

Household Expenditures & Fuel Efficient Vehicles

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Abstract

Fuel price fluctuations, coupled with increasing transportation costs YoY, have resulted in increased demand for hybrid or electric powered vehicles. These vehicles promise savings through decreased reliance on gasoline, leading to smaller day-to-day expenses and hedging adopters from macroeconomic fuel shocks. This paper aims to analyze the extent of these claims by answering the question of if fuel-efficient vehicle adoption results in reduced vehicle expenditures and increased discretionary spending through savings reallocation. I utilize a U.S.-wide, household-level, rotating panel dataset constructed using Consumer Expenditure Survey data from 2013-2023. I employ matching & reweighting methods to construct treatment-specific counterfactuals, then use WLS and DiD to estimate adoption effects and hedging responses. Overall, my findings suggest that fuel-efficient vehicles provide significant operational cost savings, but substantial acquisitional costs create a barrier to entry that delays welfare gains until financing of the vehicle concludes. Shock response hedging exists for hybrids but remains inconclusive for EVs. Overall, future policy should thus be targeted at increasing adoption through reducing acquisitional barriers.

1. Introduction

Rising concerns over the environment, economic fluctuations, and increasing household costs have resulted in heavier consideration of fuel-efficient vehicles, (like hybrid and electric cars). The justification is straightforward: a more fuel-efficient vehicle spends less on gasoline, leaving a household less exposed to price shocks, and generating savings to spend. Additionally, these vehicles are optimized for efficiency, which leads to longevity improvements & potential

savings in other categories. Considering that transportation is the second-highest cost for American households, accounting for 17% of a household's expenditure in 2023 & increasing YoY¹, any reductions in this cost category would be beneficial for households. Savings in this category allows households to adjust their internal budgets and meaningfully improve household welfare. Even modest savings can allow families to be slightly more flexible with personal care, food, or entertainment budgeting. However, these fuel efficient vehicles are more than just instant cost savers that should be purchased by every American household. A number of heavy potential trade-offs can occur by adopting these vehicles that obscures the true effects of these vehicles on expenditures.

Fuel-efficient vehicles achieve efficiency through a collection of optimizations. These vehicles augment (or replace) the internal engine with a battery that can more efficiently power the vehicle, increasing longevity, power, and support. Regenerative braking systems can re-capture kinetic energy to recharge the battery to provide increased range and reduce wear on the brakes². In combination with optimized aerodynamics and potentially reduced maintenance costs from previous modifications, fuel-efficient vehicles are poised as an easy way to cut back on costs. However, there are significant drawbacks that question these cost-saving benefits. First and foremost is a significantly higher purchase price, especially when considering electric vehicles. The internal batteries make fuel-efficient vehicles heavier and are extremely expensive to replace if damaged. Complex electrical systems to manage the battery present more failure points and often require specialized maintenance by certified repair technicians. These issues lead to potentially higher registration and insurance costs and all add up to a bigger price tag.

¹ "Consumer Expenditures--2023 - 2023 A01 Results," U.S. Bureau of Labor Statistics, September 25, 2024, [https://www.bls.gov/news.release/cesan.nr0.htm#:~:text=Other%20components%20of%20spending%20include:%200*%20**Housing**%20experienced%20the%20largest%20increase%20in%20income%20\(+9.9%25\)](https://www.bls.gov/news.release/cesan.nr0.htm#:~:text=Other%20components%20of%20spending%20include:%200*%20**Housing**%20experienced%20the%20largest%20increase%20in%20income%20(+9.9%25).).

² Regenerative braking systems allow the battery to re-capture lost charge by using the internal electric motor as a generator to capture kinetic energy during deceleration of the vehicle.

Thus, several questions emerge: does adoption of these fuel-efficient vehicles generate significant savings for households? What trade-offs accompany the potential benefits? More importantly, what is the household discretionary response to adoption of these vehicles?

Existing fuel-efficient vehicle research focuses on drivers of adoption and market segmentation, which motivates cost analysis of these vehicles. Notably, hybrid and EV markets seem to be relatively separated from one another. A study by Xing et al. (2021) finds that electric vehicles draw from a separate pool of adopters through a discrete choice model, mainly replacing gasoline vehicles, not hybrid vehicles. This indicates that hybrid and electric vehicle adopters are a part of two separate markets under the fuel-efficient space, prompting an analysis of the two separately. A paper focusing on adoption drivers by Bushnell et al. (2022), through panel fixed effects, found that gasoline prices are a significantly strong driver of electric vehicle demand. As gasoline prices have begun to fluctuate through recent years, more demand is being steadily generated toward EVs in specific. While the markets are separated, price volatility continues to drive demand toward fuel-efficiency as a whole.

A natural extension is questioning if savings truly manifest upon adoption. Total cost analysis studies have been conducted on hybrids and EVs, and all generally arrive at the same conclusion: these vehicles have drawbacks to their operational savings. A literature survey by Rapson & Muehlegger (2023) analyzed existing studies on total cost of ownership (TCO) for electric vehicles and concluded that more cost-saving channels exist other than fuel, noting that maintenance costs for EVs are roughly 60% of gasoline vehicles. In specific, Breetz & Salon (2018) conducted a study analyzing the TCO of electric vehicles across 14 U.S. cities. The study concluded that while fuel savings significantly manifest, they are often swamped by increased acquisitional costs & depreciation on the vehicles. A similar study by Lebeau et al. (2013)

analyzed TCO for EVs with a suite of cost categories, and found that EVs are only cost-effective when confined to the luxury vehicle market. Emerging research like Agarwal et al. (2025) analyzed expenditure patterns in discretionary categories through proximity toward electric vehicle charging infrastructure in Singapore. The study found that households with greater exposure to vehicle chargers experience increases in discretionary category spending, with hybrids experiencing bigger trade-off effects than electric vehicles.

Thus, prior work focuses on adoption incentives for fuel-efficient vehicles, markets for fuel-efficient vehicles, and total cost of ownership analysis in city-specific studies. While emerging work like Agarwal et al. (2025) has begun to link fuel-efficient exposure to discretionary spending, studies often focus on narrow markets like specific collections of US cities or international spaces. Additionally, research often focuses primarily on electric vehicles, despite hybrids being a more mature market. Most importantly, existing literature does not formally extend savings analysis upon adoption of fuel-efficient vehicles toward discretionary expenditure patterns. My study seeks to address these gaps by analyzing both hybrid and electric vehicles separately across operational and acquisitional cost categories. Using cross-sectional analysis, I examine household-level expenditure responses to determine adoption effects of these fuel-efficient vehicles on the average American household.

To access granular expenditure data across the United States, the primary data used for this study is sourced from the Consumer Expenditure Survey, a rotating panel conducted by the Bureau of Labor Statistics (BLS CEX). Household-level expenditure data from 2013 through 2023 is broken down into specific cost categories like fuel, maintenance, discretionary, etc. Supplementary data such as gasoline prices, Petroleum Administration Defense District (PADD), and 2023Q4 CPI data for adjustment are retrieved from the Energy Information Administration

(EIA) and Federal Reserve of Economic Data (FRED). The sample is restricted to single-vehicle households who are financing their vehicles and have complete expenditure data.

I utilize this dataset to analyze fuel-efficient vehicle markets & construct treatment-specific counterfactuals to analyze adoption effects on households. Propensity Score Matching (PSM) common support analysis is used to test overlap between hybrid and EV markets. High AUC/c-statistic values motivates the usage of entropy balancing to create a treatment-specific counterfactual to enable causal inference between groups. The entropic weights produced underpin all expenditure comparisons for the analysis. Household clustered, year-quarter fixed effects Weighted Least Squares (WLS) is used to calculate expenditure responses to owning fuel-efficient vehicles across cost categories in the full sample, including luxury and economy market subsamples. Additionally, to measure hedging and discretionary shock effects, entropic weights are used for Difference-in-Difference (DiD) analysis of the 2022 fuel price shock.

Overall, results align with existing literature on fuel-efficient vehicles, and challenge the common perception that these vehicles are straightforward cost-savers. Adopting households experience significant savings in fuel with increased acquisitional costs like quarterly payments offsetting savings in the short-term. Electric vehicles, in particular, experience steep increases in acquisitional, electricity, and administrative costs, but save significant amounts on fuel and maintenance. Households burdened with acquisitional costs (like quarterly payments) do not significantly increase discretionary spending across most categories. However, in the long term, when financing has concluded, adopters are able to take advantage of perceived savings effects due to feeling less pressured at the gasoline pump day-to-day. This results in increased discretionary spending across all major categories. Electric vehicles diverge from this

significantly, as the significantly more burdensome acquisitional payments potentially cause longer-lasting budget constraints that prevent significant discretionary increases. Both vehicles improve cost-competitiveness within their respective market segments (economy for hybrids, luxury for EVs), and enjoy significantly reduced acquisitional burdens and increased operational savings. Shock analysis revealed that hybrids roughly double their fuel savings during shocks, while suggesting that shock-induced constraints may reverse discretionary gains. Disappointingly, EV shock analysis was inconclusive due to parallel trends failures between groups.

These findings suggest that fuel-efficient vehicles are a wash in the short-run due to acquisitional costs, while delivering on their promised operational savings in the long run. These vehicles are able to significantly alleviate pressure from frequent expenditures like fuel and maintenance costs. However, the barrier to entry for these vehicles prevents savings from manifesting earlier, and even prevents households from entering the market in the first place. Future policy should aim to alleviate the short-term pressure placed on household budgets from acquisitional burdens to enable earlier realization of savings benefits, and allow more households to enter the fuel-efficient market.

2. Data & Setup

For this analysis, the goal is a household-quarter level rotating panel dataset, with interview period cohorts being analyzed cross-sectionally in aggregate. This dataset will be used to examine the effect of fuel-efficient vehicle adoption on household expenditures. The data should only contain interview respondents who are, 1) financing their vehicles, 2) own only one vehicle, and 3) have consistent information (no missing variable entries). The time period of the

study will be from 2013-2023. Thus, various files of the Consumer Expenditure Survey (CEX), conducted by the Bureau of Labor Statistics (BLS), need to be synthesized into one dataset. Additionally, all expenditures need to be adjusted to 2023Q4 dollars through Federal Reserve Economic Data (FRED), and merged with regional gasoline price data from the Environmental Information Agency (EIA). Specific dataset construction details are provided in the **Appendix**.

2.1. Input Files

To account for the rotating panel structure of the CEX, all regression standard errors are clustered at the household level. Household demographics and core spending on categories like food away from home and vehicle maintenance spending are taken from the FMLI files. Specific vehicle-related expenditures such as amount spent on tire maintenance and specific mechanical components are taken from the MTBI files and merged into cost categories. Vehicle ownership characteristics like brand, car type, and purchase information are drawn from the OVB files. From 2017Q2 onward, VOT files are used to isolate electric vehicle expenditures and improve measurement of operating costs. Instead of a state or regional level variable, Petroleum Administration for Defense Districts (PADDs) are used to be able to distinguish between district-level gasoline price differences. Gasoline price data and PADD data is taken from the Energy Information Administration (EIA).

2.2. Sample Restrictions & Limitations

The sample is restricted to households that merge consistently across relevant CEX files, and only single-vehicle households. Limiting the study to single vehicle households drops a majority of households from the study, which is unfortunate due to the limited number of

fuel-efficient vehicle adopters in the United States. However, the strength of this approach is being able to directly isolate the treatment effect of adoption of a fuel-efficient vehicle on the household budget. While a multi-vehicle household lens has more observational power, there is a lot of complex interplay between vehicle purpose, choice, and usage that complicates interpretation of adoption effects. Extensions of this study should strongly consider using a multi-vehicle dataset. All monetary values are converted into 2023Q4 dollars using CPI data from Federal Reserve Economic Data (FRED). Additionally, all vehicle purchase data is adjusted according to FRED data on used and new car markets. Merging all four CEX files results in a rotating panel dataset with 134,271 household-quarter level observations. Restriction to single vehicle households cuts the sample down to 83,428 observations. Cleaning the data and only including complete observations, the final count is 66,949, a significant decrease, but enough to conduct a robust study.

