Recharged: Used electric vehicles and the clean vehicle tax credit*

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Abstract

Ubiquitous adoption of plug-in electric vehicles (PEVs) will ultimately rely on used vehicle sales. Using millions of listings from an automobile marketplace, we estimate the incidence and impacts of a federal tax credit supporting used PEV adoption. On average, \$0.49 of each \$1 in tax credit materializes in higher PEV prices. Teslas experience higher passthrough of the credit to prices than other battery electric vehicles, and we estimate full passthrough for plug-in hybrid electric vehicles. We estimate used vehicle supply elasticities to explain these differences and show that the credit increased the number of eligible listings by 14%.

Keywords: Electric vehicles, used vehicles, tax credit, subsidy, incidence
JEL classification: H22, R48, Q58, L91

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I Introduction

The transition to plug-in electric vehicles (PEVs) is well underway. In the US, recent executive orders and EPA emission standards suggest that the PEV share of new vehicle sales could reach or eclipse 50% by 2030.[1] Adoption of new PEVs is only the first step in this transition. Successful electrification of passenger vehicles will ultimately rely on used vehicle sales—which constitute over 70% of the passenger car and light truck market, and on average, cost around half as much as a new vehicle (BTS, 2023). While critical for continued electrification, the used plug-in electric vehicle market is volatile, uncertain, and understudied.

This paper fills a gap in the literature by providing insights into the increasingly important used PEV market and estimating the incidence and impacts of a federal tax credit that could both incentivize used PEV adoption and stabilize the market. We study the federal Used Clean Vehicle Credit implemented as part of the Inflation Reduction Act in 2023. The credit provides the buyers of eligible used PEVs with a purchase subsidy of up to $4,000. We use a new national data set of 12 million vehicle listings collected from a major online vehicle marketplace (Autotrader) and variation in credit eligibility to estimate passthrough of the credit to listing prices and the supply elasticity of used PEVs. We also provide insights into how these parameters differ across fuel types (Battery Electric Vehicles (BEVs) and Plug-in Hybrid Electric Vehicles (PHEVs)), manufacturers, regional characteristics, and changes to how the credit was administered.

We find that, on average, $0.49 of every credit dollar is passed through to sellers of PEVs in the form of higher vehicle prices, but substantial heterogeneity exists. Approximately half of the credit subsidizes the adoption of PEVs for consumers who may not be able

[1] See Executive order 14037 (https://www.federalregister.gov/documents/2021/08/10/2021-17121/strengthening-american-leadership-in-clean-cars-and-trucks) and the EPA Final Multi-Pollutant Emissions Standards for Model Years 2027 and Later Light-Duty and Medium-Duty Vehicles rule for PEV projections under potential compliance pathways (https://www.epa.gov/regulations-emissions-vehicles-and-engines/final-rule-multi-pollutant-emissions-standards-model).

to afford a new PEV, and, in some ways, this portion of the credit addresses concerns that PEV subsidies have traditionally gone to high-income households that would have purchased PEVs even without the subsidy (Borenstein and Davis, 2016; Xing et al., 2021). The other half of the subsidy is captured by sellers and may act as a stabilizing force in the market—alleviating concerns that PEVs depreciate faster than internal combustion engine vehicles (ICEVs) (Schloter, 2022; Breetz and Salon, 2018). We find that the supply response to the credit varied across vehicle characteristics, but that the credit increased the total number of eligible listings by 14%.

We use variation in the eligibility requirements for the tax credit to identify these estimates. Beginning in 2023, PEVs sold for less than $25,000 that are at least two years old are eligible for a credit of 30% of the sale price of the vehicle with a cap of $4,000. For example, a 2022 model year vehicle sold for $24,000 in 2024 would be eligible for a $4,000 credit, but the same vehicle sold in 2023 would receive no credit due to its age. The tax credit also required the vehicles to be sold at a licensed dealership, meet certain weight and battery thresholds, for the purchasers to meet income and other limitations, and imposed restrictions on how frequently the tax credit could be applied to a vehicle or individual.

The qualifying price threshold of $25,000 provides a clear pricing incentive—vehicles sold for $25,000 receive a tax credit of $4,000 while those sold for $25,001 receive nothing. The credit also varies continuously with price until it reaches the $4,000 maximum. We use this variation in the credit amount as a function of price and the age cut-off to examine credit passthrough for PEVs in a differences-in-differences model. The tax credit structure also provides another natural counterfactual in ICEVs, allowing for a layered identification strategy. ICEVs, which do not receive a subsidy at any price, can be used as a control group to remove biases from underlying dynamics in the used automobile market at large or in specific regions and better control for depreciation of vehicles over time. We incorporate this third layer of variation in a triple differences-in-differences model estimating credit passthrough. We use a similar triple differences-in-differences model to estimate supply elasticities by examining how the credit affects the quantity of listings. Requirements for dealerships, changes in the administration of the tax credit, and other variations allow us to further test the robustness of our results and the mechanisms driving them.

When examining heterogeneity across fuel types, we estimate that \$0.48 of each credit dollar is passed through to asking prices for BEVs, but credit values are fully passed through to PHEV prices. Given that the incidence of a tax credit is determined by relative supply and demand elasticities, we can provide some insights into what drives the incidence of the tax credit. We estimate that the supply of PHEV listings is relatively more elastic than BEV listings. This finding suggests that the difference in passthrough is likely due to very elastic consumer demand for used PHEVs. Similar to Barwick et al. (2023), we also find differential impacts for Teslas.[2] Teslas have higher passthrough of the credit than other BEVs, and again have a relatively elastic supply compared to non-Tesla BEVs. Further, we find BEVs with longer ranges have higher passthrough of the credit to prices, suggesting the greater Tesla passthrough may be a function of range rather than a manufacturer-specific effect.

In addition, we examine the impact of an administrative change to the tax credit that allowed buyers to fully redeem the credit at the time of sale as opposed to the subsidy being a non-refundable credit filed with tax returns. These changes likely made the policy more salient and valuable to purchasers. We find evidence of reductions in the amount of the credit captured by sellers for PHEV listings, bringing the passthrough for these vehicles more in line with what we estimate for BEVs. This result is consistent with prior work that found the ability to claim the incentive—whether it be a tax credit, sales tax exemption, or other policy—at the time of sale and greater public awareness of incentive programs led to larger impacts (Diamond, 2009; Jenn et al., 2018; Bjerkan et al., 2016; Gallagher and Muehlegger, 2011).

We fill a significant gap in the literature by providing the first study to specifically analyze

[2]Teslas differ from other BEVs in many dimensions (e.g., range, price), but the brand may also hold "symbolic" value to consumers. For example, Kahn (2007) discusses how consumers may have viewed alternatives to the Toyota Prius, a symbol of environmentally conscious consumption, as poor substitutes.

a policy targeting the used PEV market. Past research has focused on the numerous purchase and other incentives at the international, federal, state, and local levels for *new* electric vehicles. Policies promoting new electric vehicle purchases are often criticized for subsidizing expensive high-end vehicles. This shortcoming has meant that high-income households claimed the majority of early federal electric vehicle subsidies in the US (Borenstein and Davis, 2016). In contrast, the used tax credit is aimed at incentivizing the adoption of cheaper PEVs and has several other stipulations (e.g., income) which may make it less regressive.[3] Many studies have also found that a high percentage of subsidized new vehicles would have been bought even if a new vehicle incentive was not offered (Xing et al., 2021; Li et al., 2022; Chandra et al., 2010; Azarafshar and Vermeulen, 2020; Jenn et al., 2018). In contrast, our data are better suited to investigate the supply side of the used market, where we find that 86% of the eligible PEVs observed would have been listed without the credit. The tax credit led some additional PEV owners to sell their vehicles on the secondary market, and it likely induced some prospective buyers on the used market to switch from ICEVs to PEVs. The supply elasticity of used vehicles has further implications for other policies, like new vehicle tax credits, which can have equilibrium effects on used vehicle prices.

While our study is unique in estimating pass-through in the used electric vehicle market, some prior work has estimated subsidy pass-through in the new vehicle market. Though there is great variation across the policies examined and market contexts, studies have generally found buyers capture high rates of the credit (Beresteanu and Li, 2011; Barwick et al., 2023; Muehlegger and Rapson, 2022).[4] For example, Sallee (2011) found buyers captured 100% of subsidies for Toyota Prius hybrids in the US. In contrast, we find that sellers completely captured the used electric vehicle credit for plug-in hybrids. The market context likely explains the difference in results. Toyota had a financial interest in the future expansion of the hybrid market and was willing to forego current profits to ensure broader adoption of

[3]Other policy measures have attempted to address regressivity concerns as well. For example, Muehlegger and Rapson (2022) study a California subsidy targeted specifically at low- and middle-income households.

[4]Given our setting where buyers receive the tax credit, we generally refer to passthrough as the amount of the credit passed through to asking prices—how much the *seller* captures.

the technology and their future success in the market (Heutel and Muehlegger, 2015). In the used vehicle market, sellers lack this type of long-run profit motivation, so the incidence of a used vehicle credit is likely to be very different.

Finally, our data set allows for an up-to-date analysis of the PEV market. In the ever-changing world of electric vehicles, it can be difficult to draw firm conclusions from analysis based on data that is lagged by even a few years—an unfortunate limitation noted in previous works (Zhao et al., 2023; Nehiba, 2024). Similar to Sallee (2011), but unlike much of the literature, we analyze vehicle sale microdata, rather than relying on aggregate statistics. In addition to our main empirical findings, linking the Autotrader data to local economic and demographic information allows us to answer broader questions about the used PEV market. For instance, we find evidence that higher gasoline prices increase PEV prices, a result consistent with increased demand for these vehicle due to high energy prices found in Diamond (2009) and Bushnell et al. (2022)

The remainder of the paper is organized as follows. Section II provides additional information on the Used Clean Vehicle Tax Credit and its implementation. Section III describes the data used and provides descriptive statistics. Section IV outlines the empirical methodology for estimating tax credit passthrough and supply elasticities. Results are provided in Section V, a discussion of the scale of the tax credit's impact on the used PEV market is in Section VI, and Section VII concludes.

II The *used* electric vehicle tax credit

The used clean vehicle credit was implemented as part of the Inflation Reduction Act and became effective on January 1, 2023. The credit will impact used vehicle markets for the foreseeable future as it applies to vehicles purchased through December 31, 2032. As we are at the beginning of the credit's lifetime, the current work can inform on future impacts as well as the impacts of changes to the credit. As its name suggests, the credit provides a purchase subsidy to qualifying preowned plug-in—battery or hybrid—and fuel-cell vehicles.[5] The tax credit is valued at 30% of the sale price of the qualifying vehicle with a maximum cap of $4,000.

There are several stipulations on which vehicles qualify for the tax credit. First and foremost, the vehicle must be a plug-in hybrid, battery electric, or fuel cell vehicle. There are also age, price, and feature requirements for qualification. A vehicle must be at least 2 years old at the time of purchase, as determined by the vehicle's model year. The vehicles must also have a sale price of $25,000 or less—not inclusive of taxes, title costs, registration fees, or other costs required by law. For plug-in vehicles, a battery capacity of at least 7 kWh is required.[6] All vehicles must have gross vehicle weight ratings under 14,000 pounds and be purchased to be primarily used in the US.

