price	141755.5**	204374.7	143594.7***	204302.7***	315.2348*
	(60392.38)	(58476.28)	(47803.1)	(59355.21)	(155.301)
Constant	-473094.6 **	-690382.9***	-479457***	-690134.2***	17259.24***
	(208938.9)	(202307.5)	(165415.8)	(205345.8)	(546.797)
Observations	2,574	2,352	2,574	2,352	2574
Number of i	22	22	22	22	22
R-squared	0.9091	0.9200	0.9084	0.9196	0.781
time FE	YES	YES	YES	YES	YES
entity FE	YES	YES	YES	YES	YES

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Note: this table demonstrates the regression with filtered sample by their price volatility. The sample was picked based on their standard deviation with price. The standard deviation and variance are shown in Appendix A.1. Column (1) and (3) include all price range, and Column (2), (4) exclude the car price over $25,000. Column (5) is 2SLS regression. Since (1),(2) are run with endogenous variable, the result is not valid. We include these regressions to check whether the value correspond with the valid one, (5).

VII. Discussions and Possible Interpretation

Although the result from Kaul et al (2016) corresponds with ours, our results differ from previous literature studying similar tax credit program on HEVs. Therefore, our results require further analysis for interpretation. There exist potential reasons for the decrease in seller received price with subsidy provided. Firstly, it is possible that our price data may not perfectly capture the real transaction price. Our price data is collected based on the market price listed by sellers, and we assume that seller received price is identical to those market price. Although I predict there would not be phenomenal different with real transaction data, there still exist possibility of errors. The market price may differ from the real transaction price due to negotiation between buyers and sellers (Appendix B.2). It requires having richer and more accurate transaction data set to estimate the true incidence of subsidy more accurately. Secondly, people may not be aware of the tax credit for used vehicle yet. The tax subsidy on used vehicle purchases is relatively new compared to the new vehicle purchases. Hence, it is possible that people who are in used car market are not aware of this credit. In this case, the enaction of credit policy would have small impact on the price. Thus, it may need longer time to accurately estimate the impact of used car credit on their price.

VIII. Conclusions

This paper used empirical data to estimate two relationships: the impact of federal tax credit on used vehicle price and the pass through of the HEVs tax subsidy between sellers and buyers focusing on year of 2022 and 2024. We run two regression models to make more accurate estimation. Firstly, we find that the seller received price from used HEVs decreases after the enaction of used vehicles tax credit program in 2023. More surprisingly, our result demonstrates that $1 increase in tax subsidy decrease the seller received price about between $0.07 to $0.18 which showing over-shifted tax incidence. It means the buyers of used HEVs benefit more than the amount of tax subsidy. The result corresponds with the study from Kaul et al (2016) especially for their regression with high price segment. Our result is interesting and surprising because according to the classic tax incidence theory (Figure 2), the tax credit normally increases the seller received price and decreases the buyer's price. However, our result illustrates that the subsidy on HEVs rather work as taxation for sellers because they are losing money from every transaction. Moreover, it means that the buyer captures more than 100% of the subsidy.

Since the tax credit policy has been only a year and half and the price change in used-vehicle market is driven by more variables compared to new-vehicle market, it requires more sufficient data to accurately address the incidence problem. Also, recently, the tax policy related to energy efficient vehicle change frequently; therefore, the impact of tax subsidy on HEVs requires further study. In conclusion, our results may be directly applied to the debate about whether the tax credit policy on HEV market has an impact or not.