Vehicle ownership and purchase information comes from the owned-vehicle section of the interview survey (OVB). Leased vehicles are recorded in separate CEX files (LSD) and are not included in this OVB-based study. Electric vehicles in particular have extreme leasing incentives that vary by dealership and automaker to entice buyers into trying out an electric vehicle for a short timeframe. As such, true savings by adopting these leased vehicles are generally more difficult to interpret, and are excluded from this study. Additionally, when comparing purchasing costs, I restrict to those who actively participated in the market (i.e, purchased a vehicle during their interview period) to better capture actual differences in payment burdens across vehicle types. Financing a vehicle provides a significant burden on a households' expenditures, thus, discretionary spending analysis is separated on financing status. Within regressions, the sample size is cut down to around 20,000 for each purchasing category.

With electric vehicles only recently gaining public attention, coupled with surveys like the CEX not formally tracking EV households until 2017Q2, there are only 135 EV observations in the dataset. While lackluster, this more so reflects adoption patterns of these fuel-efficient vehicles. Hybrids, which have been tracked since the late 2000s, only have 1,348 adopters in the dataset. Despite this, a rich amount of control observations in the final dataset (64,991), coupled with entropy balancing, allows us to conduct a robust, causal examination of the effects of fuel-efficient vehicle adoption on household expenditures. It should be noted that while adequate statistical power is present cross-sectionally, per-quarter analysis is constrained due to the limited number of treated households per-quarter. Full dataset sample details are included in the **Appendix**.

2.3. Specialized Variables

Finally, specific variables are constructed to aid analyses and account for missing information in the CEX. Gasoline usage quartile is used as a proxy for driving habits and mileage, and is constructed by taking lagged real gasoline expenditure divided by lagged real gasoline prices to split households into quartiles. Vehicle age and recent purchase indicators are derived from vehicle purchase year to fairly draw comparisons between households with new or old vehicles. Brand type measures whether or not a vehicle is an economy, mid-range, or luxury car, based on vehicle make and comparing average purchase prices of vehicles within the sample. This allows sample restriction to test where fuel-efficient vehicles are most competitive. Vehicle cost categories are constructed for the following: total, fuel, maintenance, administrative (insurance, registration), and decomposed acquisition costs (payments, downpayment, net price). Similarly, cost categories for discretionary expenditures are as follows: total, food away from

home, vacations, entertainment, and personal care costs. Due to the more volatile and personally influenced nature of discretionary spending, the outcomes are winsorized at the 1st & 99th percentile to reduce outlier impact on averages³. All outcome variables are either quarterly in nature or adjusted to be quarterly for ease of interpretation excluding one-time expenditures like downpayment and net purchase price. Summary statistics for key variables between household vehicle types are as follows:

Table 1: Summary Statistics Sorted by Fuel Type

³ Winsorizing is a method to reduce extreme outliers, which are more present in personal discretionary spending, where a single large vacation can easily skew results, especially in quarters where treated observations are limited. Rather than deleting outliers outright, these observations have their values replaced with the value of the 99th percentile (meaning they are essentially “capped” at the 99th percentile) to reduce their impact on the overall average.

	Vehicle Fuel Type		
	Gasoline	Hybrid	Electric
N	64,991 (97.8%)	1,348 (2.0%)	135 (0.2%)
Individual Level Characteristics			
After-Tax Income	52,017 (48536.53)	74,801 (65565.04)	148,435 (107281.82)
Age	53 (18.73)	55 (18.48)	47 (16.40)
Family Size	2 (1.30)	2 (1.03)	2 (1.08)
Years in Education	13 (1.78)	15 (1.41)	15 (1.54)
Homeowner Status			
0 (<i>Renter</i>)	30,237 (46.5%)	560 (41.5%)	36 (26.7%)
1 (<i>Owner/Mortgage</i>)	34,754 (53.5%)	788 (58.5%)	99 (73.3%)
Urban Status			
0 (<i>Rural</i>)	838 (1.3%)	0 (0.0%)	0 (0.0%)
1 (<i>Urban</i>)	64,153 (98.7%)	1,348 (100.0%)	135 (100.0%)
Vehicle Specific Characteristics			
Vehicle Age (years)	5 (4.91)	5 (3.90)	2 (1.72)
Luxury Vehicle Status			
0 (<i>Non-luxury</i>)	61,407 (94.5%)	1,255 (93.1%)	28 (20.7%)
1 (<i>Luxury</i>)	3,584 (5.5%)	93 (6.9%)	107 (79.3%)
Vehicle Body Type			
0 (<i>SUV/Truck</i>)	28,541 (43.9%)	269 (20.0%)	20 (14.8%)
1 (<i>Sedan/Coupe</i>)	36,450 (56.1%)	1,079 (80.0%)	115 (85.2%)
Gas Usage Quartile			
Low	8,593 (13.2%)	168 (12.5%)	----
Med-Low	38,538 (59.3%)	860 (63.8%)	----
Med-High	8,822 (13.6%)	204 (15.1%)	----
High	9,038 (13.9%)	116 (8.6%)	----
Average Cost Characteristics			
Operating Costs	366 (548.94)	332 (516.31)	409 (620.69)
Discretionary Costs	586 (1394.43)	1,032 (2343.05)	1,682 (3474.51)
Net Purchase Price	7,048 (13478.75)	10,139 (17228.56)	27,309 (34004.83)
Continuous Variables reported as Mean (SD).			
Binary Variables reported as N (%).			

Notes: Summary statistics for key dataset variables are categorized by vehicle fuel type post data cleaning. Gas usage quartiles are unavailable for EVs since they cannot be organized into quartiles due to not spending on gasoline. There are distinct differences in individual level characteristics, vehicle specific characteristics, and cost characteristics across all groups. These differences would introduce bias in typical regressions.

3. Empirical Strategy

Households with gasoline vehicles are fundamentally different from households with a fuel-efficient vehicle, as shown in **Table 1**. Income, regional, and personal differences skew spending and driving choices, which would result in biased estimates of the effects of fuel-efficient vehicles. The goal then is to assess the state of the treated and control groups, and reduce the bias present between the groups to enable causal inference of adoption effects by

using matching methods. I assess common support between markets and test overlap via Propensity Score Matching (PSM). Furthermore, I utilize entropy balancing and weighted least squares (WLS) to match covariate moments between the gasoline counterfactual and separate hybrid and electric vehicle households. This allows me to analyze spending differences between gasoline and fuel-efficient vehicles in different markets. The balancing additionally serves as the foundation for a weighted Difference-in-Differences (DiD) to analyze hedging effects during the 2022 gasoline shock.

3.1. Propensity Score Matching Assessment

To assess common overlap between fuel-efficient vehicle households and gasoline households, I utilize a one-nearest-neighbor logistic PSM. The main metric of measurement is common support / AUC. The more overlap a treatment household has with control households, the more comparable the two groups are. The logistic model has demographic and limited vehicle preference choices (i.e, size of vehicle, new/used status) to ensure the model is not overly restrictive, as it is trying to assess broad overlap between the two groups. The logit is then:

$$(1) \log \frac{P(X=treatment)}{1-P(X=treatment)} = \beta_0 + \beta Controls_{it}$$

where we estimate the probability of adoption of a hybrid or electric vehicle based on our observed covariates. With the results from the logistic regression, I test the Area Under the Curve (AUC/C-statistic), a measure of how well the logistic model can predict a treated observation based on observable characteristics. A higher AUC implies that the model can very accurately separate a treated observation from a control observation, indicating there is very little overlap between both groups among the covariates included. An AUC exceeding 0.7 indicates limited

overlap between treatment groups, highlighted by Stürmer et al. (2021). The full logistic model is provided in the **Appendix**.

3.2. Entropy Balancing Strategies

Entropy balancing is an alternative weighting approach that will serve as the foundation for this paper, due to the fragmented nature of the fuel-efficient vehicle market. A study by Matsouaka & Zhou (2020) indicate that limited overlap in propensity score distributions and violations of the positivity assumption⁴ leads to unstable estimators via PSM. The study concluded that alternative methods like entropic weights consistently outperform PSM estimation when under limited overlap constraints, justifying its use in this scenario. Entropy balancing is a data preprocessing technique that assigns unique weights to individual control observations. As noted by Hainmueller (2012), other propensity score methods first estimate treatment probability and derive weights and balance as a result. Entropy balancing directly incorporates covariate balance as a constraint within its optimization problem, whilst keeping weights as uniform as possible. Thus, weights are created such that a counterfactual that matches the treated group on covariate moments, with as little outliers as possible, is created. In this paper, entropy balancing is implemented separately for hybrid and EV household analyses due to inherent differences between adopters. I balance on three covariate moments (mean, variance, skewness) to: 1) account for high amounts of variation between households and outliers present within the treatment groups, and 2) account for highly skewed distributions of income and

⁴ The positivity assumption in Propensity Score Matching assumes that every observation has a non-zero and non-one probability of receiving treatment across observable covariates. If observations are consistently clustered around very little possibility of treatment (near zero) and very high probability of treatment (near one), then there is little overlap (“common support”) resulting in causal estimators becoming unreliable.

spending variables within treated groups. The weights created are inputted into a Weighted Least Squares (WLS) model.

The set of covariates used for balancing (and for regression) include characteristics that affect spending patterns. Vehicle specific characteristics include vehicle age, new vs. used status, and vehicle body type. Household level characteristics included are income, age, education, race, family size, and housing status. Additionally, to capture specific regional and behavioral differences that might affect spending, PADD (region), gas usage quartile, and vehicle luxury status are included. The same set of covariates is used for EV analyses, with the exception of gas usage quartile, as it cannot be constructed from gasoline usage data due to EVs not purchasing gasoline. Again, due to the fact that miles driven is not recorded in the CEX, residual differences in driving intensity are now an unobservable characteristic. This limitation is a motivation for the luxury-segment comparisons, where vehicle usage and budgets are more comparable, but this should be noted as a drawback for the EV analyses.

This model additionally reuses the covariates to take advantage of the “double robustness” property of entropically balanced regressions indicated by Zhao & Percival (2016)⁵. The general WLS framework for this paper is then:

$$(2) y_{it} = \beta_0 + \beta_1 treatment_{it} + \beta Controls_{it} + \Pi_t + e$$

where y_{it} represents the outcomes like discretionary or vehicle related spending. *treatment* is specific to either hybrids or EVs depending on the model, *Controls* includes the full set of covariates, and Π_t represents year-quarter fixed effects to absorb time variant shifts. Electricity spending captured in the household utility bill is utilized as an additional outcome variable in EV

⁵ The double robustness property of entropically balanced models states that if either the matching model or the outcome regression model is correctly specified, the estimators are statistically correct. If either the covariate set used to balance the treatment and control groups or the covariate set used to create estimators with those weights are correctly specified, then the model is robust.

analyses to further trace costs. Discretionary outcome WLS regressions are restricted based on whether or not the vehicle is currently facing quarterly payments to capture the effect of payment burdens on savings reallocation. The full WLS & entropy models are provided in the **Appendix**.

To further assess fuel-efficient vehicle performance in different market structures, the sample is adjusted to only include vehicles of certain types. As an extension of the electric vehicle analysis, I restrict the sample to include only “luxury” tier vehicles to capture EV performance within higher cost markets. Similarly, I extend the hybrid vehicle analysis by restricting to only “economy” vehicles to test costs within low cost markets. The entropic WLS models are unchanged besides these restrictions.