There are also limitations on who qualifies for the tax credit. Only individuals purchasing a vehicle for their own use qualify. In other words, businesses and those who would resell the vehicle are ineligible. These individuals must have a modified adjusted gross income (AGI) not exceeding: $150,000 for those married filing jointly or a surviving spouse, $112,500 for heads of households, or $75,000 for all other files. An individual can qualify if their AGI meets these limits in the year they take delivery of the vehicle or the prior year. To avoid fraudulent sales receiving a credit, claimants cannot be the vehicle's original owner or be a claimed dependent on another person's tax return. An individual can also only claim the credit once every 3 years. However, households can claim up to 2 clean vehicle tax credits (new or used) in a single year.

Our data only covers listings of vehicles and not actual sales of vehicles. We are therefore unable to determine if the eventual buyers are eligible for the tax credit based on their income or past credit use. However, this is unlikely to pose an empirical issue as dealers price their vehicles according to market forces, understanding that some buyers will be ineligible for the credit.

[5] We focus on BEVs and PHEVs in this work due to the rarity of fuel cell vehicles in the current market.
[6] In practice, this requirement eliminates low-speed vehicles, such as golf carts.

The vehicles must also be purchased through a dealership licensed to sell vehicles in the state of purchase, and the dealer must report the information required to claim the clean vehicle credit to the IRS and purchaser at the time of sale. In theory, this means that person-to-person sales do not qualify for the credit, but that may not always be true in practice. There exist online "dealerships" that facilitate private used car sales between parties. These "dealerships" facilitate sales that qualify for the credit by technically purchasing the vehicle from the original vehicle owner before selling it to the new owner.[7] We further explore how the credit impacts private sale prices as a robustness check.

The tax credit implementation was also updated in 2024 to make it easier to claim. In 2023, the subsidy was a non-refundable tax credit. Buyers claimed the credit on their taxes and only received the full potential value if their tax liabilities met or exceeded the value of the credit. Beginning January 1, 2024, the IRS allowed Clean Vehicle Tax Credits in their entirety (i.e., fully refundable) to be transferred to dealers at the time of purchase.[8] This means buyers could immediately apply the credit to the price of the vehicle (e.g., as part of the down payment) instead of receiving the credit when filing their taxes. We hypothesize that this programmatic change made the tax credit more beneficial for buyers through multiple channels.[9] First, the changes eliminated uncertainty about the value of the credit for individuals—buyers knew the exact amount of the credit they would receive at the time of purchase. Second, the changes allowed buyers to receive the credit much sooner and alleviated potential credit constraints.

[7] E.g., Caramel and Keysavvy

[8] See https://www.irs.gov/newsroom/irs-issues-guidance-for-the-transfer-of-clean-vehicle-credits-and-updates-frequently-asked-questions for more information.

[9] These changes appear to be quite popular as 19,500 of the 25,000 new and used clean vehicle credits issued from January 1–February 6, 2024, opted for the immediate transfer of the credit (Congressional Research Service, 2024).

III Data

Our primary data source consists of vehicle listings from Autotrader, a large online automotive marketplace (Autotrader, 2024). Autotrader aggregates new and used vehicle listings from licensed dealers and private sellers. These listings include characteristics of the vehicle including the make, model, model year, asking price, odometer reading, and unique Vehicle Identification Number (VIN). Some listings provide information on the fuel economy or electric driving range of the vehicle. Because not all listings include this information and it can vary across listings for the same vehicle, we use model-by-model year averages of these variables. The listings also provide some information on the dealership selling the vehicle, including their location. Private sellers are explicitly identified, allowing us to remove vehicles that do not technically qualify for the credit from the data for the main analysis.

After acquiring a listing from Autotrader, we decode each VIN using the National Highway Traffic Safety Administration's Product Information Catalog and Vehicle Listing (vPIC) tool (NHTSA, 2024). Decoding the VINs allows us to recover additional vehicle characteristics. The decoder provides information on each vehicle's fuel type, electrification level, body class, drive type, transmission, and other characteristics.

We collected Autotrader's listings for model year 2012–present vehicles monthly from October 2023 to April 2024. The number of listings retrieved each month varies between 2.3–3 million.[10] We collected over 12 million listings covering 6.6 million unique vehicles. PEVs constitute 6.1% of these listings, with BEVs and PHEVs making up 4.2% and 1.9% of the sample, respectively. In short, we receive a snapshot of the automobile market in the US every month that we link into an unbalanced panel data set where vehicles, and their asking price, can be followed over time if their listings remain active. The snapshot nature of the data poses some issues as we cannot guarantee that a removed listing is sold and the

[10]We attempted to collect all available listings, but due to limits imposed by Autotrader, we may have slightly under-sampled some of the most popular trim-model-model year combinations. However, we always collected the most recently posted listings, so any "missed" listings were likely to be observed in the previous month.

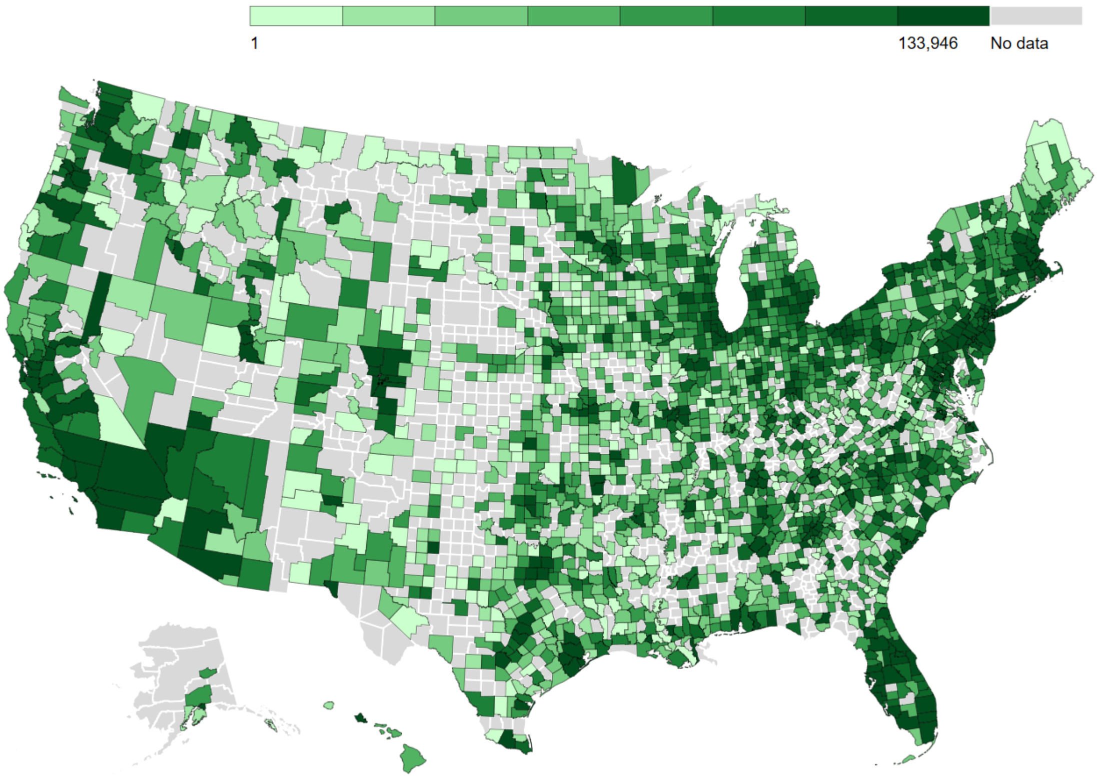
length of time a listing is online (and therefore the probability that we observe it) is likely negatively related to the quality of the deal. However, the data captures approximately 12.4% of the total new and used vehicles sold in the US annually (BTS, 2023). The wide coverage of the data as well as several sensitivity analyses discussed later suggest that these issues are minor.

We implement several sample restrictions to better align our dataset with the used vehicle market. First, we remove vehicles with odometer readings below 500 miles or above 500,000 miles. This filter removes vehicles with implausibly high odometer readings and removes new vehicles from the sample. We also restrict the analysis to vehicles priced under $50,000 to ensure our control group is more comparable to the vehicles eligible for the credit. We also remove vehicles priced under $99 as sellers have likely priced these vehicles inaccurately as a sales strategy. We explore the robustness of our results to variation in these filters in Appendix Table A3.

Figure 1 illustrates the count of listings we observe in each county during the sample period. While we do not observe data in every county, Autotrader listings are present across much of the country. The most listings we observe in a county is just under 134,000 (Los Angeles County, CA) with the most dense concentrations of vehicles along the coasts and major metropolitan areas. Listing counts are strongly correlated with population—where there are people, there are cars.

In Figure 2 we show where BEV and PHEV listings are most highly concentrated. The map separately plots the BEV and PHEV percent of listings, allowing for the identification of areas with relatively high concentrations of both, one fuel type, or neither. We see that coastal and major metropolitan areas most frequently have high concentrations of both BEVs and PHEVs, but that the level of penetration is still very low compared to ICEVs. The middle of the country tends to be dominated by ICEVs. In, Washington, DC, 100% of the 39 vehicles listed during the sample were BEVs, but no other areas come close to reaching the same level of penetration.

Figure 1: Total listings in each county

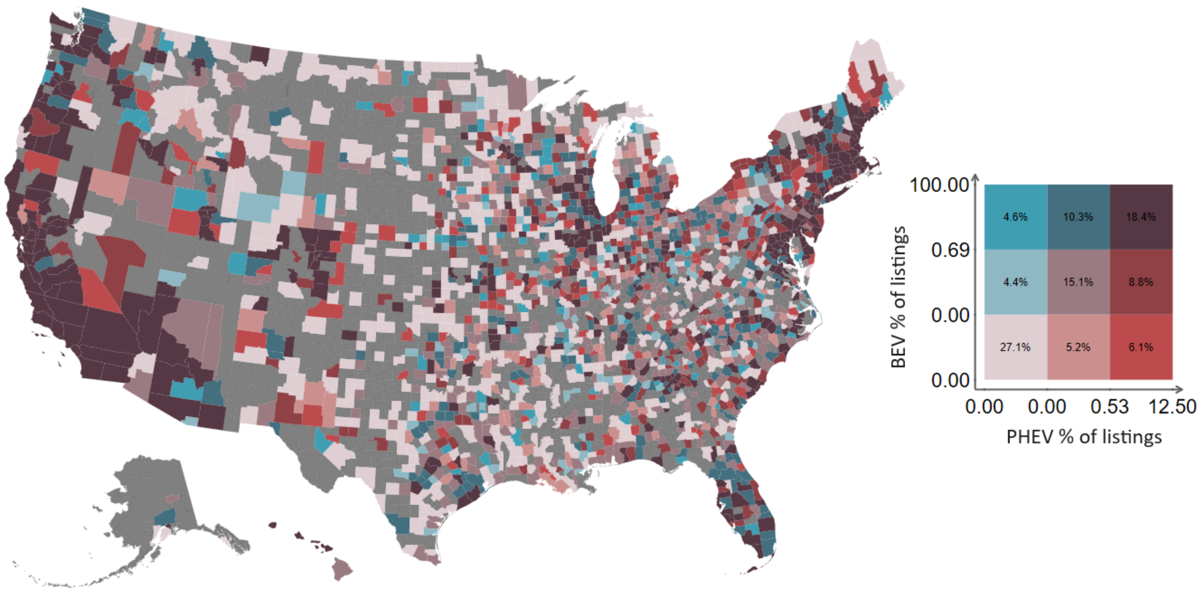


Notes: Figure depicts the total number of listings in each county across the entire sample.