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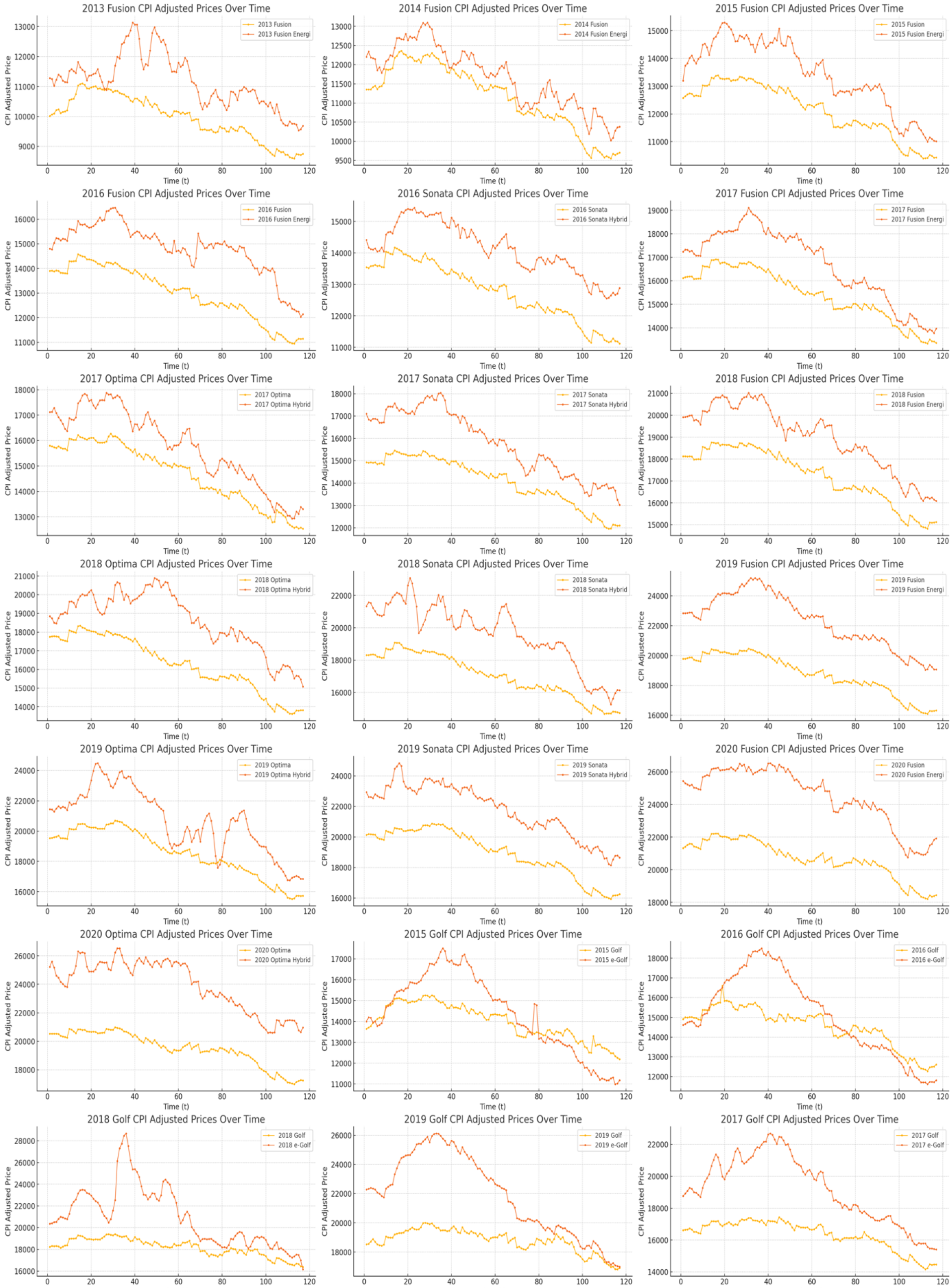
APPENDIX A.

Table: Appendix A.1

Car Type	Mean	Variance	Standard Deviation	Difference in S.D
2013 Fusion	9954.202	536437.9	732.419	139.12
2013 Fusion Energi	11190.53	759587.5	871.543	
2014 Fusion	11143.42	716484.8	846.454	50.17
2014 Fusion Energi	11665.29	634064.1	796.281	
2015 Fusion	12144.08	888589.2	942.650	295.01
2015 Fusion Energi	13436.25	1531805	1237.661	
2015 Golf	13986.98	709456.9	842.293	1019.31
2015 e-Golf	14388.3	3465564	1861.602	
2016 Fusion	13010.67	1151287	1072.98	38.96
2016 Fusion Energi	14813.39	1069190	1034.017	
2016 Golf	14547	994706.1	997.350	1036.89
2016 e-Golf	15133.59	4138118	2034.237	
2016 Sonata	12771.29	815876.2	903.259	91.32
2016 Sonata Hybrid	14131.64	659244.6	811.939	
2017 Fusion	15416.14	1174435	1083.714	434.81
2017 Fusion Energi	16696.64	2305899	1518.519	
2017 e-Golf	19195.6	4339317	2083.103	1189.04
2017 Golf	16327.29	799347.6	894.062	
2017 Optima	14691.74	1372781	1171.657	307.90
2017 Optima Hybrid	15768.67	2189094	1479.559	
2017 Sonata	14089.61	1106706	1052.001	379.69
2017 Sonata Hybrid	15801.98	2049737	1431.69	
2018 Fusion	17240.09	1517168	1231.734	238.46
2018 Fusion Energi	18996.96	2161466	1470.193	
2018 e-Golf	20965.26	7406724	2721.53	1925.99
2018 Golf	18186.69	632881.4	795.538	
2018 Optima	16299.08	2088425	1445.138	97.44
2018 Optima Hybrid	18610.12	2379535	1542.574	
2018 Sonata	17023.88	1773743	1331.819	596.49
2018 Sonata Hybrid	19626.68	3718382	1928.311	
2019 Fusion	18760.22	1745229	1321.071	470.52
2019 Fusion Energi	22294.29	3209802	1791.592	
2019 e-Golf	21891.95	7582695	2753.669	1977.80
2019 Golf	18785.64	601968.5	775.866	
2019 Optima	18549.24	2388726	1545.551	542.80
2019 Optima Hybrid	20706.33	4361202	2088.349	
2019 Sonata	18957.66	2303404	1517.697	180.66
2019 Sonata Hybrid	21761.15	2884415	1698.356	
2020 Fusion	20657.2	1292684	1136.963	610.74
2020 Fusion Energi	24502.7	3054451	1747.699	
2020 Optima	19514.66	1311135	1145.048	641.49
2020 Optima Hybrid	23943.06	3191714	1786.537	