3.3. Entropically Weighted Difference-in-Differences

To evaluate whether fuel-efficient vehicles hedge households against gasoline price shocks, and to gauge additional savings after shocks, I use an entropy-weighted, time-fixed effects Difference-in-Differences (DiD) model around the 2022 gasoline price spike. Similar to the WLS model, the DiD model will use weights constructed by the entropy balancing model and utilize the double robustness property of entropic weights. The period before 2016Q1 is excluded due to the oil price crash in 2014-2015, which shocked fuel prices and resulted in extreme volatility. This is to allow for stable pre-trends to be established for the DiD model, which is:

$$(3) \ y_{it} = \beta_0 + \beta_1 treatment + \beta_2 post2022 + \beta_3 (treatment \times post2022) + \beta Controls_{it} + \Pi_t + e$$

where y_{it} represents the fuel expenditure outcome, *treatment* represents either hybrids or EVs depending on the model, and *post2022* represents the post period after the shock. The full DiD framework is presented in the **Appendix**.

3.4. Robustness Checks

Finally, as robustness checks, all models are re-run with alternative weighting schemes and differing methodologies to ensure results are consistent with bias-reduction effects. Entropically weighted WLS models are validated through three main methods, and one supplementary method. The first is reduced controls, where only demographic covariates (income, housing status, marital status, etc.) are used for weighting estimation. This is used to test if the results are dependent on the vehicle-specific set of controls. The second is unweighted OLS, where instead of using entropy balancing weights, a fixed-effects, clustered OLS model with the full suite of covariates is used to test if entropy balancing is adjusting outcomes significantly by accounting for observable imbalance. The third method is falsification, where the full entropy-weighted WLS model is tested on placebo outcomes (like amount owed on mortgage and medical expenses) to ensure that the weighted counterfactual and treatment groups do not significantly differ on unrelated categories. The supplementary check is a comparison of within-household switchers and their means on spending categories before and after switching to a fuel-efficient vehicle from a gasoline vehicle (and vice-versa). These are limited in nature, as households are only interviewed for four quarters, leaving very few who switched from a gasoline to a fuel-efficient vehicle in the middle of their interview. However, enough switchers exist to use effects as directional / real-world tests of the main results. All robustness check specifications are listed in the **Appendix**.

4. Results

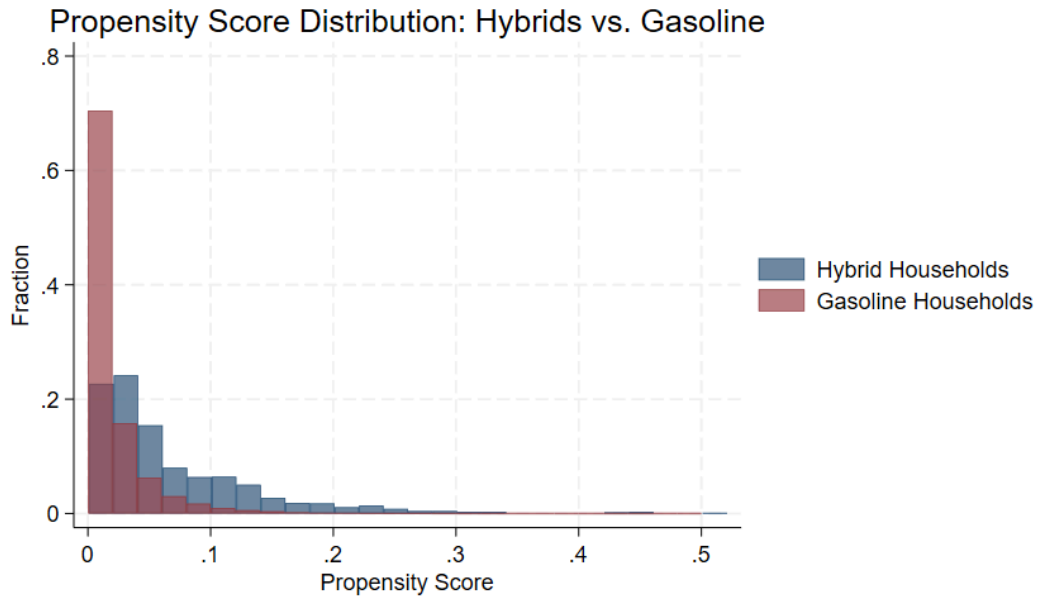
Overall, results indicate that fuel-efficient vehicle adopters are distinctly different from the gasoline vehicle market. Electric vehicle adopters are particularly separated from the wider

vehicle market, even being very distinct from hybrid adopters. This limited overlap justifies the use of entropy balancing over PSM in this scenario, which is utilized to determine causal effects of adoption on expenditures. Results reveal that hybrid vehicles households derive significant savings from fuel costs, but pay a considerable purchase premium (that lessens in strictly economy-only vehicle markets, resulting in more competitiveness). Regardless, hybrid households experience significant increases in discretionary spending across all categories when not burdened by acquisitional payments. Hybrid households additionally experience significant hedging during fuel shocks & suggest reductions in discretionary spend. Similarly, EV households find significant savings in operational costs such as fuel and maintenance, but experience heavy increases in acquisitional costs (with the purchase premium disappearing in the luxury market). Despite this, EV households do not significantly increase discretionary spending across most categories, even when the vehicle is paid off. Additionally, EV household hedging remained inconclusive.

4.1. Results of Market Assessment via Propensity Score Matching

Propensity score matching and common support analysis revealed distinct differences between gasoline households and adopters of fuel-efficient vehicles. Electric vehicle adopting households prove to be extremely distinct from the rest of the market, with hybrids having significantly more overlap with gasoline households. In totality, results justify the usage of alternative weighting specifications like entropy balancing.

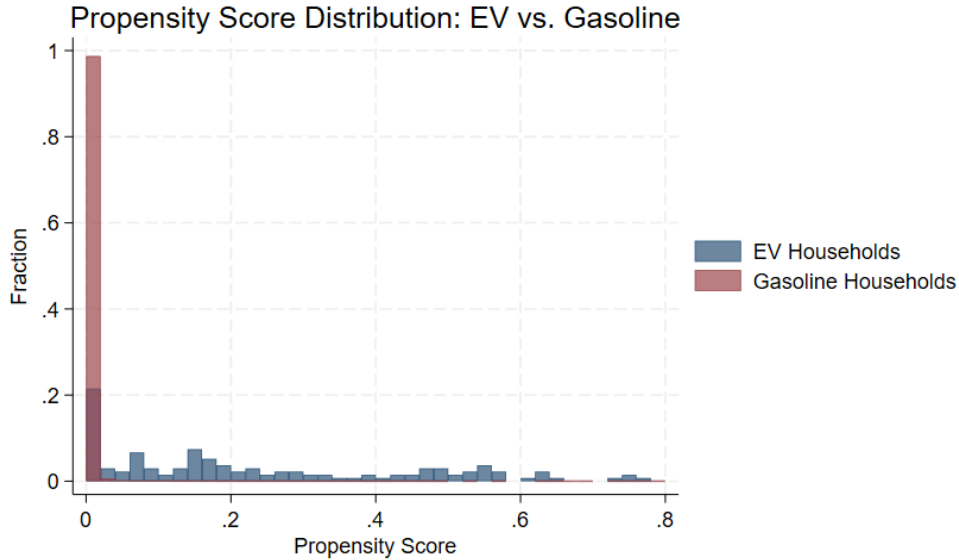
Figure 1: Propensity Score Distribution: Hybrid vs. Gasoline Households



Note: Propensity Score Matching utilizing 1-nearest-neighbor matching, a logistic model, and a caliper of 0.05, was used to produce propensity scores. The hybrid treatment group visually has a lot of overlap between raw gasoline observations, clustered at low propensity scores.

Hybrid households display significant common overlap with the gasoline group (see **Figure 1**). However, many control observations are clustered at low propensity scores, with a more significant amount of hybrid observations tailing toward higher propensity scores. This suggests that while matches exist, they are predominantly low quality matches.

Figure 2: Propensity Score Distribution: EV vs. Gasoline Households



***Note:** Propensity Score Matching utilizing 1-nearest-neighbor matching, a logistic model, and a caliper of 0.05, was used to produce propensity scores. There is, visually, insufficient common support between the groups, exacerbated by low quality matches due to disparities in p-scores.*

Electric vehicles households suffer from the same low-quality matching issue, exacerbated by limited common support. In **Figure 2**, a vast majority of EV households have propensity scores far outside the range of gasoline households, resulting in scarce overlap. This additionally would lead to lower quality matches, especially on the far right tail of p-scores.

Table 2: Common Support & AUC in Propensity Score Matching Results

Metric	Hybrid & Gas	EV & Gas	Hybrid (C) & EV (T)
% Treated On Support	99.9% (1347)	100% (135)	96% (126)
% Treated Off Support	0.01% (1)	0% (0)	3% (4)
% Control On Support	93.6% (58,383)	33.6% (21,384)	43% (585)
% Control Off Support	6.4% (3,998)	66.4% (42,319)	57% (755)
AUC (c-statistic)	0.8151	0.9828	0.9608
N (Treated)	1,348	135	130
N (Control)	64,991	64,991	1340

***Note:** Numbers within parenthesis () are raw on/off support values. Propensity Score Matching utilizing 1-nearest-neighbor matching, a logistic model, and a caliper of 0.05, was used to produce on/off support and AUC values. An AUC over 0.7 indicates limited overlap between treatment*

groups, highlighted by Stürmer et al. (2021). In the case of Hybrid & EV matching, hybrids act as the control, while EVs act as the treated observation. Some observations were dropped due to collinearity, but overall, Hybrid & EV matching has marginally improved matching & AUC statistics than EV & Gasoline matching. Even so, EVs remain a distinct group, removed from the broader market.

In **Table 2**, common support and AUC/c-statistic values are quantified between three combinations: Hybrid-Gas, EV-Gas, and EV-Hybrid (where hybrids act as the control group). From the results, hybrid vehicles are extremely predictable, as observable characteristics strongly predict adoption with an AUC of ~ 0.81 . This high AUC will result in lower quality matches for most treated observations. For electric vehicle households an AUC of 0.98 indicates observables can predict treated electric vehicle households with extreme accuracy, resulting in extremely low quality matching. Even EV-Hybrid matching, which shows marginally improved AUC over EV-Gas matching (0.96 vs. 0.98), fails to achieve adequate overlap⁶ (see **Appendix**). Thus, electric vehicle households exist in their own market segment, far removed from the households in the wider vehicle market. Even households with hybrids, commonly viewed as a “middle-ground” between a full-gas and full-electric vehicle, only marginally improve overlap.

As referenced by Stürmer et al. (2021), an AUC over 0.7 indicates limited common support⁷. Overall, overlap results indicate that fuel-efficient vehicle households inhabit a significantly different market segment from gasoline households. EV homes occupy an even more distinct segment of the market. Thus, entropy balancing is justified as an alternative weighting specification to achieve covariate balance to enable causal inference.

⁶ These results are consistent with Xing et al. (2021), whose study focused on finding what electric vehicles replace in a household. Overall, results from the paper indicate that EVs primarily replace gasoline vehicles, not hybrids. Thus, EVs do not significantly serve as a “successor” to a hybrid vehicle. Marginally improved overlap (AUC of 0.96 vs. 0.98) indicate that hybrid households are not significantly more “suited” as an EV household than a gasoline household.

⁷ Treated observations consistently having higher propensity scores than control observations indicates limited overlap within groups. An AUC of 0.85, for example, indicates that 85% of the time, a treated observation will have a higher propensity score than a control observation. This means that while some treated observations will be able to find close matches in terms of propensity score, 81% of the time, hybrid observations will need to “match down” to the closest available propensity score, which may be a low quality match, which may result in low balance across both groups.