We augment our main data set using several other sources. We obtained state-level gasoline prices from GasBuddy, a crowd-sourcing website used to help consumers compare gasoline prices at local retail stations (GasBuddy, 2024).[11] We use residential electricity prices at the state level provided by the EIA (EIA, 2024). We also include sociodemographic characteristics in some regressions at the zip code tabulation area (ZCTA) from the 2022 5-year American Community Survey (ACS) (ACS, 2024). These variables include population, median income, male share, white share, car commute share, share of commutes that last under 15 minutes, share of commutes that last over 90 minutes, and the share of residents that rent their primary residence.

[11]There are currently no publicly available datasets that provide historical gasoline prices for every US state. The EIA does provide data for a handful of states and Petroleum Administration Defense Districts. Prices from GasBuddy are very similar to these prices.

Figure 2: BEV and PHEV share of listings in each county



Notes: Figure depicts the share of BEV and PHEV listings in each county across the entire sample.

Descriptive statistics for the sample can be seen in Table 1. PEV, BEV, and PHEV shares are relatively low. In the final cleaned sample, PEVs make up just 2.2% of listings on average, with BEVs being around 1.5% of those listings. The average asking price for a vehicle is just under $26,000. We collect data on vehicles with model years ranging from 2012 to 2025, but all 2025 model year vehicles are removed from the sample due to odometer reading restrictions. The average vehicle is around 5–6 years old at the time we observe it. There is also substantial variation in odometer readings with the average vehicle having almost 60,000 miles. Gasoline and electricity prices vary significantly across space and temporally despite the limited duration of the sample. The ACS variables are cross-sectional because of the short sample, but they can still be useful in understanding variation in the used PEV market.

Table 1: Summary Statistics

Variable	Mean	Std. Dev.	Min.	Max.
PEV Share	0.022	0.148	0	1
BEV Share	0.015	0.121	0	1
PHEV Share	0.008	0.087	0	1
Tesla Share	0.006	0.079	0	1
Asking Price ($)	25849.633	10103.595	99	50000
Model Year (MY)	2018.964	2.885	2012	2024
Odometer	59079.97	41294.852	500	500000
Gas Price ($/gal.)	3.368	0.591	2.56	5.592
Electricity Price (Cents/kWh)	16.789	5.392	9.85	45.25
Population	33367.967	17609.583	58	134008
Median Income ($)	79192.153	27885.682	13137	250001
Male Share	0.494	0.022	0.356	0.93
White Share	0.678	0.204	0.015	1
Car Commute Share	0.830	0.089	0.029	1
Commute < 15 Min. Share	0.285	0.119	0	0.836
Commute > 90 Min. Share	0.024	0.019	0	0.411
Renter Share	0.373	0.154	0	1

N=6,786,132

Notes: Demographic characteristics are measured at the ZCTA level.

IV Empirics

A Credit passthrough estimation

Our first goal is to estimate the passthrough of the pre-owned electric vehicle tax credit to asking prices. We begin by estimating the differences-in-differences model in equation 1 where each observation represents an individual vehicle listing. The first layer of identifying variation comes from differences in potential credit payment amounts across vehicle prices. The second layer segments vehicles based on their eligibility as determined by their model year and the time of the observation. For this portion of the analysis, we restrict the sample to PEVs and present separate results for all PEVs as well as results for only BEVs and PHEVs. We estimate:

$$
\begin{aligned}
\mathrm{P}_{imykt} = \beta_0 + \beta_1[\mathrm{Credit(P)}_{imykt} \times \ \mathrm{Eligibility}_{yt}] + \beta_2\mathrm{Credit(P)}_{imykt} + \beta_3 \ \mathrm{Eligibility}_{yt} + \\
\beta_4 X_{imykt} + \gamma_m + \omega_y + \mu_t + \kappa_k + \eta_{imykt}
\end{aligned} \tag{1}
$$

We observe the list price P of vehicle i which is of model m, model year y, for sale in locality k, at time t. Credit payments, denoted as Credit, depend on the sale price of the vehicle such that:

$$
\mathrm{Credit} = \begin{cases} (0.3 * P_{imytk}) & \text{if} \quad 0 < P_{imytk} \leq 13,333 \\ 4,000 & \text{if} \quad 13,333 < P_{imytk} < 25,000 \\ 0 & \text{if} \quad 25,000 \leq P_{imytk} \end{cases}
$$

Eligibility is a function of both model year and time. Vehicles that are at least two years old at the time of sale meet the age requirement for the credit. For example, a 2021 model year vehicle would meet the age requirement if it were sold in 2023 or 2024. In contrast, a 2022 model year vehicle only meets the age requirement if sold in 2024.

The coefficient of interest, β_1, estimates how an additional dollar of potential credit payment differentially impacts eligible and ineligible vehicles based on age. In other words, the passthrough of the tax credit to asking prices. An estimate of 0 would indicate that the credit is fully captured by consumers while an estimate of 1 would indicate that the credit is fully captured by sellers—potentially split between the original vehicle owners and dealerships.

Equation 1 controls for eligibility requirements (when not fully subsumed by fixed effects) and potential credit amounts to control for the mechanical relationship between price and the credit. We also include a matrix of controls for vehicle and locality characteristics like odometer readings and gasoline prices. Finally, we include a rich set of fixed effects controlling for individual vehicle model-by-model year effects as well as time and ZCTA effects. Our results are robust to the inclusion of various other controls and fixed effects though, as illustrated in Appendix Table A1. Standard errors, η, are clustered at the model-by-model year level.

We also implement several sample restrictions. This credit is aimed at pre-owned PEVs, but it may have broader equilibrium effects on the new PEV market. We therefore limit our control group to other used vehicles. We do this by removing vehicles with odometer readings below 500 miles. These are primarily 2023 or 2024 model year vehicles, but there are a small number of older low-mileage vehicles too. We also remove missing odometer readings that are recorded as zeros. We restrict the sample to vehicles with asking prices below \$50,000. As the tax credit eligibility is capped at \$25,000, this restriction should make the control group more comparable to the vehicles that receive the credit.

Our results vary slightly in magnitude—though relative differences across groups remain consistent—depending on the price restriction imposed, as can be seen in Appendix Table A3. We hypothesize that these differences are driven by a contamination bias. Dealerships may increase their *asking prices* for vehicles beyond the \$25,000 threshold anticipating buyers will haggle the prices down. Dealers may also increase prices of some vehicles to move them far enough away from the threshold that buyers cannot reasonably negotiate the price down to a level where they qualify for the tax credit. In essence, some of the vehicles above the threshold are likely still impacted by the tax credit. Appendix Tables A2 and A3 provide several robustness tests that suggest that the contamination bias likely makes our estimates conservative. In these tables, we change the data restrictions, estimate "donut" models that remove the likely contaminated observations as well as biases that may arise from bunching of observations near the price threshold, and estimate models with "fuzzy" tax credit thresholds that explicitly count vehicles just above the \$25,000 credit thresholds as treated.

Beyond this contamination bias, the use of asking prices as opposed to actual sales prices is unlikely to impact our results because of our empirical design. For this distinction to bias our results, credit eligibility itself would need to have an affect on a buyer's ability to negotiate better prices. Put differently, we do not believe that the gap between asking and sale price would be systematically different for eligible and ineligible vehicles.

Our preferred specifications use a continuous measure of the tax credit for ease of interpretation, but our results are robust to defining credit as a discrete variable equal to one if the vehicle meets the price requirement (i.e., asking price is below $25,000). This discretization simplifies the identifying variation by comparing vehicles above and below the $25,000 threshold as opposed to exploiting underlying variation in credit amounts offered. Table A4 provides these alternative specifications.

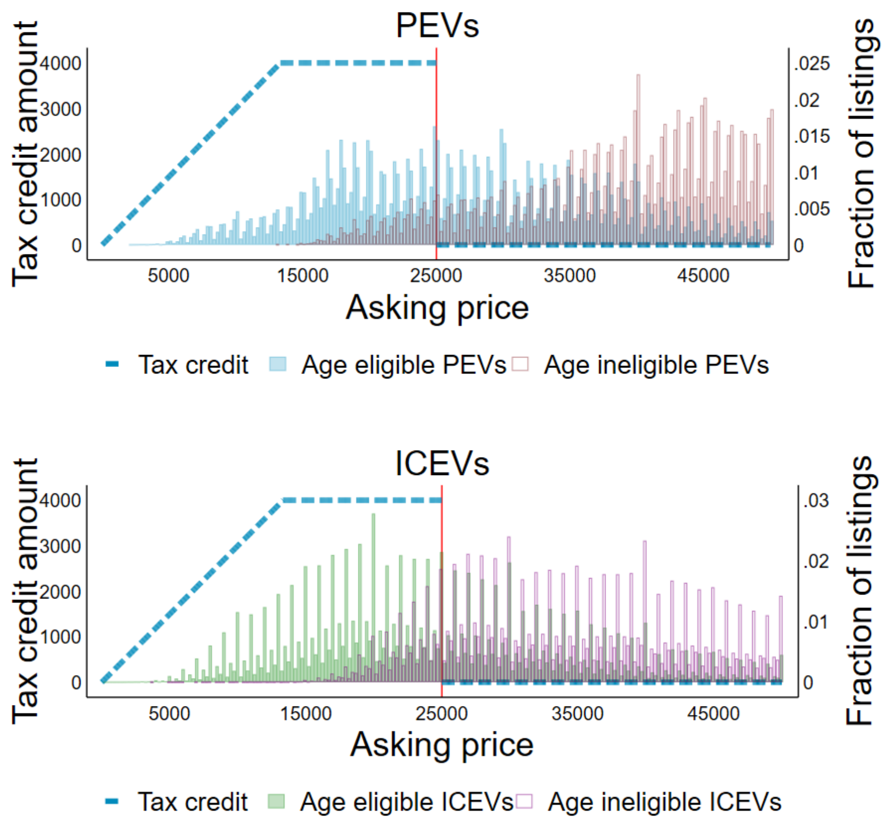
We also estimate a triple differences-in-differences model that adds ICEVs, which are never eligible for the credit at any price or age, as an additional control group. The triple differences-in-differences model improves upon the differences-in-differences model by better controlling for vehicle market dynamics, depreciation of vehicles, and other factors. This model is estimated using equation 2. For readability, we collect the controls and fixed effects already included in equation 1 into the matrix X here.

$$\begin{aligned} \mathrm{P}_{imykt} = \psi_0 + \psi_1[\mathrm{PEV}_{im} \times \mathrm{Credit(P)}_{imykt} \times \ \mathrm{Eligibility}_{yt}] + \\ \psi_2[\mathrm{PEV}_{im} \times \mathrm{Credit(P)}_{imykt}] + \psi_3[\mathrm{PEV}_{im} \times \mathrm{Eligibility}_{yt}] + \psi_4 X_{imykt} + \theta_{imykt} \end{aligned} \tag{2}$$

PEV is an indicator variable for electric vehicles, but we also separately estimate impacts for BEVs and PHEVs. We exclude the group of PEVs not of interest from the estimating sample when estimating effects for one subgroup to better restrict the control group. For example, we remove PHEVs from the sample when estimating the effect of the tax credit on BEV prices.