Note: this table was created to compare the price volatility of HEVs and non-HEVs of each car model.
FigureA.2. Difference in S.D is calculated by same model with different powered. For instance S.D of 2019 Optima – 2019 Optima Hybrid.

Appendix A.2



Note: these graphs illustrate the price trend of electric and gasoline powered vehicles for each model. The graphs show that some vehicles have significantly different price trend between green energy and gasoline powered modes.

APPENDIX B.

We run the regression with different data set which exclude the samples over the market price of $25,000, and column (6), (7) show the result of their regression. By comparing (3) and (6), we conclude that the high price vehicles do not have significant impact on our result.

Appendix B.1: Regression on subsidy

	Dependent Variable: CPI adjusted Price						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES	All Price	All Price	All Price	All Price	All Price	P < 25000	P < 25000
subsidy	-.1817373***	-.1855166***	-.1880382***	-.201414***	-.2013204***	-.1145128**	-.1145141**
	(.04516)	(.0461901)	(.051682)	(.0503441)	(.0501612)	(.0518179)	(.0521332)
age	-.7159846***	-.71372***	-2.552977***		-2.48131***	-3.481142**	
	(.0345443)	(.0345607)	(.6182125)		(.6335043)	(1.094819)	
gas_price	131.1779	133.6744	154955.8***			227964.1**	
	(145.014)	(144.931)	(47486.81)			(83571.7)	
Constant	18399.14 ***	18388.98***	-518545.9***	17405.38***	18025.95***	-773228.1 **	15106.66***
	(821.637)	(526.037)	(164286.7)	(104.047)	(186.952)	(289034.4)	(123.294)
Observations	4,914	4,914	4,914	4,914	4,914	3,042	3,042
Number of i	42	42	42	42	42	26	26
R-squared	0.6748	0.6748	0.8249	0.8264	0.8266	0.8537	0.8532
time FE	NO	NO	YES	YES	YES	YES	YES
entity FE	NO	YES	YES	YES	YES	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: This table shows the regression on subsidy with endogenous variable. Column (1) to (5) include all price range of vehicles, but (6) and (7) exclude the price over $25,000.

As we discussed in Section IV, we assume seller received price is CarGurus' market price for our study. To check the impact of negotiation, we adjusted our price by average negotiation percentage suggested by dealers and experts. After careful researching, we find that the average negotiation of used vehicle is about 20% of the price.[10] Thus, adjust our CPI adjusted

[10] https://www.consumerreports.org/cro/2012/12/negotiate-effectively/index.htm

price by this negotiation rate. The following table shows the result from this new independent variable. We utilize 2 SLS regression here. The coefficient of subsidy in column (3) is similar to the one from Table 5, -0.175. We conclude the negotiation may not have significant impact on the estimation.

Appendix B.2 : regression on subsidy with excluding stronger price volatility

	Dependent Variable: Negotiation adjusted price					
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	All	All	All	Filtered	Filtered	Filtered
subsidy	-.867***	-.138***	-.140***	-.780***	-.055***	-.060***
	(.015)	(.019)	(.019)	(.020)	(.018)	(.019)
age		-.582***	-.579***		-.560***	-.589***
		(.013)	(.013)		(.013)	(.013)
gas_price			101.129**			252.188**
			(125.495)			(124.241)
Constant	14420.66***	15093.99***	14738.32***	14004.96***	14694.34***	13807.39***
	(22.578)	(20.652)	(441.848)	(28.649)	(20.472)	(437.437)
Observations	4,914	4,914	4,914	2,574	2,574	2,574
Number of i	42	42	42	22	22	22
R-squared	0.179	0.675	0.675	0.088	0.780	0.781
time FE	YES	YES	YES	YES	YES	YES
entity FE	YES	YES	YES	YES	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: this table shows the 2SLS regression result with negotiation adjusted price as a dependent variable. Column (1),(2),(3) was run with all of the samples. Column (4),(5),(6) was run with sample filtered by stronger price volatility vehicles.