Table 3: Standardized Mean Differences Pre vs. Post Entropy Balancing

Variable	Hybrid Vehicles		Electric Vehicles	
	Pre-SMD	Post-SMD	Pre-SMD	Post-SMD
Vehicle Age	-0.172	0.000	-2.167	0.001
Recent Vehicle Purchase (Y/N)	0.054	0.000	1.036	0.005
Income	0.344	0.000	0.894	0.001
Age of Reference Person	0.127	0.000	-0.374	0.003
Education (Years)	0.757	0.001	0.755	0.009
Housing Tenure	-0.106	-0.001	-0.409	-0.007
Urban Status (Y/N)	.	.	.	.
Family Size	-0.211	0.000	0.059	0.002
Marital Status (Y/N)	-0.063	-0.001	-0.132	-0.007
Race of Reference Person	0.052	0.000	0.298	-0.005
Sex of Reference Person	-0.106	0.000	-0.465	-0.004
Hispanic Status (Y/N)	0.256	0.000	0.201	0.003
PADD	-0.085	-0.001	-0.009	-0.007
# of Earners	0.019	0.000	0.560	0.002
Vehicle New or Used Status	-0.441	0.000	-1.788	-0.002
Brand Type (Econ, Mid, Lux)	-0.083	0.000	1.589	0.005
Vehicle Make (Sedan/SUV)	-0.598	0.000	-0.802	-0.004
Gas Usage Quartile	-0.109	0.000	.	.
Year-Quarter	0.498	0.001	2.359	0.037
Effective Sample Size (ESS)	14,497		265	
N (Treated)	1,348		135	
N (Control)	64,991		64,991	

***Note:** All covariates balanced on the mean, variance, and skewness. Urban Status standard mean difference (SMD) is omitted because all Hybrid and Electric Vehicle observations are all located within urban cities. Additionally, "Gas Usage Quartile" in EV SMDs is omitted due to the variable not being included within entropy balancing, as EVs do not use gas and do not fit within a usage quartile.*

Both entropically-weighted counterfactuals in **Table 3** meet common standardized mean difference (SMD) thresholds of below 0.1 (Austin, 2009), indicating negligible bias exists between groups on observed covariates in the first three moments. Thus, these treatment specific

counterfactuals are utilized to examine effects of fuel-efficient vehicle adoption on household expenditures.

4.2. Results for Entropically-Weighted Effects of Hybrids on Household Expenditure

Hybrid vehicles experience significant operational cost savings, driven primarily by fuel cost reductions. Whilst not experiencing any significant changes across other subcategories, acquisitional costs are significantly elevated for hybrid adopting households. When burdened with acquisitional payments, discretionary spending remains unchanged. However, when a household does not have any financing obligations, their discretionary spending elevates significantly above the gasoline counterfactual.

Table 4: Effects of Hybrid Vehicles on Household Spending

Hybrid Vehicle Outcomes	Coefficient	SE	Confidence Interval	N
Vehicle Spending Categories				
Total Operational Cost	-25.53*	15.32	[-55.55, 4.50]	66280
Total Cost (Incl. Quarterly Pmt)	43.57	42.40	[-39.53, 126.67]	66280
Fuel Cost	-31.75***	5.16	[-41.87, -21.63]	66280
Maintenance Cost	2.57	7.69	[-12.51, 17.65]	66280
Administrative Cost	2.18	7.84	[-13.19, 17.56]	66280
(F) Quarterly Payment	157.77***	58.86	[42.39, 273.15]	17665
(F) Net Purchase Price	3738.33***	804.80	[2160.74, 5315.92]	18683
(F) Downpayment	1169.95**	554.42	[83.02, 2256.88]	10054
(F) Discretionary Spending Categories I				
Total Discretionary Spending	124.67	76.95	[-26.16, 275.50]	17665
Food Away From Home Spending	53.35*	31.39	[-8.19, 114.88]	17665
Entertainment Spending	17.16	23.91	[-29.70, 64.03]	17665
Personal Care Spending	3.98	5.21	[-6.22, 14.19]	17665
Vacation Spending	40.76	30.39	[-18.80, 100.33]	17665
(P) Discretionary Spending Categories II				
Total Discretionary Spending	202.35***	88.44	[88.44, 316.26]	48,615
Food Away From Home Spending	35.00*	19.7	[-3.61, 73.60]	48,615
Entertainment Spending	54.10***	17.27	[17.27, 90.92]	48,615
Personal Care Spending	7.39**	1.08	[1.08, 13.69]	48,615
Vacation Spending	93.74***	42.2	[42.20, 145.28]	48,615

*p < 0.10, **p < 0.05, *** p < 0.01

Notes: All regressions utilize quarterly time fixed effects. All regressions utilize the "double robustness" property of entropy weighted regressions. All standard errors clustered at the household level. All variables are adjusted to be in 2023Q4 dollars. Administrative costs include insurance and registration fees. Outcomes with the (F) prefix have samples restricted to households who are burdened by vehicle payments. Outcomes with the (P) prefix have their vehicles paid off and do not experience acquisitional cost burdens. Acquisitional costs are solely restricted with the (F) prefix because only market participants (i.e, those who purchased a vehicle during their interview period) incur these costs, and including the full sample would dilute results.

As presented in **Table 4**, hybrid households derive operational cost savings mainly from fuel cost reductions of \$31.75/quarter. Other operational cost categories such as maintenance and admin costs are not significantly different from the weighted gasoline counterfactual. This itself is a noteworthy result: a net neutral result means these vehicles do not save the vehicle from more frequent visits to the shop, and do not fail more often for the average household. Hybrid households face elevated costs primarily from acquisitional burdens, with higher quarterly vehicle payments of \$157.77 nullifying total true costs (operational + quarterly car payments). Fuel savings are offset by acquisitional costs for households currently financing their vehicle (represented by prefix (F) within tables). Thus, savings do not translate into discretionary spending category increases.

However, if households are not burdened by quarterly payments (represented by prefix (P)), hybrid adopters experience significant increases in spending across all major categories. This increase is substantially larger than the \$31.75 in quarterly fuel savings. This suggests the savings-to-spending mechanism is more so a perceived savings effect: households who visit the gas station less frequently or spend less at the pump, experience a sense of psychological financial relief that translates into increased spending, despite modest tangible savings. Results were consistent across alternative specifications, and within-household switcher analysis spending moved in the same direction as regression results (see **Appendix**).

Table 5: Effects of Hybrid Vehicles on Household Spending in the Economy Car Market

Hybrid Vehicle Outcomes (Economy Sector)	Coefficient	SE	Confidence Interval	N
Vehicle Spending Categories				
Total Operational Cost	-24.99	15.52	[-55.41, 5.44]	54135
Total Cost (Incl. Quarterly Pmt)	-9.92	33.86	[-76.29, 56.45]	54135
Fuel Cost	-32.10***	4.87	[-41.64, -22.56]	54135
Maintenance Cost	3.37	8.09	[-12.48, 19.23]	54135
Administrative Cost	2.93	8.38	[-13.50, 19.36]	54135
(F) Quarterly Payment	60.56*	34.40	[-6.88, 127.99]	14165
(F) Net Purchase Price	2833.30***	702.75	[1455.71, 4210.90]	14980
(F) Downpayment	1001.16**	491.97	[36.59, 1965.72]	7995
(F) Discretionary Spending Categories I				
Total Discretionary Spending	133.51*	78.08	[-19.56, 286.58]	14165
Food Away From Home Spending	69.97**	33.03	[5.21, 134.72]	14165
Entertainment Spending	10.61	22.34	[-33.18, 54.40]	14165
Personal Care Spending	4.91	5.67	[-6.19, 16.02]	14165
Vacation Spending	46.94	33.31	[-18.35, 112.23]	14165
(P) Discretionary Spending Categories II				
Total Discretionary Spending	196.56***	56.94	[84.95, 308.17]	39970
Food Away From Home Spending	38.21*	20.08	[-1.15, 77.57]	39970
Entertainment Spending	54.82***	19.07	[17.43, 92.20]	39970
Personal Care Spending	6.62**	3.12	[0.50, 12.74]	39970
Vacation Spending	83.50***	25.68	[33.16, 133.83]	39970

*p < 0.10, **p < 0.05, *** p < 0.01

Note: Sample restricted to vehicles with “Economy” brands (Honda, Nissan, etc). Same specifications as the main entropically weighted hybrid model. Overall, hybrid vehicles become more cost competitive, with a reduced acquisition premium relative to the full sample.

When restricting the sample to include only economy vehicles in **Table 5** for cost-competitiveness analysis, results are similar. Hybrid households in this sector of the market do not experience additionally significant savings in operational costs, but experience less of an acquisitional burden on their budgets. Most notably, the quarterly payment premium drops from \$157.7 down to only \$60/quarter and becomes marginally significant ($p < 0.10$), indicating increased cost-competitiveness within this market. Increased flexibility from reduced acquisitional burdens within this market allows for savings reallocation to manifest even when

constrained by vehicle financing payments. Savings are more pronounced when households are not currently paying off their vehicle.

Thus, hybrids paint a relatively mild picture: their adopting households save a good amount of money on fuel, but pay a slight premium to purchase the car. Results suggest that this ultimately delays reallocation of their fuel savings into discretionary categories. This delay makes the vehicle a wash in the short-term, while being a net positive in the long-term. After acquisitional burdens are cleared, the decision to spend more may be linked to reduced daily/frequent constraints from gasoline station visits and perceived savings from their vehicle choice. Regardless, the relief of pressure provided by hybrid vehicles is enough to cause significant increases in spending, despite modest savings.

4.3. Results for Entropically-Weighted Effects of EVs on Household Expenditure

Electric vehicle households experience similar, but magnified effects on expenditures as hybrid households. While EVs enjoy significantly reduced operational costs, their adopters face steep increases in acquisitional burdens, along with additional increases in electricity spending at home. Due to these heavy increases in burdens, EV households do not significantly alter their spending across most discretionary categories. This effect persists even when households are not burdened by acquisitional costs.

Table 6: Effects of Electric Vehicles on Household Spending

Electric Vehicle Outcome	Coefficient	SE	Confidence Interval	N
Vehicle Spending Categories				
Total Operational Cost	-137.56**	65.48	[-265.90, -9.22]	65067
Total Cost (Incl. Quarterly Pmt)	447.55**	196.25	[62.90, 832.20]	65067
Fuel Cost	-167.24***	18.79	[-204.07, -130.42]	65067
Maintenance Cost	-29.27	26.41	[-81.03, 22.50]	65067
Administrative Cost	66.54	47.03	[-25.65, 158.72]	65067
(U) Electricity Bill Spending	52.37**	21.95	[9.35, 95.40]	65067
(F) Quarterly Payment	786.30***	170.28	[452.51, 1120.10]	17313
(F) Net Purchase Price	10707.21***	3596.35	[3657.48, 17756.94]	18299
(F) Downpayment	951.96	2376.69	[-3707.50, 5611.42]	9864
(F) Discretionary Spending Categories I				
Total Discretionary Spending	145.29	271.49	[-386.90, 677.49]	17313
Food Away From Home Spending	137.35	116.19	[-90.40, 365.11]	17313
Entertainment Spending	-49.71	66.36	[-179.80, 80.37]	17313
Personal Care Spending	24.27**	11.99	[0.77, 47.76]	17313
Vacation Spending	113.13	86.04	[-55.53, 281.78]	17313
(P) Discretionary Spending Categories II				
Total Discretionary Spending	29.05	256.14	[-473.01, 531.10]	47754
Food Away From Home Spending	82.29	101.75	[-117.15, 281.73]	47754
Entertainment Spending	135.84*	73.14	[-7.52, 279.20]	47754
Personal Care Spending	12.36	13.73	[-14.54, 39.26]	47754
Vacation Spending	-101.69	106.95	[-311.31, 107.93]	47754

*p < 0.10, **p < 0.05, *** p < 0.01

Notes: All regressions utilize quarterly time fixed effects. All regressions utilize the "double robustness" property of entropy weighted regressions. All standard errors clustered at the household level. All variables are adjusted to be in 2023Q4 dollars. Administrative costs include insurance and registration fees. Outcomes with the (U) prefix are not a vehicle cost, but are from decomposed utility bill costs. Outcomes with the (F) prefix have samples restricted to households who are burdened by vehicle payments. Outcomes with the (P) prefix have their vehicles paid off and do not experience acquisitional cost burdens. Acquisitional costs are solely restricted with the (F) prefix because only market participants (i.e, those who purchased a vehicle during their interview period) incur these costs, and including the full sample would dilute results.