Figure 3 illustrates the underpinning of our differences-in-differences model in the top panel and the added layer for the triple differences-in-differences in the bottom panel. The dashed line in both panels illustrates the potential credit amount as a function of asking price. The credit amount increases linearly with asking price until the credit reaches $4,000 and then remains flat until an asking price of $25,000 is reached. Beyond this threshold, illustrated by the red vertical line, the credit amount drops to $0. The top panel also includes histograms for age-eligible PEVs and age-ineligible PEVs across price. To the left of the $25,000 threshold, the age-eligible (blue) PEVs receive the credit indicated by the dashed line. The age-ineligible (red) PEVs on that side of the threshold *would have* received the credit had they been two years old at that time. In contrast, none of the vehicles on the right side of the threshold received a credit. The age-eligible PEVs on that side of the threshold *would have* received a credit had they been priced differently though.

Figure 3: Vehicle listings and tax credit across asking price



Notes: The tax credit as a function of asking price is illustrated along with histograms of vehicle quantities. PEVs are depicted in the top panel and ICEVs in the bottom. Both fuel types are segmented by vehicles that are or are not eligible for the credit as a function of vehicle age and date. However, ICEVs are never actually eligible because of their fuel type.

These different groups illustrate our treatment and controls in the differences-in-differences model. Intuitively, the age-ineligible PEVs do have higher average prices as they are newer vehicles. To this end, we include controls for depreciation and model-by-model-year fixed effects in our specifications. However, the general pricing patterns appear similar across the groups with spikes in vehicles near round numbers (e.g., $30,000 or $40,000).

The bottom panel of Figure 3 presents an analogous representation for ICEVs. Again the vehicles are segmented by age eligibility and the potential credit amount based on asking prices. No ICEVs received the credit though, presenting an additional control group.

B Supply elasticity estimation

To estimate the impacts of the pre-owned electric vehicle tax credit on the supply of vehicles, we aggregate our data across model years (MY), prices, fuel types, and dates. We count the total number of listings for a fuel type—PEV, BEV, PHEV, or ICEV—and model year within $1000 price buckets ranging from $1000–$50,000 at each date in the sample. An observation could therefore be the count of 2020 model year PEVs priced between $21,000–$21,999 observed in January of 2024. In that way, we construct a balanced panel for each model year-price bucket-fuel type combination across the months of our sample. To estimate the elasticity of listings with respect to the tax credit we estimate the following triple differences-in-differences model:

$$
\begin{aligned}
\mathrm{Q}_{ypdt} = \epsilon_0 + \epsilon_1[\mathrm{PEV}_d \times \mathrm{Credit}_p \times \ \mathrm{Eligibility}_{yt}] \\
+\epsilon_2 X_{ypdt} + \omega_y + \mu_t + \tau_p + \Theta_{ypdt}
\end{aligned}
\tag{3}
$$

Where Q is a non-negative count of vehicles. Again, y denotes model year and t time. d denotes the fuel type of the vehicles and p refers to the $1,000 price buckets. X is still a matrix of controls that includes the fully saturated set of interaction terms for the triple differences-and-differences estimator not displayed above for brevity. The model includes fixed effects for model year, time, and price buckets. These fixed effects should control for depreciation and scrappage probabilities of vehicles across time and model years. The price bucket fixed effects should also control for the simultaneous relationship between quantity and prices. However, we show that the results are robust to controlling for price linearly, quadratically, or not at all in Appendix Table A7. Standard errors, Θ, are clustered at the price bucket level.

As Q is a count variable, we estimate the above equation using Poisson Pseudo Maximum Likelihood. For ease of interpretation, we report the point estimates as marginal effects calculated as elasticities. Therefore the coefficient of interest, ϵ_1, can be interpreted as the supply elasticity of pre-owned PEVs with respect to the tax credit.

As with the passthrough estimate, we separate the results by PEVs, BEVs, and PHEVs where each fuel type is compared to ICEVs individually. We also provide estimates for Tesla and non-Tesla BEVs.

V Results

This section presents the results of our analysis. We begin by examining the passthrough of the tax credit to asking prices. We present results from both differences-in-differences and triple differences-in-differences models, and we explore the robustness of these results. Next, we discuss how passthrough of the tax credit varies across vehicle and regional characteristics. An analysis of the impacts of the 2024 tax credit administrative changes—which may have improved the salience of the credit—is then presented. Finally, we estimate the supply elasticity of PEV listings and heterogeneity in elasticities across fuel types and manufacturers.

A Tax credit passthrough results

Table 2 presents results from the differences-in-differences model shown in equation 1, estimating the passthrough of the credit to listing prices. The sample for these regressions is limited to the set of PEVs being studied. Columns 1–2 use data for all PEVs while columns

3–4 and 5–6 present results for only BEVs or PHEVs, respectively. Each column includes controls for the vehicle's odometer reading and its square as well as gasoline and electricity prices in the state. All regressions include month of the sample and model-by-model year fixed effects. Columns 1, 3, and 5 also control for local (ZCTA-level) characteristics including population, median income, male share, white population share, car commuting share, very short and very long commutes, and the share of residents that rent their primary residence. Columns 2, 4, and 6 replace these local characteristics with a ZCTA fixed effect, which should control for any time-invariant characteristics of the local area—including idiosyncratic vehicle market characteristics. Standard errors are clustered at the model-by-model year level throughout.

We find a positive and statistically significant effect of the tax credit on vehicle asking prices, as measured by the Credit x Eligible MY variable, in each specification. In column 1, we estimate that \$0.527 of every credit dollar provided for used PEV purchases is passed through to the listing price. Replacing local characteristics with ZCTA fixed effects in column 2 modestly reduces the magnitude of this effect from 0.527 to 0.496. We see similar modest changes in the magnitude of the effect when adding the more granular fixed effects into the models for BEVs and PHEVs. Given the potential for location-specific depreciation or other factors to be correlated with both the tax credit amount and asking price, we prefer the specifications in columns 2, 4, and 6.

We see disparate results for BEVs and PHEVs. In our preferred specifications (columns 4 and 6), passthrough for BEVs is estimated to be 0.484 while passthrough for PHEVs is a far larger 1.257. The point estimate for PHEVs exceeds 1—the point of full passthrough—but it is not statistically different from 1. We interpret this result as evidence of full passthrough for PHEVs.

These results suggest that the buyers and sellers of used PEVs split the tax credit on average, but the incidence depends on the vehicle fuel type. Under perfect competition, economic theory predicts that a greater portion of the incidence of a tax or subsidy will fall

Table 2: Credit passthrough estimates: Differences-in-differences

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable: Asking price	PEVs		BEVs		PHEVs	
Credit x Eligible MY	0.527***	0.496***	0.480***	0.484***	1.352***	1.257***
	(0.107)	(0.091)	(0.126)	(0.108)	(0.217)	(0.257)
Credit Amount	-1.492***	-1.270***	-1.463***	-1.243***	-2.198***	-1.904***
	(0.106)	(0.092)	(0.122)	(0.110)	(0.194)	(0.244)
Eligible MY	-1454.503***	-1332.117***	-1664.370***	-1541.606***	-959.855***	-836.283***
	(498.651)	(449.131)	(585.621)	(502.392)	(264.311)	(197.629)
Odometer	-0.122***	-0.125***	-0.121***	-0.121***	-0.126***	-0.132***
	(0.008)	(0.007)	(0.009)	(0.008)	(0.012)	(0.010)
Odometer^2	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Gas Price ($/gal)	307.362***	76.155	254.413***	178.483	456.023***	-76.543
	(46.806)	(91.425)	(59.668)	(110.137)	(74.901)	(115.412)
Electricity Price (Cents/kWh)	-12.262***	8.845	-10.909**	-17.263	-18.104***	62.223***
	(3.912)	(17.810)	(5.164)	(21.181)	(5.972)	(23.163)
Population	0.002*		0.003**		-0.001	
	(0.001)		(0.001)		(0.001)	
Median Income	-0.003**		-0.004***		0.001	
	(0.001)		(0.001)		(0.001)	
Male Share	-986.909		-953.293		-1045.148	
	(753.986)		(945.956)		(1034.138)	
White Share	693.617***		724.330***		610.920***	
	(122.883)		(169.754)		(138.853)	
Car Commute Share	-804.381***		-1227.380***		139.261	
	(270.961)		(379.918)		(233.129)	
Commute<15 Min. Share	1577.559***		1400.185***		1893.280***	
	(240.152)		(357.206)		(270.716)	
Commute>90 Min. Share	-4667.637***		-6049.497***		-1649.390	
	(937.782)		(1176.684)		(1399.873)	
Renter Share	86.764		-3.729		337.878	
	(189.993)		(244.155)		(261.714)	
Constant	35798.898***	35434.293***	35834.330***	34790.403***	35372.532***	36218.122***
	(770.484)	(564.075)	(938.773)	(649.551)	(723.249)	(720.126)
Model-by-Model Year FE	Y	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y	Y
ZCTA FE	N	Y	N	Y	N	Y
R^2	0.917	0.934	0.900	0.924	0.948	0.963
N	152559	152124	101240	100758	51319	50789

Notes: Standard errors clustered at the model-by-model year level. Demographic controls are at the ZCTA level. Sample includes stated PEVs priced under $50,000 with over 500 miles. Significance levels: $*$: 10% $**$: 5% $***$: 1%.

on the more inelastic party between sellers and consumers. Whether the passthrough for PHEVs is a story of relatively inelastic supply or elastic demand is an empirical question, which we will examine in the supply elasticity analysis.

The portion of the tax credit accruing to sellers itself could also be split between the original vehicle owners and dealerships. While we are unable to empirically disentangle these splits, the original vehicle owners capturing a portion of the credit may help support additional electric vehicle adoption. This outcome relies on the captured credit influencing the original vehicle owners to purchase a new *plug-in electric* vehicle that they would not have otherwise purchased. The newly purchased PEV itself may also be eligible for a tax credit that could again be split between buyers and producers/dealerships (Muehlegger and Rapson, 2022; Barwick et al., 2023; Burra et al., 2024).