In **Table 6**, operational cost savings of \$137/quarter are driven primarily by massive fuel cost savings of \$167/quarter. However, these savings are drowned out by steep quarterly payment increases over the gasoline counterfactual of \$786/quarter, along with increased electricity bills of \$52.37/quarter. This makes EVs a net negative in totality while the car is still

facing quarterly payments, along with fuel costs being partially distributed to the home electricity bill. Notably, maintenance and administrative costs are null again, indicating that the argument that “EVs don't visit the mechanic” is overstated and does not result in significant savings overall. EVs also do not experience increased insurance or registration costs compared to the gasoline counterfactual. Most interestingly, even when facing no acquisitional burdens, EV households do not significantly alter their spending across categories.

This presents a contrast to the hybrid household results. Despite heightened fuel savings, the “perceived savings” effect does not occur in EV households, as discretionary spending remains the same as gasoline households⁸. Pre-balancing summary statistics (**Table 1**) revealed that EV households spent \$1682/quarter on discretionary categories, compared to \$586/quarter for gasoline households, nearly three times as much. A possible explanation for the null effects is that EV adopters may simply have limited room to increase their discretionary spending further, already having high consumption patterns relative to their higher incomes. There might not be as much psychological relief to gain compared to hybrids, as EV households do not feel significantly constrained day-to-day. On the opposite spectrum, EV households may also experience longer-lasting budget effects that do not allow them to immediately increase their discretionary spending, even when vehicle financing has concluded. Future research should aim to revisit this finding with a more robust dataset with more behavioral-level data. Results were consistent across specifications (see **Appendix**).

⁸ Interestingly, EV households, even when burdened with quarterly payments, find themselves significantly elevating personal care spending. This effect disappears when restricted to households that do not face acquisitional payments, and instead manifests as marginally significant entertainment spending. These results are likely artifacts of limited treatment sample size (N = 64 EVs financing, N = 71 EVs paid off), or reflect inherent differences present within paid off and financing groups. This is further reinforced by luxury restriction yielding similar increases in personal care spending, indicating that households potentially do not alter / cut back on more frivolous spending but increase personal care spending, which is viewed as more “necessary.” Future research with a larger sample size should aim to revisit this discretionary spending reallocation.

Table 7: Effects of Electric Vehicles on Household Spending in the Luxury Car Market

Electric Vehicle Outcome (Luxury Sector)	Coefficient	SE	Confidence Interval	N
Vehicle Spending Categories				
Total Operational Cost	-90.45	74.78	[-237.12, 56.23]	3846
Total Cost (Incl. Quarterly Pmt)	-123.07	421.88	[-950.52, 704.38]	3846
Fuel Cost	-139.29***	18.28	[-175.13, -103.44]	3846
Maintenance Cost	-82.19**	36.39	[-153.56, -10.82]	3846
Administrative Cost	136.09***	52.44	[33.23, 238.94]	3846
(U) Electricity Bill Spending	57.24**	23.61	[10.94, 103.55]	3846
(F) Quarterly Payment	-269.39	384.14	[-1024.06, 485.28]	1030
(F) Net Purchase Price	4263.38	5094.92	[-5744.22, 14270.97]	1115
(F) Downpayment	-5108.68*	2875.80	[-10765.39, 548.04]	680
(F) Discretionary Spending Categories I				
Total Discretionary Spending	-50.17	353.21	[-744.09, 643.74]	1030
Food Away From Home Spending	232.73	141.37	[-45.00, 510.45]	1030
Entertainment Spending	-213.26**	92.87	[-395.72, -30.81]	1030
Personal Care Spending	48.39***	12.63	[23.57, 73.21]	1030
Vacation Spending	92.22	117.45	[-138.52, 322.96]	1030
(P) Discretionary Spending Categories II				
Total Discretionary Spending	374.55	324.13	[-261.37, 1010.47]	2816
Food Away From Home Spending	325.09**	134.99	[60.25, 589.93]	2816
Entertainment Spending	156.24*	91.01	[-22.32, 334.80]	2816
Personal Care Spending	28.11	17.41	[-6.04, 62.27]	2816
Vacation Spending	-30.61	140.58	[-306.41, 245.19]	2816

*p < 0.10, **p < 0.05, *** p < 0.01

***Note:** Sample restricted to luxury car brands (Tesla, BMW, etc). Full entropic model framework used. Overall, electric vehicles become cost competitive in the luxury car market, with households no longer suffering from increased total or acquisitional costs. However, electric vehicles do suffer an insurance premium even when restricted to the luxury car market, evident in significantly higher administrative costs. Results overall align with findings from Lebeau et al. (2013).*

While EVs in comparison to the wider market negatively affect households in the short-run, restrictions to the luxury car market result in cost-competitiveness and makes EVs significantly more appealing. In **Table 7**, EVs continue to enjoy fuel savings, but additionally save in maintenance costs, and now face no changes in acquisitional costs⁹. However, even in the luxury sector, EVs do face insurance / administrative cost premiums of \$136/quarter, and

⁹ EVs do face marginally significant lower downpayment burdens, mainly due to incentives placed on EV adoption that vary from dealer to dealer. Many automakers offer \$0 down to reduce upfront burdens of purchasing these expensive vehicles, giving them an edge over other luxury vehicles that do not provide these offers.

continue to face electricity bill increases over gasoline households. Regardless, discretionary spending within this category shifts significantly compared to the wider market. When burdened with acquisitional payments, EV households decrease entertainment spending while elevating personal care spending per quarter. However, when not paying off their vehicle, these households increase food away from home spending and marginally elevate entertainment spending. This potentially reflects prioritization of perceived necessities over discretionary luxuries amid budgeting pressure from acquisitional burdens, and appropriate responses when no longer under such pressure. Overall, luxury EV results align with Lebeau et al. (2013).

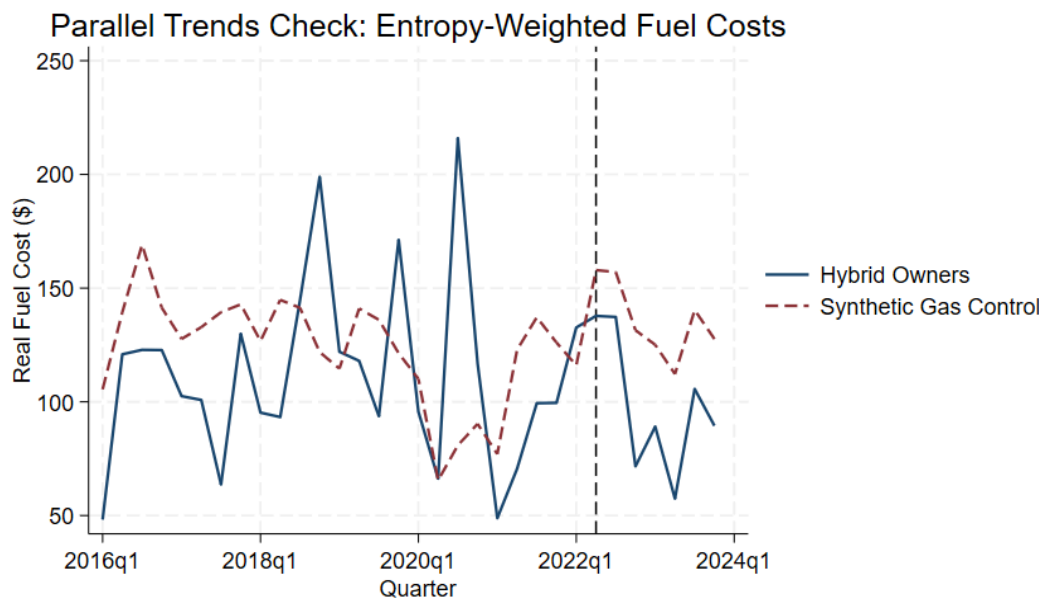
Overall, EVs are very efficient operational cost savers. The trade-off for these heavy operational savings are steep acquisitional cost burdens. These costs result in widely unchanged discretionary category spending, with only slight increases in small categories like personal care. Interestingly, even when facing no acquisitional payments, EV households do not significantly alter spending across major discretionary categories. Despite this, EVs remain an extremely efficient way to reduce operational costs, burdened with significant drawbacks such as elevated administrative costs, higher electricity bills, and steeper acquisitional costs. While not enjoying the same hybrid-style discretionary reallocation, increased cost-competitiveness within luxury sectors and operational savings still show EVs as cost-savers in the long-run, and burdens in the short-run.

4.4. Difference-in-Difference Hedging Results

Weighted Difference-in-Difference regression analysis revealed varying interactions between shocks and vehicle adoption. With strong parallel trends between hybrid and gasoline households on fuel, regression analysis revealed that hybrids roughly double their fuel savings

after the 2022 shock period. Additionally, parallel trends were established between hybrids and gasoline households with discretionary spending as the outcome. However, placebo tests approached marginal significance, suggesting resulting spending reductions reflect regression to the mean rather than a causal response to the shock. While hybrid-gasoline groups were able to establish parallel trends, EV-gasoline groups were unable to do so, inhibiting causal inference on EV hedging effects.

Figure 3: Parallel Trends Check: Hybrids & Weighted Gas Counterfactual



Note: Years before 2016Q1 are excluded due to the oil shock in 2014-2015 which interferes with stable pre-trends. Outcome adjusted to be in 2023Q4 dollars. Trends look roughly parallel, with the gasoline counterfactual tracing the levels of the hybrid group. At points, the limited amount of hybrid observations per quarter emerge and result in spikes above trend. However, a joint F-test on the interaction between the hybrid indicator and the year-quarter variable yields a p-value of 0.6583, indicating that we fail to reject the null hypothesis of parallel trends.

Entropy balancing resulted in consistent pre-trend differences within the synthetic gasoline household and the hybrid household groups. While the graph, presented in **Figure 3**, has significant variance in pre-trends before the 2022 shock, this is largely due to the smaller per-quarter sample size of hybrids. Combined with the volatility of gasoline prices, the graph is

noisy, but pre-trends seem relatively stable with gasoline and hybrid fuel spending rising and falling. To supplement this, a joint significance test on the interaction between the hybrid indicator and the year-quarter variable results in a p-value of 0.6583, indicating that we fail to reject the null hypothesis of parallel trends.

Table 8: Effects of the 2022 Gasoline Price Shock on Hybrid Households

Fuel Spend Outcome	2022 Fuel Shock	2018 Placebo Shock
Treatment Effect	-32.01***	-17.13
SE	10.27	13.34
Confidence Interval	[-52.13, -11.89]	[-43.28, 9.02]
N	48228	48228

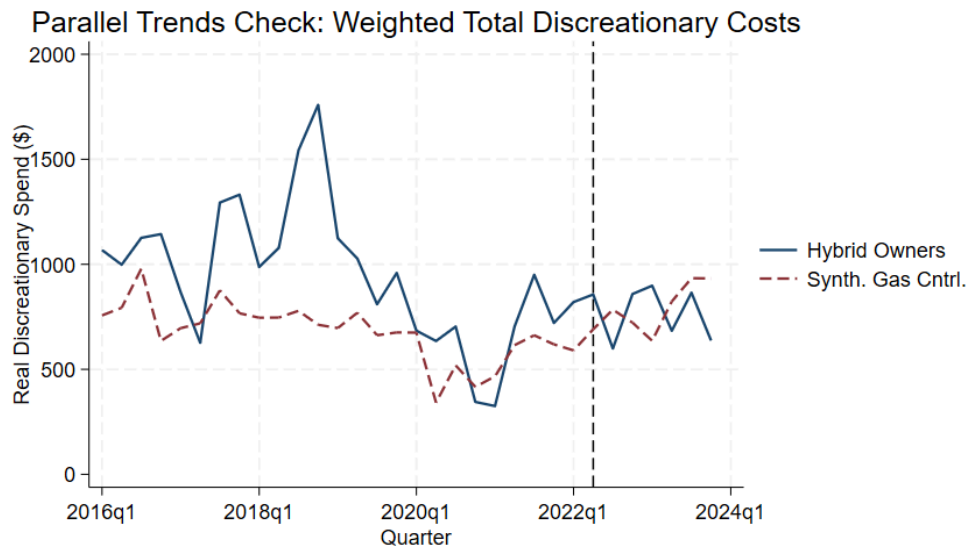
*p < 0.10, **p < 0.05, *** p < 0.01

Note: Years before 2016Q1 are excluded due to the oil shock in 2014-2015 which interferes with stable pre-trends. All regressions utilize quarterly time fixed effects. All regressions utilize the "double robustness" property of entropy weighted regressions. All standard errors clustered at the household level. Outcomes adjusted to be in 2023Q4 dollars. Results indicate that after a shock to fuel prices, hybrid households enjoy significantly higher fuel savings of \$32 per quarter post shock. The model passes a falsification test on a placebo 2018 shock, with no significant effects found.

Thus, the weighted DiD regression found significant effects on the interaction term between the hybrid indicator and the 2022 fuel shock indicator. As seen in **Table 8**, during & after the fuel shock, hybrid vehicles enjoyed roughly double the fuel savings, with increased savings of \$32/quarter during the shock period (added on top of previously established baseline savings of \$31/quarter). Additionally, the DiD model did not find any significant effects on a placebo shock situated in 2018. In totality, hybrid households are safely hedged against macroeconomic fuel shocks compared to their gasoline counterparts.

From the hybrid DiD fuel estimation, a natural extension of the hedging question is how discretionary spending is affected as a result of a fuel shock¹⁰. In theory, during a fuel shock, all spenders on fuel naturally feel more constrained during a shock, which would potentially erase the "perceived savings" effect generated by hybrids.

Figure 4: Parallel Trends Check: Hybrids & Weighted Gas Counterfactual (Discretionary)



***Note:** Same specifications used as previous DiD models. Parallel trends look visually noisy, but a joint significance test between the hybrid indicator and all year quarter variables with discretionary costs as the outcome yields a p-value of 0.4681, meaning we fail to reject parallel trends. Discretionary outcomes are not restricted to whether or not the vehicle is being paid off, as limited sample size per quarter would result in amplified noise per quarter.*

Parallel trends between discretionary spending in both hybrid and gasoline groups are roughly visible (see **Figure 4**). Visually we can discern that hybrids generally have elevated discretionary spend during normal periods. During the 2022 fuel shock, however, it appears that

¹⁰ I do not split the discretionary spending specification on payment status (i.e, if a household is paying off their vehicle or not). This is due to the fact that the number of per-quarter treated observations is low, and further restricting the sample would introduce even more fragility into the Difference-in-Differences estimation. Future research with larger samples should aim to explore this heterogeneity further, as previous results indicate that households who are paying off their vehicle would potentially face decreases in discretionary spending during shock periods.

spending doesn't move much, at least not as dramatically as the shift in fuel costs. A joint significance test yields a p-value of 0.4681, meaning we safely fail to reject parallel trends.

Table 9: Effects of the 2022 Gasoline Price Shock on Hybrid Discretionary Spend

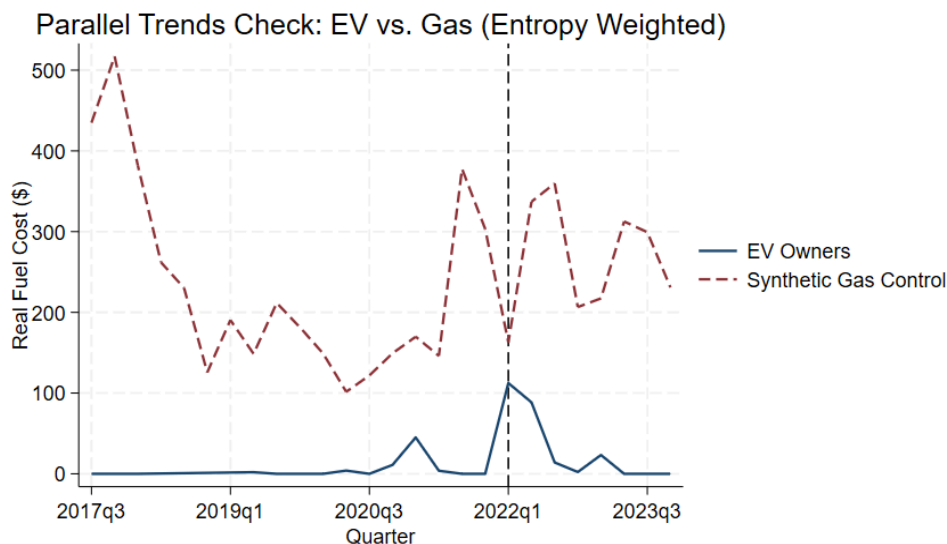
Discretionary Outcome	2022 Fuel Shock	2018 Placebo Shock
Treatment Effect	-274.4096**	-182.2958*
SE	113.0472	110.8945
Confidence Interval	[-495.991, -52.82822]	[-399.65768, 35.06612]
N	48228	48228

*p < 0.10, **p < 0.05, *** p < 0.01

Note: Same specifications used as previous DiD models. While significant effects of discretionary spending are found during the 2022 shock, marginal significance of the placebo shock indicates that the model may be confounding causal effects of the fuel shock with general regression to the mean. Thus, results for this DiD specification should be interpreted as suggestive rather than causal.

Difference-in-differences analysis reveals that during & after the shock, hybrids suffered a dramatic spending decrease of \$274.4/quarter (see **Table 9**). However, a placebo shock test in 2018 approaches significance at the 5% level (p=0.10). This suggests a return to the mean effect rather than a causal response to heightened fuel prices. Thus, these effects should be interpreted as suggestive. While shocks could very well erase the "perceived savings" due to feeling more constrained day-to-day at the gas station and cause a drop in discretionary spending, sensitivity to placebo effects impair causality. Thus, discretionary hybrid outcomes remain a question that future research should aim to properly address.

Figure 5: Parallel Trends Check: Electric Vehicles & Weighted Gas Counterfactual



Note: EV parallel trends regression & graphing uses the same specifications as the hybrid tests, except for inclusion of the gas usage quartile variable. Combined with the small number of EV households in the sample, parallel trends cannot be established. With a p-value less than 0.001, we reject the null hypothesis that parallel trends exist between the groups.

While parallel trends could not be rejected between the hybrid group and its counterfactual, the EV group fails basic parallel trends tests, evident in **Figure 5**. This is confirmed by a joint-significance test between the EV indicator and the year-quarter interaction term, with a p-value of below 0.001. Thus, a difference-in-differences analysis is not conducted. This is no doubt due to the loss of the driving intensity proxy, gas usage quartile, combined with a smaller amount of treated observations. Future research should include a larger treated sample and data on miles driven, which would vastly improve trends between control and treated groups.

4.5. Discussion of Results

Thus, operational cost savings translate to discretionary spending increases only when not burdened by acquisitional payments in hybrids. Intuitively, this makes sense. The fuel savings are relatively modest, and while households may feel less constrained day-to-day, financing the

vehicle causes any perceived savings to disappear. Once the vehicle is paid off, the “price” of those savings is no longer present, and households can enjoy the feeling of less pressure when refueling their vehicle. This allows them to spend more on discretionary categories, despite still enjoying the same modest savings. While this aspect is more behavioral and not directly testable without behavioral survey data due to CEX limitations, it is a plausible explanation for the reallocation of savings.

Interestingly, this effect does not extend to electric vehicles. This, again, could be due to a multitude of reasons. EV adopters, with naturally higher income levels, potentially have no “room” to increase their discretionary spending upon receiving additional savings. This is supplemented by the pre-balancing levels of discretionary spending in **Table 1**, with EV discretionary spending (\$1,682) far above gasoline spending (\$586). Another potential explanation is that heavier debt burdens cause lasting budget conservatism that doesn’t dissipate even when the vehicle is paid off. Another explanation would be limited statistical power. The inconsistency of personal care spending significance across financing and luxury subsampling restrictions may reflect statistical fragility rather than a true behavioral effect.

Another point of interest is the hybrid DiD discretionary spending marginal significance. From **Figure 4**, it is evident that during periods of normalcy, there were elevated discretionary spending levels. A possibility is a small amount of treated observations per quarter leading to extreme outliers, even with winsorization. Thus, the reversion to the mean is more so an “evening out” of effects as more treated observations naturally become available in recent years due to increased adoption. As an addition to this “increasing adoption” explanation, shifting demographics could contribute to explaining the reversion. As a wider range of people begin to adopt, the reversion to the mean effect may simply be the true, widespread effects of hybrid

adoption beginning to manifest as the general U.S. population begins to adopt. More consideration on adoption effects, behavioral channels, and policy implications are in the **Appendix**.

5. Conclusion

This paper evaluated the question of whether or not fuel efficient vehicles significantly reduced vehicle operating costs and translated those savings into increased welfare and discretionary spending for American households. Upon discovery of fragmented fuel-efficient vehicle markets and limited overlap between hybrid, electric, and gasoline vehicle households, I utilized entropy balancing as an alternative matching method. I created treatment-specific gasoline counterfactuals for both hybrids and EVs, generated by matching covariates on the first three moments. Additionally, I utilized entropically weighted difference-in-differences to examine responses to the 2022 gasoline price shock.

Results suggested that these fuel-efficient vehicles are very efficient at reducing operational costs. Hybrids are more modest, only significantly cutting down quarterly fuel costs (\$31/quarter) and not significantly affecting other cost categories. Savings roughly double during shock periods like 2022. Electric vehicles help households massively cut down fuel costs (-\$167/quarter), while not affecting other cost categories. Both of these fuel-efficient vehicles, however, significantly burden households with acquisitional costs. Again, hybrids are more modest in their effects, only elevating total quarterly payments by \$157 (or ~\$40/mo.), and total purchase price by \$3738. EVs however, burden their households with extreme increases of \$786 in quarterly payments (~\$200/mo.) and avg. purchase price increases of \$10707. This translates to increased discretionary spending in hybrid households across all major categories when the

vehicle is paid off, with EV homes not increasing spending across most categories, even when the vehicle is paid off. However, in their respective markets (hybrid-economy, EV-luxury), both vehicles become significantly more cost competitive and beneficial.

Thus, results imply that the fuel-efficient market is a walled garden, with a steep barrier to entry. Fuel-efficient vehicles lead to operational cost savings and less day-to-day pressure on budgets, along with macroeconomic hedging benefits. However, in the short-run, these benefits are offset by significantly higher acquisitional costs—the entry fee to the garden. The walls to the hybrid vehicle garden are significantly lower, and almost disappear in the economy sector of the market, allowing more people to adopt and enter. While people in the hybrid market are slightly closer to households in the electric vehicle market—the EV garden is still far away. The walls to the EV garden are higher, but the benefits are more pronounced. Therefore, if the objective is to maximize widespread adoption and realization of fuel-efficient vehicle benefits, policy should be aimed at bringing down the walls of the gardens. Federal subsidies and incentives to lower total purchase price and reduce quarterly and down payments can easily lower the barrier to entry and allow for more Americans to enjoy the benefits of these vehicles in the long-run.