The effects of control variables included in columns 1, 3, and 5, while not causally estimated, may still be informative of the used PEV market. We find high gas prices are associated with higher used PEV prices, while higher electricity prices are associated with lower used PEV prices. The results suggest local PEV demand is responsive to potential fuel cost savings. We find that population and the share of the population that is white are generally positively correlated with vehicle prices. These areas may have higher overall vehicle demand and in particular for these vehicles due to racial differences in PEV adoption. The lack of a significant effect for renter share is somewhat surprising given the differences in adoption rates between renters and homeowners (Davis, 2019). We hypothesize that this statistical insignificance is due to the multicollinearity with the other included variables.

Table 3 offers a placebo test of the differences-in-differences estimates. This table presents results using only vehicle listings that were offered by private sellers. Recall that only vehicles sold through a licensed dealer are eligible for the credit. This means that—with some unobservable exceptions due to loopholes—these otherwise similar vehicles are left untreated due to the identity of the seller.[12] As expected, we fail to find a statistically significant effect of the credit when limiting the sample to private sale listings for any fuel type.

As discussed previously, our results prove robust to a battery of additional sensitivity analyses. We test alternative specifications by including additional control variables at the ZCTA level and different fixed effects in Table A1. We also examine the potential for various sample restrictions, contamination bias imposed by the use of asking prices as opposed to

[12]Section II goes into more detail about a potential loophole that allows online retailers to act as a middleman and buyers to still redeem the tax credit. It is unclear how popular this loophole is currently. However, given the insignificant estimates seen in this placebo test, this behavior is not an empirical concern.

Table 3: Credit passthrough: Private seller placebo

	(1)	(2)	(3)
Dependent variable: Asking price	PEVs	BEVs	PHEV
Credit x Eligible MY	-0.092	-0.146	-0.489
	(0.220)	(0.290)	(0.373)
Model-by-Model Year FE	Y	Y	Y
Month FE	Y	Y	Y
ZCTA FE	Y	Y	Y
R^2	0.952	0.940	0.994
N	14709	11698	2797

Notes: Standard errors clustered at the model-by-model year level. Controls for gas price, electricity price, odometer, and odometer^2 included. Sample includes stated PEVs priced under $50,000 with over 500 miles that were listed by private sellers. Significance levels: $*$: 10% $**$: 5% $***$: 1%.

sale prices, bunching of observations near the credit eligibility threshold, and the continuous treatment of the credit variable to influence the results in Tables A2, A3, A4.

Next, Table 4 presents results from our triple differences-in-differences estimation strategy, illustrated in equation 2, which adds ICEVs as an additional layer of control. Adding this third layer of identifying variation helps alleviate concerns that underlying vehicle market dynamics, differences in the value of vehicles above or below the tax credit or age thresholds, and other conflating factors bias the results. Given these benefits, these triple differences-in-differences estimates are our preferred estimates of credit passthrough. The variable of interest is an indicator for the type of electric vehicle being studied (all PEVs, BEVs, or PHEVs) interacted with the continuous credit amount and an indicator for eligibility based on vehicle age and date. The controls and fixed effects included mirror those from columns 2, 4, and 6 in Table 2.

In column 1, the average effect of an additional credit dollar on all PEVs is almost identical to what we found in column 2 of Table 2. The coefficient has decreased in magnitude slightly to 0.489 between the models. This minor downward shift in magnitude is consistent across PEVs, BEVs, and PHEVs. We once again estimate higher credit passthrough to PHEV prices than for BEVs, and we fail to reject the null hypothesis that the PHEV estimate

Table 4: Credit passthrough estimates: Triple differences-in-differences

	(1)	(2)	(3)
Dependent variable: Asking price	PEVs	BEVs	PHEV
PEV x Credit x Eligible MY	0.489***	0.476***	1.116***
	(0.137)	(0.125)	(0.188)
Model-by-Model Year FE	Y	Y	Y
Month FE	Y	Y	Y
ZCTA FE	Y	Y	Y
R^2	0.912	0.912	0.912
N	6786082	6734757	6684834

Notes: Standard errors clustered at the model-by-model year level. Controls for gas price, electricity price, odometer, and odometer^2 included. Sample includes stated PEVs and ICEVs priced under $50,000 with over 500 miles. Significance levels: $*: 10\%$ $**: 5\%$ $***: 1\%$.

is statistically different from 1. By and large, the triple differences-in-differences estimates support the previous results. In future tables, we generally provide both differences-in-differences and triple differences-in-differences estimates, with the triple differences models being our preferred specification due to the more relaxed identifying assumptions and more conservative estimates.[13]

B Passthrough heterogeneity

We next explore how passthrough of the pre-owned PEV tax credit to listing prices varies across dimensions other than fuel type. Heterogeneity in this passthrough can provide insights into which vehicles or regions are impacted by the policy and the mechanisms behind those impacts.[14]

We begin by testing for heterogeneity in the passthrough of the credit between Teslas and non-Tesla BEVs. Teslas are a particularly interesting subgroup of BEVs both because of the vehicles themselves but also their owners' characteristics. Teslas can be considered "luxury"

[13] In some situations, only one of the models is feasible. For example, Table 6 only provides differences-in-differences estimates because it explores how credit passthrough varies with BEV driving range. Because ICEVs do not have a corresponding electric range, we do not include them as a control group in a triple differences-in-differences model.

[14] In addition to the analysis in this section, we examine heterogeneity in passthrough based on a vehicle's age in Appendix Table A5.

vehicles, but they constitute the largest BEV market share in the sample (42%). They are also notable for their long ranges, and in particular, having early model year vehicles with relatively long ranges. Likely as a function of these long ranges and their low fuel efficiency (relative to other BEVs), Tesla owners have been shown to consume more electricity, drive more, and be less responsive to fuel costs than other BEV owners (Nehiba, 2024; Burlig et al., 2021). In short, there are many dimensions along which Teslas differ from other BEVs, some of which may impact the rate of passthrough for the tax credit.

Table 5 provides differences-in-differences (columns 1 and 3) and triple differences-in-differences (columns 2 and 4) estimates from samples isolating Tesla and non-Tesla BEVs. We find evidence that more of the tax credit is passed through to listing prices for Tesla vehicles than other BEVs. This result suggests that the sellers of Teslas receive relatively large benefits from the tax credit. Focusing on the triple differences-in-differences results, the passthrough for Teslas is just less than double what we find for non-Tesla BEVs. Again, these passthrough rates are determined by the relative supply and demand elasticities for the goods, and we investigate the mechanisms driving these results below.

Table 5: Heterogeneity in credit passthrough for Teslas

	(1)	(2)	(3)	(4)
Dependent variable: Asking price	Tesla		Non-Tesla BEVs	
PEV x Credit x Eligible MY		0.618***		0.321***
		(0.118)		(0.114)
Credit x Eligible MY	0.654***	0.022	0.430***	0.023
	(0.122)	(0.030)	(0.057)	(0.030)
Model-by-Model Year FE	Y	Y	Y	Y
Month FE	Y	Y	Y	Y
ZCTA FE	Y	Y	Y	Y
R^2	0.871	0.912	0.944	0.912
N	42469	6676503	57757	6691763

Notes: Standard errors clustered at the model-by-model year level. Controls for gas price, electricity price, odometer, and odometer^2 included. Sample includes BEVs with stated range in each column priced under $50,000 with over 500 miles. Significance levels: $*$: 10% $**$: 5% $***$: 1%.

Table 6 explores how passthrough varies with vehicle technology, as proxied by electric driving range. For this analysis, we restrict the sample to only BEVs because we segment the vehicles across electric driving range. This limits us to differences-in-differences models. Column (1) shows results for BEVs with under 250 miles in range, column (2) includes BEVs with 250 miles or more of range, and column (3) includes non-Tesla BEVs with ranges of 250 miles or more.

Table 6: Heterogeneity in credit passthrough by vehicle range

	(1)	(2)	(3)
Dependent variable: Asking price	<250 Miles	≥250 Miles	≥250 Miles + Non-Tesla
Credit x Eligible MY	0.198**	0.613***	0.704***
	(0.092)	(0.098)	(0.117)
Model-by-Model Year FE	Y	Y	Y
Month FE	Y	Y	Y
ZCTA FE	Y	Y	Y
R^2	0.949	0.900	0.867
N	40808	59385	36063

Notes: Standard errors clustered at the model-by-model year level. Controls for gas price, electricity price, odometer, and odometer^2 included. Sample includes only BEVs with stated electric ranges priced under \$50,000 with over 500 miles that were listed by private sellers. Significance levels: $*$: 10% $**$: 5% $***$: 1%.

We find that low-range BEVs have much lower passthrough of the credit into list prices. Sellers only capture around \$0.20 of every subsidy dollar for these vehicles. In contrast, the long-range BEVs have passthrough rates triple that — \$0.61 of every subsidy dollar is captured by sellers of BEVs with ranges of 250 miles or more. When we remove Teslas from this group in column (3), we find slightly higher rates of passthrough. This result suggests that the higher passthrough for Teslas in Table 5 is likely a function of technology as opposed to brand-specific factors.

We next examine regional variation in the passthrough of the tax credit due to the penetration of PEVs in the area. We first determine each county's share of Autotrader listings that are PEVs and segment the data into counties above or below the median PEV share. Areas with high penetrations tend to be coastal or more metropolitan areas. Table 7 columns 1 and 2 provide differences-in-differences and triple differences-in-differences estimates for counties below the median penetration while columns 3 and 4 provide identical models for counties with higher penetration.

Table 7: Heterogeneity in passthrough by PEV penetration

	(1)	(2)	(3)	(4)
Dependent variable: Asking price	Below Median PEV %		Above Median PEV %	
PEV x Credit x Eligible MY		0.499***		0.458***
		(0.158)		(0.130)
Credit x Eligible MY	0.334***	0.000	0.559***	0.052
	(0.077)	(0.030)	(0.102)	(0.032)
Model-by-Model Year FE	Y	Y	Y	Y
Month FE	Y	Y	Y	Y
ZCTA FE	Y	Y	Y	Y
R^2	0.940	0.911	0.933	0.914
N	47123	3775866	104986	3010139

Notes: Standard errors clustered at the model-by-model year level. Controls for gas price, electricity price, odometer, and odometer^2 included. Sample includes stated PEVs in each column and ICEVs in columns (2) and (4) priced under $50,000 with over 500 miles. Significance levels: $*$: 10% $**$: 5% $***$: 1%.

While we find some difference in passthrough for PEVs in counties above and below the median in the differences-in-differences model, we find essentially identical estimates between the triple differences-in-differences models. Further, which set of counties has higher passthrough is inconsistent across the models. We characterize these results as suggestive evidence that PEV passthrough does not vary across markets depending on PEV penetration. While past research has shown that urbanization affects PEV and ICEV usage (Nehiba, 2022, 2024), the factor does not appear to impact passthrough. However, we use a coarse measure here and do not believe this constitutes concrete evidence that market power (for buyers or sellers) does not exist in this setting.

C Impacts of administrative changes to the tax credit

We are also interested in how the tax credit's administration may impact these results. Beginning January 1, 2024, the IRS allowed Clean Vehicle Tax Credits to be transferred to dealers at the time of purchase.[15] This means buyers could immediately apply the credit

[15] See https://www.irs.gov/newsroom/irs-issues-guidance-for-the-transfer-of-clean-vehicle-credits-and-updates-frequently-asked-questions for more information.

to the price of the vehicle (e.g., as part of the down payment) instead of receiving the credit when filing their taxes. It also allowed for the full potential value of the credit to be redeemed whereas in the past the subsidy was a non-refundable tax credit. In other words, buyers would not receive the full potential value if their tax liabilities did not meet or exceed the credit value. These programmatic tweaks could have plausibly increased the saliency and value of the tax credit starting in 2024.

While these administrative changes provide an additional layer of variation, their implementation coincided with the 2022 model year vehicles becoming eligible for the tax credit. We therefore propose two empirical analyses revolving around these administrative changes. In both, we will introduce a post-period indicator equal to one if the year is 2024 and restrict the sample to PEVs. We interact this indicator with the credit amount and eligibility variables used previously to estimate another triple differences-in-differences model. In the first analysis, we restrict the sample to exclude all 2022 model year vehicles. Thus, this triple differences-in-differences estimate, presented in columns 1–3 of Table 8, indicates how the passthrough of the credit changed after the administrative changes. Conversely, in columns 4–6 we estimate the same model while restricting the sample to *only* 2022 model year vehicles—estimating the passthrough of the credit to newly eligible vehicles.

Table 8: Effect of tax credit reforms

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable: Asking price	No 2022 MY			Only 2022 MY		
	PEVs	BEVs	PHEV	PEVs	BEVs	PHEV
Post x Credit x Eligible MY	-0.016	-0.033	-0.648*	0.445***	0.577***	0.407***
	(0.088)	(0.095)	(0.338)	(0.095)	(0.101)	(0.119)
Model-by-Model Year FE	Y	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y	Y
ZCTA FE	Y	Y	Y	Y	Y	Y
R^2	0.940	0.931	0.968	0.914	0.918	0.924
N	123666	81390	41671	27879	18833	8548

Notes: Standard errors clustered at the model-by-model year level. Post is an indicator equal to one for observations collected in 2024. Controls for gas price, odometer, and odometer^2 included. Sample includes stated PEVs in each column priced under \$50,000 with over 500 miles. Significance levels: $*: 10\%$ $**: 5\%$ $***: 1\%$.

The small and statistically insignificant estimates in columns 1 and 2 suggest that the passthrough of the credit did not change for PEVs on average or for BEVs after the administrative changes. However, we estimate a large and marginally significant effect for PHEVs. Column 3 suggests that passthrough for PHEVs fell by 0.648 after the changes. In other words, the tax credit became more valuable to the buyers of PHEVs because less of the credit was being passedthrough to listing prices.

When restricting the analysis to only 2022 MY vehicles, columns 4 and 5 of Table 8 are relatively similar to the main passthrough estimates for PEVs and BEVs. However, the PHEV estimate is far smaller at only 0.407. Combining this estimate with the reduction in passthrough estimate for PHEVs in column 3 approximates the full passthrough we saw in Tables 2 and 4. Cumulatively, these results reinforce each other and suggest that the administrative changes were "buyer-friendly" for PHEVs.

D Supply elasticity

Table 9 presents estimates of the supply elasticity of used vehicle listings with respect to the tax credit. These models use variation in the credit amount, the age-based eligibility requirement, and vehicle fuel type to identify the elasticities. The data are transformed such that the dependent variable is the count of listings within $1,000 bins for each fuel type, model year, and date. The noted PEV set (all PEVs, BEVs, PHEVs, Teslas, non-Tesla BEVs) are each compared to the ICEV control group. The models are estimated using a Poisson with the marginal effects presented as elasticities.

In columns 1 and 2, we fail to estimate a statistically significant effect of the elasticity on listings for all PEVs and BEVs, respectively. In column 3, we estimate a statistically significant elasticity of 0.211 for PHEVs. A 10% increase in credit value would increase the supply of PHEV listings by 2.11%. Teslas have a similar elasticity of 0.187, but non-Tesla BEVs are less responsive to the credit with an estimate of 0.079.

Under standard economic theory, the incidence of a tax or subsidy on sellers is determined

Table 9: Supply elasticity estimates

Dependent variable: Count of listings	(1)	(2)	(3)	(4)	(5)
	PEVs	BEVs	PHEVs	Teslas	Non-Tesla BEVs
PEV x Credit x Eligible MY	0.010	-0.031	0.211***	0.187***	0.079***
	(0.019)	(0.020)	(0.030)	(0.052)	(0.014)
Model Year FE	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y
Price Bin FE	Y	Y	Y	Y	Y
N	9100	9100	9100	9100	9100

Notes: Dependent variable is the count of listings of the specified drivetrain or ICEVs in a price bucket for a model year and month. Coefficients are marginal effects estimated using Poisson Pseudo Maximum Likelihood calculated as elasticities. Standard errors clustered at the price bin level. Significance levels: $*: 10\%$ $**: 5\%$ $***: 1\%$.

by the relative supply and demand elasticities. All else held constant, the more inelastic party between buyers and sellers will receive more of the tax credit. We estimated full passthrough of the tax credit to PHEV listing prices in Tables 2 and 4 and, relative to non-Tesla BEVs, elastic supply above. It would follow that PHEVs likely have correspondingly high demand elasticity. We also saw more complete passthrough for Teslas than non-Tesla BEVs in Table 5. Given the more elastic supply response for Teslas, we conclude that demand for Teslas is also relatively more elastic.

While the above supply elasticity comparisons can be instructive, the pathways through which a tax credit can affect used supply are less direct than a new vehicle credit. Unlike new vehicles, which can be manufactured to meet demand, the ability of the market to expand the supply of used vehicles is limited due to the fixed number of vehicles available. Increases in used vehicles being placed on the market is produced by either delaying scrappage for a vehicle or current owners being pushed across the margin of selling due to the increased value of their used vehicle (and then possibly purchasing another vehicle themselves). In the next section, we further quantify the extent that the tax credit increased the supply of used PEVs.

We also perform several robustness checks of these supply elasticity models. First, we observe the vehicles listed at one point in the month and do not know with certainty how long they stay on the market. Because we only observe these snapshots, it could be that there is a simultaneous increase in the quantity supplied and quantity demanded such that we would observe no difference in total number of listings. However, we do observe many vehicles in multiple months. As a sensitivity analysis, we can include only the new vehicles we see each month in the sample. Appendix Table A6 uses this flow of newly listed vehicles finding slightly smaller but qualitatively similar results. Next, we test the sensitivity of the results to the type of price controls included. In Appendix Table A7, we replace the price bin fixed effects with: (1) no price controls, (2) linear price controls, or (3) quadratic price controls. We find that the magnitude of the supply elasticity falls as the price controls become more granular, as we would expect if there were a simultaneity concern between prices and quantity. This result suggests that the price bin fixed effects—the most granular form of control—are the preferred and most conservative strategy. Finally, Appendix Table A8 varies the credit threshold amount, as was done with the passthrough estimates in Appendix Table A2, to examine how the use of listing prices as opposed to sales prices may impact the results. This robustness test allows for vehicles on the high-price side of the credit pricing threshold to be treated (i.e., the potentially contaminated vehicles), but we find qualitatively similar results.

VI How much did the tax credit impact the used PEV market?

In the previous section, we estimated both the passthrough of the tax credit to asking prices and the supply elasticity of PEV listings with respect to the tax credit. We now turn to contextualizing these results in terms of their impact on the used PEV market.

We saw that the value of the credit varies for buyers and sellers depending on the fuel type of the vehicle being sold. In total, we observed 53,146 vehicles that would have been eligible for the credit. If we assume we observe 12.4% of the vehicle market—based on BTS (2023) calculations—the tax credit could be affecting prices for around 428,597 vehicles in the US in 2024.[16] Assuming a 49% passthrough of the credit to prices on average, that's 428,597 vehicles that are more affordable for households. Among qualifying vehicles in our sample, the average vehicle was eligible for a $3,843 subsidy. If 100% of eligible vehicles claimed the subsidies, the government outlays supporting the program would total $1.65 billion in 2024. Given our passthrough calculation, sellers would collect $807 million, while buyers would benefit by $840 million. Although the credit provided direct financial benefits to used PEV buyers, further research is needed to determine how the sellers use their share of the captured tax credit, in particular if they use that credit to fund a new vehicle purchase.

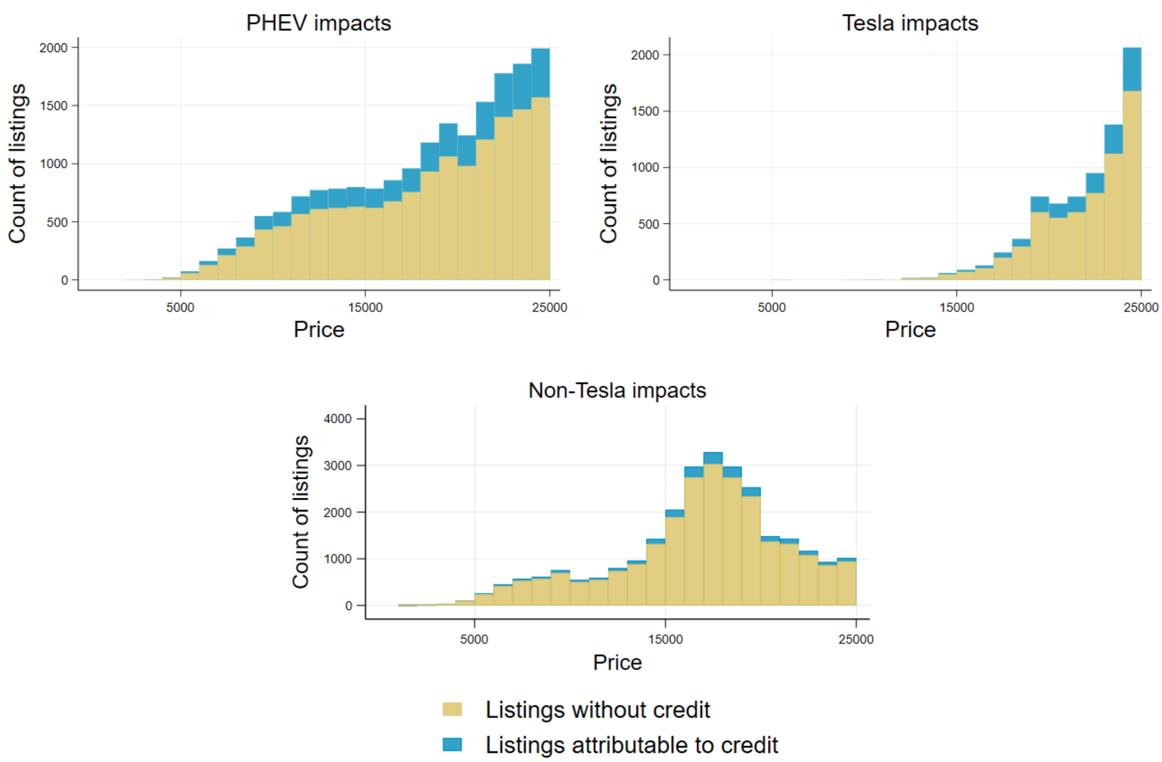
Moving to supply impacts, we can use the estimated elasticities in Table 9 to determine how many PHEV, Tesla, and non-Tesla BEV listings can be attributed to the implementation of the tax credit. Figure 4 illustrates the number of listings in $1,000 price bins for each group for age-eligible vehicles priced below $25,000. We present quantities for a counterfactual where the tax credit was never implemented (a 100% decrease in the credit) as well as the additional quantities attributable to the tax credit. These numbers are aggregated across all model years and months of the sample.

As can be seen, the model predicts that a non-insignificant number of vehicles were listed due to the policy. Across the three panels which cumulatively capture all eligible PEVs (by both price and age), we estimate an increase of 7,460 listings during the sample. That equates to an approximately 14% increase in listings over what would have occurred without the credit. Put differently, 86% of the used PEVs on the market that were at least 2 years old and priced below $25,000 would have been listed without the credit.

There is some heterogeneity acorss the groups though. PHEVs, which had the most elastic supply, contribute 53% of the listings that otherwise would not have been put on the market. Teslas experience large increases in listings between the $20,000 and $25,000 price points, but there is limited availability of these vehicles below $15,000. Finally, we see that non-Tesla vehicle listings primarily increased between the $15,000 and $20,000 price points.

[16] This calculation serves as an upper bound because not all vehicles will be purchased by individuals with qualifying incomes, sold at dealerships, etc.

Figure 4: Additional listings attributable to the tax credit



Notes: Figure depicts the difference in observed listings and predicted listings if the tax credit did not exist in each $1,000 price bin for the specified fuel type.

This is due to differences in the distribution of vehicle values. The tax credit appears to have increased listings across the price distribution, with the type of vehicle being offered dependent on the price.

Some prior studies have shown that subsidies for new PEVs can raise societal PEV adoption because subsidy passthrough raises prices—incentivizing producers to make and sell more PEVs—while also lowering prices for buyers. The mechanisms that would translate a *used* PEV subsidy into higher societal adoption are less direct. On the margin, receiving a higher price for a used PEV may incentivize some owners to sell their vehicle on the used market rather than scrapping the vehicle. We see some evidence of this here, but a majority of the additional listings are at price points that exceed scrap values. Increases in listings for used vehicles not on the scrappage margin do not directly impact penetration as these vehicles are and would continue to be on the road though. Additionally, a used PEV subsidy could incentivize purchases of new PEVs because the buyer will expect to receive a higher price, from subsidy passthrough, when they eventually attempt to resell the vehicle in the used market. The results of this section suggest that tax credits can shift the number of used vehicles listed, but their cumulative impact on societal PEV adoption requires further research.

VII Conclusion

Research on PEVs has largely revolved around the new vehicle market, but the used PEV market will become increasingly important as PEV technology matures. Our paper studies the incidence and impact of the Used Clean Vehicle Tax Credit—a policy offering up to a $4,000 subsidy for the purchase of a PEV vehicle priced under $25,000 and at least two model years old. The tax credit has the potential to both incentivize PEV adoption among populations that have historically not opted for PEVs and stabilize the market for current PEV owners. In addition to providing the first analysis of incentives for used PEVs, we importantly use up-to-date data on millions of vehicles across the entire US in a setting where data availability has historically lagged behind PEV technological progress.

We find that on average $0.49 of each dollar in credit value is passed through to the sellers of PEVs. The credit reduces the cost for buyers while also boosting the value of PEVs for sellers. We estimate substantial heterogeneity in this passthrough though. PHEV sellers capture the entirety of the credit, and Tesla sellers capture more than sellers of non-Tesla BEVs. We find that administrative changes to the tax credit that allowed buyers to immediately redeem the full value of the credit at the time of purchase—as opposed to it being a non-refundable credit filed with their taxes—reduced passthrough of the credit to PHEV sellers. This finding suggests that the administration of the credit can have important implications for its incidence. Finally, our supply elasticity estimates suggest that the credit increased the number of eligible listings by 14% during our sample. Our passthrough and supply elasticity estimates may also be applicable when evaluating policies that affect the new vehicle market as their impacts can trickle down into the used vehicle market.

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Appendix

Table A1 presents difference-in-differences estimates of credit passthrough to listing prices using alternative specifications to those presented in Table 2. Odd numbered columns include controls at the county level as opposed to the ZCTA level, do not include any spatial fixed effects, replace the model-by-model year fixed effects with separate model and model year fixed effects, and control for the electric range of the PEVs. Even numbered columns include ZCTA-level controls, model-by-model year fixed effects, and county fixed effects as opposed to spatial fixed effects at the ZCTA level used in the main analysis. Every regression controls for the odometer reading and its square, gasoline prices, electricity prices, and month fixed effects. Standard errors are clustered at the model-by-model year level.

We find that the magnitude of the passthrough estimates are larger in the odd-numbered columns where we include coarser control variables and fixed effects, but the interpretation of the results remain similar. When moving to the more granular controls in the even columns, we find nearly identical results to our main specifications (which use even more granular controls). We believe that these more granular controls help better satisfy the identifying assumptions and remove potential bias from omitted variables.

The price data available from Autotrader are asking prices, not actual sales prices. This discrepancy introduces some degree of measurement error into our analysis if buyers can haggle their way to a lower price. We hypothesize that this behavior would be especially important near the $25,000 threshold for tax credit eligibility. To examine the sensitivity of our results to this issue, Table A2 introduces a "fuzzy" threshold. Across the columns we provide both differences-in-differences and triple differences-in-differences estimates while increasing the eligibility threshold by $1,000. For example, we assume that vehicles with listing prices of $26,000 are eligible for the full $4,000 credit in columns 1 and 2, vehicles up to $27,000 are eligible in columns 3 and 4, and so on.

We find that the results do not vary substantially across specifications as this threshold

Table A1: Credit passthrough estimates: Alternative specifications

	(1)	(2)	(3)	(4)	(5)	(6)
	PEVs		BEVs		PHEVs	
Credit x Eligible MY	0.834***	0.501***	0.686***	0.471***	1.464***	1.260***
	(0.106)	(0.100)	(0.116)	(0.120)	(0.195)	(0.238)
Credit Amount	-1.836***	-1.376***	-1.668***	-1.346***	-2.311***	-2.014***
	(0.114)	(0.099)	(0.124)	(0.118)	(0.162)	(0.223)
Eligible MY	-1561.211***	-1390.327***	-1753.822***	-1587.461***	-987.386***	-888.787***
	(473.880)	(474.353)	(536.498)	(545.783)	(289.018)	(218.166)
Odometer	-0.127***	-0.124***	-0.123***	-0.122***	-0.135***	-0.129***
	(0.008)	(0.007)	(0.009)	(0.009)	(0.012)	(0.010)
Odometer^2	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Gas Price ($/gal)	339.829***	82.071	284.983***	213.471*	531.065***	-136.739
	(50.727)	(98.414)	(66.940)	(111.774)	(76.409)	(123.148)
Electricity Price (Cents/kWh)	-5.327	19.831	-1.786	2.419	-17.845***	52.983**
	(3.889)	(18.453)	(4.941)	(23.219)	(6.096)	(24.567)
Electric Range	4.429		42.775***		115.951***	
	(4.883)		(13.362)		(42.353)	
Population	-0.000***	0.001	-0.000***	0.001	-0.000***	0.000
	(0.000)	(0.001)	(0.000)	(0.002)	(0.000)	(0.001)
Median Income	-0.007***	-0.001	-0.010***	-0.001	-0.002	0.001
	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
Male Share	9321.472***	-598.846	14134.370***	-303.083	3945.755	-1174.054
	(2259.935)	(740.505)	(3346.608)	(950.061)	(2719.462)	(1100.315)
White Share	853.739***	641.563***	804.471**	886.196***	751.685**	316.933
	(275.680)	(160.916)	(386.146)	(221.837)	(313.535)	(207.713)
Car Commute Share	-1427.097***	-470.291	-1851.263***	-493.456	-89.741	-250.248
	(412.115)	(334.961)	(589.951)	(432.496)	(454.392)	(503.153)
Commute<15 Min. Share	895.913*	267.922	656.949	-407.986	1460.732**	1087.075**
	(484.795)	(377.706)	(684.912)	(488.482)	(641.523)	(502.718)
Commute>90 Min. Share	-7995.930***	2826.270**	-11097.886***	3467.450*	-2645.130	463.983
	(1538.088)	(1362.977)	(2043.002)	(1879.384)	(1956.711)	(1777.253)
Renter Share	1053.817**	340.889	872.009	641.199**	1387.208**	0.971
	(467.581)	(254.468)	(625.698)	(308.353)	(629.583)	(356.362)
Constant	30896.440***	35401.951***	18898.764***	34277.474***	29817.764***	36935.598***
	(1493.723)	(859.883)	(4000.422)	(1006.411)	(1840.157)	(1303.224)
Controls level	County	ZCTA	County	ZCTA	County	ZCTA
Model FE	Y	N	Y	N	Y	N
Model Year FE	Y	N	Y	N	Y	N
Model-by-Model Year FE	N	Y	N	Y	N	Y
Month FE	Y	Y	Y	Y	Y	Y
County FE	N	Y	N	Y	N	Y
R^2	0.899	0.925	0.889	0.911	0.927	0.955
N	152305	152454	101195	101126	51110	51186

Notes: Standard errors clustered at the model-by-model year level. Demographic controls are at the level specified. Sample includes stated PEVs priced under $50,000 with over 500 miles. Significance levels: $*: 10\%$ $**: 5\%$ $***: 1\%$.

is increased. We also note that the direction of change for the coefficients is not monotonic as the threshold is increased. These small differences and lack of a systematic trend as the threshold is increased suggests that any bias introduced by this measurement error is minor and localized.

Table A3 examines the sensitivity of the results to alternative sample restrictions. Our main analysis removes vehicles priced under $50,000 and those with fewer than 500 miles.

Table A2: Passthrough estimates: Fuzzy threshold

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable: Asking price	26k		27k		28k		29k	
PEV x Credit x Eligible MY		0.538***		0.549***		0.544***		0.530***
		(0.139)		(0.141)		(0.142)		(0.141)
Credit x Eligible MY	0.515***	0.021	0.518***	0.022	0.515***	0.028	0.507***	0.036
	(0.101)	(0.032)	(0.102)	(0.035)	(0.100)	(0.037)	(0.095)	(0.037)
Model-by-Model Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y	Y	Y	Y
ZCTA FE	Y	Y	Y	Y	Y	Y	Y	Y
R^2	0.936	0.914	0.937	0.916	0.939	0.918	0.941	0.920
N	152124	6786082	152124	6786082	152124	6786082	152124	6786082

Notes: Standard errors clustered at the model-by-model year level. Significance levels: $*$: 10% $**$: 5% $***$: 1%.

Columns 1 and 2 reduce the maximum allowed price to \$45,000 and \$40,000, respectively. Column 3 restricts the opposite side of the price distribution by imposing a \$15,000 minimum price. Columns 4 and 5 create "donut" restrictions near the \$25,000 credit threshold as an additional sensitivity analysis for manipulation around the credit threshold. Column 4 removes vehicles priced \$25,000–\$30,000 as these vehicles may suffer from contamination bias. As our data only captures the asking prices for vehicles, dealer pricing behavior could lead to vehicles on the high-price side of the threshold being impacted by treatment as well. Similarly, column 5 removes a symmetric window that encompasses both sides of the threshold from \$22,500–\$27,500. Columns 6 and 7 lower and raise the minimum number of miles restriction to 100 and 1,500 miles respectively.

We find that the coefficient estimates decrease in magnitude in columns 1 and 2 when the maximum price restriction is lowered. We also find that coefficient estimates increase in size when we remove the potentially contaminated vehicles in columns 4 and 5. We believe these patterns are consistent with a contamination bias where vehicles near the threshold are also "treated." Reducing the maximum price leads these contaminated control observations to hold a higher weight in the estimation, biasing the results downward. While our main estimates may suffer from this bias, it makes our estimates conservative. We find that raising the minimum price for inclusion in the sample or altering the minimum mileage requirements does not have a notable impact on the results.

Table A3: Credit passthrough estimates: Alternative sample restrictions

Dependent variable: Asking price	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Restriction:	<$45k	<$40k	>$15k	Remove $25k-$30k	Remove $22.5k-$27.5k	<100 miles	< 1500 miles
Credit x Eligible MY	0.429***	0.294***	0.520***	0.587***	0.632***	0.569***	0.505***
	(0.083)	(0.061)	(0.094)	(0.121)	(0.112)	(0.096)	(0.094)
Model-by-Model Year FE	Y	Y	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y	Y	Y
ZCTA FE	Y	Y	Y	Y	Y	Y	Y
R^2	0.934	0.933	0.915	0.950	0.942	0.933	0.935
N	138706	122462	139793	128452	128065	155254	149176

Notes: Standard errors clustered at the model-by-model year level. The base sample includes PEVs priced under $50,000 with over 500 miles with the modifications noted at the top of each column. Significance levels: $*$: 10% $**$: 5% $***$: 1%.

Table A4 provides alternative difference-in-differences and triple differences-in-differences models that replace the continuous credit variable with a discrete variable equal to one if the list price for the vehicle is below $25,000. These regressions compare observations above and below the price threshold as opposed to exploiting the continuous nature of the credit amount for identification. The estimates can be interpreted as the average increase in the asking price for vehicles eligible for the credit as opposed to the share of the credit passed through. The results are positive and statistically significant, similar to those in the main tables. The magnitude of the passthrough estimates is also very similar across specifications when we consider that many of the eligible vehicles receive the maximum potential credit of $4,000 (see Figure 3). For eligible MY PEVs that are priced below $25,000, the average credit amount is $3,844, and approximately 84% of those vehicles receive the full $4,000 credit. That means that the majority of the identification in the continuous and discrete credit specifications comes from the same source. As a result, we see passthrough estimates around $2,000 for PEVs and BEVs (equivalent to the approximately 0.5 estimate in Tables 2 and 4) and estimates that are not statistically different than $4,000 for PHEVs (equivalent to the full passthrough estimates in Tables 2 and 4).

Table A5 explores heterogeneity in passthrough across vehicles of different ages. We examine 2018 and older model years in column 1 and 2019 and newer model years in column 2. Each column includes age-ineligible (newer) vehicles in the control group. For this het-

Table A4: Passthrough estimates using discrete tax credit variable

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable: Asking price	PEVs	BEVs	PHEVs	PEVs	BEVs	PHEVs
PEV x Credit x Eligible MY				1995.754***	1988.421***	4470.472***
				(566.842)	(541.942)	(741.627)
Credit x Eligible MY	1908.130***	1891.565***	4920.425***	-221.905*	-219.175*	-225.319*
	(370.779)	(443.390)	(1010.064)	(126.468)	(126.203)	(125.909)
Model-by-Model Year FE	Y	Y	Y	Y	Y	Y
Model FE	Y	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y	Y
ZCTA FE	0.935	0.924	0.964	0.914	0.914	0.914
R^2	152124	100758	50789	6786082	6734757	6684834

Notes: Standard errors clustered at the model-by-model year level. Significance levels: $*$: 10% $**$: 5% $***$: 1%.

erogeneity analysis, we are only able to estimate triple differences-in-differences models due to the loss of identifying variation from the age group restrictions. Simple differences-in-differences models in this setting would rely entirely on identifying variation from the 2022 MY vehicles becoming eligible for the credit. We find some difference in passthrough across the groups. Older vehicles have more credit passthrough to sellers, with newer vehicles having an offsetting change in the opposite direction. These differences are smaller than those we see across other dimensions though (e.g., fuel type, manufacturer, or range).

Table A5: Heterogeneity in passthrough by vehicle age

	(1)	(2)
Dependent variable: Asking price	2018 and Older MY	2019 and Newer MY
PEV x Credit x Eligible MY	0.596***	0.423***
	(0.143)	(0.138)
Model-by-Model Year FE	Y	Y
Month FE	Y	Y
ZCTA FE	Y	Y
R^2	0.924	0.877
N	3825140	4259168

Notes: Standard errors clustered at the model-by-model year level. Controls for gas price, electricity price, odometer, and odometer^2 included. Sample includes stated PEVs priced under $50,000 with over 500 miles. Significance levels: $*$: 10% $**$: 5% $***$: 1%.

Table A6 limits the supply elasticity sample to the first appearance of each vehicle. In other words, we remove multiple appearances of a single vehicle. We do this because we observe the vehicles listed at one point in the month and do not know with certainty how long they stay on the market. Therefore, there may be a simultaneous increase in the quantity supplied and quantity demanded for these vehicles in such a way that we would observe no difference in the total number of listings. We use only these flows of newly listed vehicles here. We find slightly smaller but qualitatively similar results to our main estimates, suggesting that this is not a major concern.

Table A6: Supply elasticity estimates: First appearance of vehicle

	(1)	(2)	(3)	(4)	(5)
Dependent variable: Count of listings	PEVs	BEVs	PHEVs	Teslas	Non-Tesla BEVs
PEV x Credit x Eligible MY	-0.007	-0.042*	0.132***	0.155***	0.070***
	(0.021)	(0.024)	(0.027)	(0.047)	(0.016)
Model Year FE	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y
Price Bin FE	Y	Y	Y	Y	Y
N	9100	9100	9100	9100	9100

Notes: Dependent variable is the count of listings of the specified drivetrain or ICEVs in a price bucket for a model year and month. Each vehicle is only included in the data in the first month it is observed. of each vehicle Coefficients are marginal effects estimated using Poisson Pseudo Maximum Likelihood calculated as elasticities. Standard errors clustered at the price bin level. Significance levels: $*$: 10% $**$: 5% $***$: 1%.

In Table A7, we replace the price bin fixed effects used in our main supply elasticity estimation with: (1) no price controls, (2) linear price controls, or (3) quadratic price controls. We provide estimates for each PEV type in separate panels. We find that the magnitude of the supply elasticity falls as the price controls become more granular, as we would expect if there were a simultaneity concern between prices and quantity. This result suggests that the price bin fixed effects—the most granular form of control—are the preferred and most conservative strategy.

Appendix Table A8 varies the credit threshold amount as was done with the passthrough estimates in Appendix Table A2 to examine how listing prices as opposed to sales prices may impact the results. This robustness test allows for vehicles on the high-side border of the threshold to be treated (i.e., the potentially contaminated vehicles). We find qualitatively

Table A7: Supply elasticity estimates: Alternative specifications

	(1)	(2)	(3)
Dependent variable: Count of listings			
***Panel A*: PEVs**			
PEV x Credit x Eligible MY	0.022	0.016	0.011
	(0.024)	(0.021)	(0.020)
***Panel B*: BEVs**			
BEV x Credit x Eligible MY	-0.032	-0.032	-0.031
	(0.024)	(0.022)	(0.020)
***Panel C*: PHEVs**			
PHEV x Credit x Eligible MY	0.324***	0.262***	0.220***
	(0.088)	(0.050)	(0.033)
***Panel D*: Teslas**			
Tesla x Credit x Eligible MY	0.435**	0.294***	0.206***
	(0.211)	(0.104)	(0.058)
***Panel E*: Non-Teslas**			
Non-Tesla x Credit x Eligible MY	0.091***	0.085***	0.079***
	(0.017)	(0.015)	(0.014)
Model Year FE	Y	Y	Y
Month FE	Y	Y	Y
Linear Price	N	Y	N
Quadratic Price	N	N	Y
N	9100	9100	9100

Notes: Dependent variable is the count of either PEV or ICEV listings in a price bucket for a model year and month. Each panel shows results for a separate PEV type. The degree of price controls varies across specifications. Coefficients are marginal effects estimated using Poisson Pseudo Maximum Likelihood calculated as elasticities. Standard errors clustered at the price bin level. Significance levels: $*$: 10% $**$: 5% $***$: 1%.

similar results with the exception of Panel A, which estimates a small and significant elasticity for all PEVs, and the Tesla estimates in Panel D lose statistical significance.

Table A8: Supply elasticity estimates: Fuzzy credit

	(1)	(2)	(3)	(4)	(5)
Dependent variable: Count of listings	26k	27k	28k	29k	30k
***Panel A*: PEVs**					
PEV x Credit x Eligible MY	0.025	0.040*	0.055**	0.065***	0.078***
	(0.021)	(0.022)	(0.022)	(0.022)	(0.022)
***Panel B*: BEVs**					
BEV x Credit x Eligible MY	-0.019	-0.008	0.004	0.016	0.033
	(0.021)	(0.022)	(0.024)	(0.024)	(0.025)
***Panel C*: PHEVs**					
PHEV x Credit x Eligible MY	0.223***	0.245***	0.266***	0.268***	0.265***
	(0.027)	(0.025)	(0.024)	(0.026)	(0.030)
***Panel D*: Teslas**					
Tesla x Credit x Eligible MY	0.151***	0.099	0.076	0.064	0.079
	(0.053)	(0.061)	(0.056)	(0.053)	(0.050)
***Panel E*: Non-Teslas**					
Non-Tesla x Credit x Eligible MY	0.089***	0.098***	0.108***	0.115***	0.124***
	(0.016)	(0.018)	(0.019)	(0.020)	(0.021)
Model Year FE	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y
Price Bin FE	Y	Y	Y	Y	Y
N	9100	9100	9100	9100	9100

Notes: Dependent variable is the count of listings of the specified PEV type or ICEVs in a price bucket for a model year and month. Each panel shows results for a separate PEV type. The credit threshold is increased from the actual $25,000 limit by $1,000 in each column to explore the sensitivity of the results. Coefficients are marginal effects estimated using Poisson Pseudo Maximum Likelihood calculated as elasticities. Standard errors clustered at the price bin level. Significance levels: $*: 10\%$ $**: 5\%$ $***: 1\%$.