This study faces several limitations. The Consumer Expenditure Survey (CEX) does not observe behavioral characteristics like mileage, trip frequency, or spending habit choices, meaning these have to be proxied or acknowledged as unobservables. Another limitation is the small number of treated units for both hybrid and electric vehicle groups, exacerbated by the limitation to single vehicle households in this study. A particularly disappointing limitation is the lack of ability to fully explore direct savings-to-spending channels within treated units due to the rotating panel structure of the CEX. Future research should aim to use external, driving behavior datasets like the National Highway Travel Survey (NHTS) to ensure as many unobservables are

accounted for when balancing. Easing restrictions and tailoring data to account for multiple vehicle households and adjusting models to account for leased vehicle data can significantly improve statistical power, and may reveal more interesting and intense dynamics than this study.

To conclude, fuel-efficient vehicles do significantly reduce operating expenses for households in the long-term. In the short-term, households are burdened by acquisitional costs. Hybrids are the most attainable form of cost reduction for many Americans, with the walls to their garden being significantly lower than electric vehicles. While electric vehicles provide maximum operational cost benefits, they are locked away behind steep barriers to entry. With proper policy implementation, Americans will be able to adopt these cost-saving vehicles more easily. More households will feel less burdened by their day-to-day visits at the gasoline station. Americans will be able to enjoy the long-term benefits of these fuel-efficient vehicles sooner. Most importantly, regular people will be able to save a little more on expenses today to be able to spend a little more on themselves tomorrow.

Appendix

Dataset Specifications:

The dataset for this paper uses publicly available data from the Bureau of Labor Statistics (BLS). The survey used is the consumer expenditure survey from 2013Q2-2023Q4. The four files used for inputs were the FMLI, MTBI, OVB, and VOT files. Family level data and aggregates for spending categories like amount spent on vacations are from FMLI files. MTBI files were merged with FMLI aggregate data to fine-tune expenditure categories, like maintenance and insurance costs, gaining accessory and vehicle registration costs, respectively. OVB files contained vehicle-level data like vehicle make, age, etc. VOT was used for supplemental vehicle data. Gasoline price data and regional PADD was obtained from the Environmental Information Agency (EIA). All expenditure values were deflated to 2023Q4 dollars with data from the Federal Reserve Economic Data (FRED). All discretionary variable outcomes are winsorized at the 1st and 99th percentile to account for increased volatility and variation within personal spending. Panel structure was set on a year-quarter variable and HH_ID, which was obtained from decomposing NEWID as per CEX guidelines. Specialized variables created for this dataset were the following:

- Adjusted Fuel Cost: Uses *EV charging Cost + Gasoline Cost* to create a variable to compare EV and gas vehicle spending on fuel. Regular fuel costs just contain gasoline costs for hybrid-gas comparisons.
- Gas Usage Quartile: Uses *Lagged Fuel Expenditure / Gas Price per gal. within PADD* to extract gallons of gasoline used last quarter. Households were organized into quartiles

based on these lags. Households without lags were automatically assigned the 2nd quartile of the sample.

- DiD Periods: Post 2022 is any quarter after **2022Q3**. Pre period is any quarter after **2016Q1**.
- Vehicle Brand Type: Organized based on the average price of every car brand included in the sample. High average purchase price vehicles (Like Tesla, Porsche, Jaguar, BMW, Audi), were placed in luxury samples. Mid-range brands were vehicles like Toyotas, Chryslers, Infinitis, Hummers. Economy brands were Hondas, Chevrolets, KIAs, etc.

Dataset restricted to: **single vehicle households, complete observations, only financed / paid off vehicles**. Lost observations at each stage below:

Stage	Observations	Unit	Lost Observations
FMLI Quarterly Household Data	242,731	HH-quarter	.
Merging MTBI Expenditure Data	95,315	HH-quarter	147,416
Merging Vehicle Level Data (OVb + VOT)	134,271	HH-vehicle-qrtr	.
Restricting to Single-Vehicle Households	83,428	HH-quarter	50,833
Complete Observation Restriction	66,949	HH-quarter	16,349
With Market Participant Restriction	20,804	HH-quarter	46,188
Only Net Purchasing Costs > 0	18,931	HH-quarter	1,873
Only Quarterly Payments > 0	17,913	HH-quarter	2,891
Only Down Payment > 0	10,208	HH-quarter	10,596
Final Sample	66,949	HH-quarter	214,598

Full Dataset Summary Statistics:

	Vehicle Fuel Type		
	Gasoline	Hybrid	Electric
N	64,991 (97.8%)	1,348 (2.0%)	135 (0.2%)
Covariates:			
After-Tax Income	52,017 (48536.53)	74,801 (65565.04)	148,435 (107281.82)
Age	53 (18.73)	55 (18.48)	47 (16.40)
Education	13 (1.78)	15 (1.41)	15 (1.54)
Housing Status			
Owned w/ Mortgage	18,303 (28.2%)	428 (31.8%)	57 (42.2%)
Owned Free	16,451 (25.3%)	360 (26.7%)	42 (31.1%)
Rented	29,234 (45.0%)	546 (40.5%)	32 (23.7%)
No Rent	902 (1.4%)	14 (1.0%)	4 (3.0%)
Student Housing	101 (0.2%)	0 (0.0%)	0 (0.0%)
Urban Status			
Urban	64,153 (98.7%)	1,348 (100.0%)	135 (100.0%)
Rural	838 (1.3%)	0 (0.0%)	0 (0.0%)
Family Size	2 (1.30)	2 (1.03)	2 (1.08)
Marital Status			
Married	19,724 (30.3%)	458 (34.0%)	66 (48.9%)
Widowed	8,954 (13.8%)	180 (13.4%)	5 (3.7%)
Divorced	14,827 (22.8%)	292 (21.7%)	17 (12.6%)
Separated	2,264 (3.5%)	37 (2.7%)	5 (3.7%)
Never Married	19,222 (29.6%)	381 (28.3%)	42 (31.1%)
Race			
White	50,111 (77.1%)	1,093 (81.1%)	95 (70.4%)
Black	9,232 (14.2%)	80 (5.9%)	4 (3.0%)
Native American	280 (0.4%)	0 (0.0%)	2 (1.5%)
Asian	4,077 (6.3%)	140 (10.4%)	32 (23.7%)
Pacific Islander	292 (0.4%)	8 (0.6%)	0 (0.0%)
Multi-Race	999 (1.5%)	27 (2.0%)	2 (1.5%)
Sex			
Male	27,282 (42.0%)	638 (47.3%)	87 (64.4%)
Female	37,709 (58.0%)	710 (52.7%)	48 (35.6%)
PADD			
2: Midwest	14,190 (21.8%)	229 (17.0%)	10 (7.4%)
3: Gulf Coast	8,359 (12.9%)	66 (4.9%)	1 (0.7%)
4: Rocky Mountain	2,373 (3.7%)	70 (5.2%)	5 (3.7%)
5: West Coast	14,322 (22.0%)	558 (41.4%)	79 (58.5%)
1A: New England	3,329 (5.1%)	71 (5.3%)	4 (3.0%)
1B: Central Atlantic	10,444 (16.1%)	187 (13.9%)	16 (11.9%)
1C: Lower Atlantic	11,974 (18.4%)	167 (12.4%)	20 (14.8%)
# Of Earners	1 (0.81)	1 (0.82)	1 (0.85)
Vehicle New or Used	2 (0.49)	1 (0.48)	1 (0.27)
Brand Tier			
Other	1,370 (2.1%)	0 (0.0%)	3 (2.2%)
Economy	52,523 (80.8%)	1,220 (90.5%)	24 (17.8%)

Mid-Range	7,514 (11.6%)	35 (2.6%)	1 (0.7%)
Luxury	3,584 (5.5%)	93 (6.9%)	107 (79.3%)
Vehicle Type			
Automobile	36,450 (56.1%)	1,079 (80.0%)	115 (85.2%)
Truck/Van/SUV	28,541 (43.9%)	269 (20.0%)	20 (14.8%)
Gas Usage Quartile			
Low (Q1)	8,593 (13.2%)	168 (12.5%)	0 (0.0%)
Med-Low (Q2)	38,538 (59.3%)	860 (63.8%)	0 (0.0%)
Med-High (Q3)	8,822 (13.6%)	204 (15.1%)	0 (0.0%)
High (Q4)	9,038 (13.9%)	116 (8.6%)	0 (0.0%)
Year-Quarter	233 (12.32)	239 (11.82)	248 (6.19)
Expenditures / Outcome Variables:			
Quarterly Operating Costs (2023Q4\$)	366 (548.94)	332 (516.31)	409 (620.69)
Quarterly Total Cash Flow (2023Q4\$)	738 (914.12)	816 (1108.54)	1,770 (1894.77)
Maintenance Costs (2023Q4\$)	62 (269.66)	61 (273.58)	30 (178.78)
Fuel Costs (2023Q4\$)	164 (239.47)	112 (164.86)	98 (164.85)
Admin/Insurance Costs (2023Q4\$)	124 (263.30)	141 (262.94)	268 (473.57)
Quarterly Financing Payment (2023Q4\$)	372 (691.68)	484 (939.44)	1,361 (1827.57)
Net Purchase Price (2023Q4\$)	7,048 (13478.75)	10,139 (17228.56)	27,309 (34004.83)
Down Payment (2023Q4\$)	707 (2707.82)	1,079 (3646.95)	5,803 (10950.96)
Electricity Bill This Quarter (2023Q4\$)	130 (169.49)	114 (148.24)	195 (223.64)
Total Discretionary Spending (2023Q4\$)	544 (997.10)	891 (1408.42)	1,346 (1777.90)
Total in Food Away (2023Q4\$)	225 (387.68)	318 (467.13)	554 (681.19)
Total in Entertainment Spending (2023Q4\$)	169 (319.31)	249 (424.40)	313 (468.37)
Total in Personal Care Spending (2023Q4\$)	29 (61.52)	40 (73.18)	54 (88.10)
Total in Vacation Spending (2023Q4\$)	105 (450.22)	244 (695.02)	383 (867.20)

Model Specification Notes:

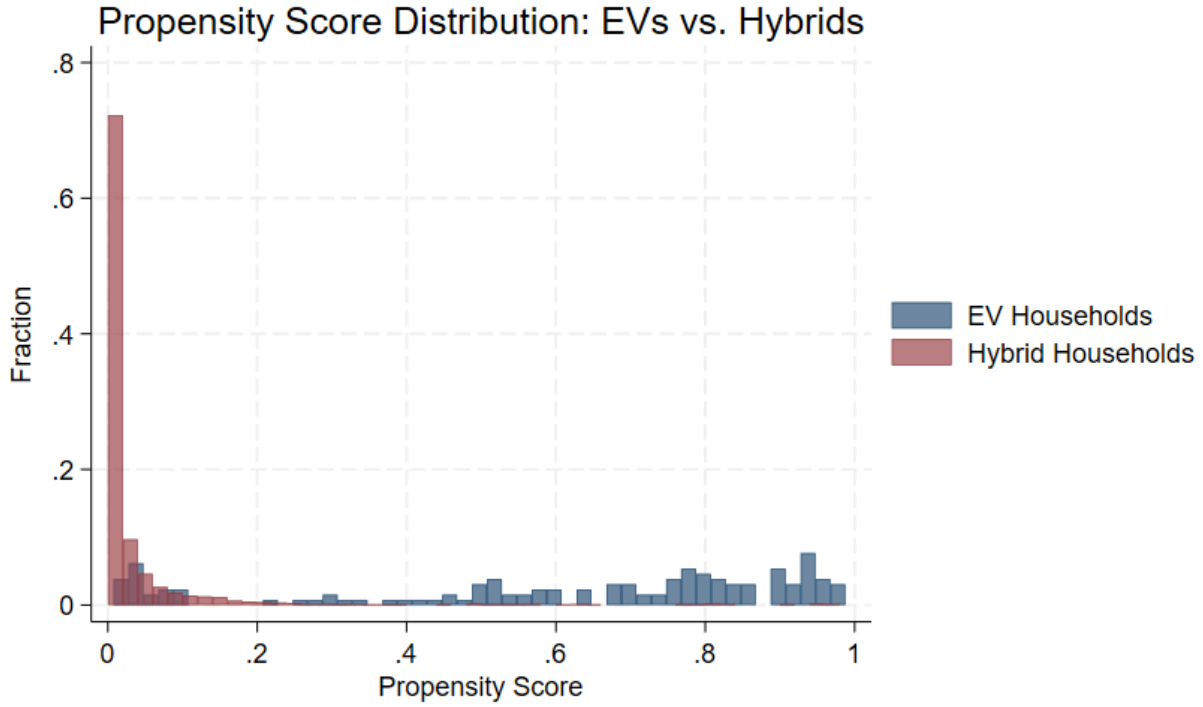
All models are balanced on three covariate moments. All models have standard errors clustered at the household-level to account for the rotating panel structure of the CEX. All models (except for unweighted robustness checks) are weighted with entropic weights and utilize double robustness properties of entropy balanced models. Within-HH switcher effects are measured as the average change in spending in fuel and discretionary spending outcomes (other costs like maintenance and purchase are not used. If the change in maintenance was measured, any effects would be a result of having a new vehicle and not because the new vehicle was a hybrid or EV).

Full Logistic Model Specifications:

$$\log \frac{P(X=\text{hybrid/electric})}{1-P(X=\text{hybrid/electric})} = \beta_0 + \beta_1 \text{income} + \beta_2 \text{age} + \beta_3 \text{education} + \beta_4 \text{housing} + \beta_5 \text{urban} + \beta_6 \text{marital} + \beta_7 \text{familysize} + \beta_8 \text{race} + \beta_9 \text{sex} + \beta_{10} \text{hispanicstatus} + \beta_{11} \text{PADD} + \beta_{12} \text{numberearner} + \beta_{13} \text{vehicleneworused} + \beta_{14} \text{vehicletype} + \beta_{15} \text{brandtype} + \beta_{16} \text{gasusagequartile} + \beta_{17} \text{yrqrtr} + \epsilon$$

Full Entropy Balancing Specifications:

Covariate	Included in Hybrid Balanci	Included in EV Balan
Vehicle Age	Yes	Yes
Recent Purchase	Yes	Yes
Income	Yes	Yes
Age	Yes	Yes
Education	Yes	Yes
Housing Tenure	Yes	Yes
Urban Status	Yes	Yes
Family Size	Yes	Yes
Marital Status	Yes	Yes
Race	Yes	Yes
Hispanic Status	Yes	Yes
Sex	Yes	Yes
PADD	Yes	Yes
# of Earners	Yes	Yes
Vehicle New or Used	Yes	Yes
Brand Type	Yes	Yes
Vehicle Type	Yes	Yes
Gas Usage Quartile	Yes	No
Year-Quarter	Yes	Yes



Note: The following propensity score graph showcases overlap between EV and Hybrid household PSM matching. EV households are clustered at high propensity scores while Hybrids are clustered at low propensity scores, indicating extremely low overlap between both groups, despite hybrids being commonly believed as a “stepping stone” toward EVs.

Full WLS Hybrid Model:

$$y_{it} = \beta_0 + \beta_1 ishybrid + \beta_2 vehicleage + \beta_3 recentpurchase + \beta_4 income + \beta_5 age + \beta_6 education + \beta_7 housing + \beta_8 urban + \beta_9 marital + \beta_{10} familysize + \beta_{11} race + \beta_{12} sex + \beta_{13} hispanicstatus + \beta_{14} PADD + \beta_{15} numberearner + \beta_{16} vehicleneworused + \beta_{17} vehicletype + \beta_{18} brandtype + \beta_{19} gasusagequartile + \beta_{20} yrqrtr + \epsilon$$

Full WLS EV Model:

$$y_{it} = \beta_0 + \beta_1 isev + \beta_2 vehicleage + \beta_3 recentpurchase + \beta_4 income + \beta_5 age + \beta_6 education + \beta_7 housing + \beta_8 urban + \beta_9 marital + \beta_{10} familysize + \beta_{11} race + \beta_{12} sex + \beta_{13} hispanicstatus + \beta_{14} PADD + \beta_{15} numberearner + \beta_{16} vehicleneworused + \beta_{17} vehicletype + \beta_{18} brandtype + \beta_{19} yrqrtr + \epsilon$$

Full DiD Hybrid Model:

$$y_{it} = \beta_0 + \beta_1 ishybrid + \beta_2 vehicleage + \beta_3 recentpurchase + \beta_4 income + \beta_5 age + \beta_6 education + \beta_7 housing + \beta_8 urban + \beta_9 marital + \beta_{10} familysize + \beta_{11} race + \beta_{12} sex + \beta_{13} hispanicstatus + \beta_{14} PADD + \beta_{15} numberearner + \beta_{16} vehicleneworused + \beta_{17} vehicletype + \beta_{18} brandtype + \beta_{19} gasusagequartile + \beta_{20} yrqrtr + \beta_{21} post2022 + \beta_{22} post2022 * ishybrid + \epsilon$$

Full DiD EV Model:

$$y_{it} = \beta_0 + \beta_1 isev + \beta_2 vehicleage + \beta_3 recentpurchase + \beta_4 income + \beta_5 age + \beta_6 education + \beta_7 housing + \beta_8 urban + \beta_9 marital + \beta_{10} familysize + \beta_{11} race + \beta_{12} sex + \beta_{13} hispanicstatus + \beta_{14} PADD + \beta_{15} numberearner + \beta_{16} vehicleneworused + \beta_{17} vehicletype + \beta_{18} brandtype + \beta_{20} yrqrtr + \beta_{21} post2022 + \beta_{22} post2022 * isev + \epsilon$$

Full Robustness Specifications:

Covariate	Reduced Controls	Falsification	Unweighted OLS
Vehicle Age	No	Yes	No
Recent Purchase	No	Yes	No
Income	Yes	Yes	No
Age	Yes	Yes	No
Education	Yes	Yes	No
Housing Tenure	Yes	Yes	No
Urban Status	Yes	Yes	No
Family Size	Yes	Yes	No
Marital Status	Yes	Yes	No
Race	Yes	Yes	No
Hispanic Status	Yes	Yes	No
Sex	Yes	Yes	No
PADD	Yes	Yes	No
# of Earners	Yes	Yes	No
Vehicle New or Used	No	Yes	No
Brand Type	No	Yes	No
Vehicle Type	No	Yes	No
Gas Usage Quartile	No	Yes	No
Year-Quarter	Yes	Yes	No

Reduced Control Hybrid Results:

Outcome	Coefficient	SE	N
Vehicle Spending Categories			
Total Operational Cost	-50.32***	17.57	66339
Total Cost (Incl. Quarterly Pmt)	62.60	47.13	66339
Fuel Cost	-49.70***	6.86	66339
Maintenance Cost	-5.58	7.80	66339
Administrative Cost	3.96	8.12	66339
Quarterly Payment	146.24*	88.34	17665
Net Purchase Price*	2827.01**	1212.73	18683
Downpayment*	833.15	657.85	10054
Discretionary Spending Categories			
Total Discretionary Spending	143.56***	53.29	66339
Food Away From Home Spending	30.17	19.00	66339
Entertainment Spending	33.36**	16.55	66339
Personal Care Spending	3.95	2.95	66339
Vacation Spending	66.06***	21.67	66339

*p < 0.10, **p < 0.05, *** p < 0.01

These are results for the hybrid entropic model balanced and regressed on reduced controls. The covariates included are only demographic controls to test if the vehicle-specific covariates are driving results. Coefficients remain similar in sign and significance like the main specification with larger magnitudes as expected due to bias adjustment from vehicle-specific controls.

Unweighted OLS Hybrid Results:

Outcome	Coefficient	SE	N
Vehicle Spending Categories			
Total Operational Cost	-33.74**	15.32	66280
Total Cost (Incl. Quarterly Pmt)	7.90	44.27	66280
Fuel Cost	-35.15***	5.37	66280
Maintenance Cost	1.28	7.51	66280
Administrative Cost	-1.12	7.72	66280
Quarterly Payment	183.64**	77.70	17665
Net Purchase Price*	3576.82***	969.10	18683
Downpayment*	782.02	695.23	10054
Discretionary Spending Categories			
Total Discretionary Spending	170.04***	50.50	66280
Food Away From Home Spending	33.34*	17.58	66280
Entertainment Spending	5.06*	2.89	66280
Personal Care Spending	39.71**	16.13	66280
Vacation Spending	80.37***	21.42	66280

*p < 0.10, **p < 0.05, *** p < 0.01

These are results for the hybrid model with no entropic balancing, regressed on full controls. This is to test if the entropy balancing is adjusting groups significantly when compared to a fully equipped OLS model. Coefficients remain similar in sign and significance like the main specification with larger magnitudes as expected due to bias adjustment from bias present between groups.

Within-HH Hybrid Switcher Results:

Switcher Outcome	Δ Mean	SE	p-value	N
Gasoline -> Hybrid				
Fuel Cost	-27.3751	45.97792	0.5611	15
Discretionary Spend	81.96953	199.1201	0.6868	15
Hybrid -> Gasoline				
Fuel Cost	74.91977	61.36976	0.2892	5
Discretionary Spend	-1587.9	1112.029	0.2265	5

*p < 0.10, **p < 0.05, *** p < 0.01

Statistical power is heavily limited for within HH switchers, as very few exist in a rotating panel structure. However, directionally, results are expected of a real world switch. Fuel prices fall by similar magnitudes as the entropic model, discretionary spend increases by similar amounts. The reverse happens when a household switches from a hybrid to a gasoline vehicle. While insignificant from t-tests, the core signal emerges from within HH switcher analysis.

Reduced Control EV Results:

Outcome	Coefficient	SE	N
Vehicle Spending Categories			
Total Operational Cost	-106.56**	51.40	65126
Total Cost (Incl. Quarterly Pmt)	810.24***	176.32	65126
Fuel Cost	-179.53***	12.15	65126
Maintenance Cost	-31.06**	14.54	65126
Administrative Cost	104.05**	41.95	65126
Quarterly Payment	1100.18***	141.88	17313
Net Purchase Price*	26348.46***	3257.62	18299
Downpayment*	8326.90***	1448.87	9864
Additional Spending Categories			
Electricity Bill Spending	64.78***	21.86	65126
Overall Utilities Spending	179.30***	50.29	65126
Discretionary Spending Categories			
Total Discretionary Spending	299.73*	160.70	65126
Food Away From Home Spending	103.03	70.80	65126
Entertainment Spending	64.52	42.13	65126
Personal Care Spending	13.27	8.23	65126
Vacation Spending	132.38**	66.37	65126

*p < 0.10, **p < 0.05, *** p < 0.01

These are results for the EV entropic model balanced and regressed on reduced controls. The covariates included are only demographic controls to test if the vehicle-specific covariates are driving results. Coefficients remain similar in sign and significance like the main specification with larger magnitudes as expected due to bias adjustment from vehicle-specific controls.

Unweighted OLS EV Results:

Outcome	Coefficient	SE	N
Vehicle Spending Categories			
Total Operational Cost	-208.84***	59.75	65067
Total Cost (Incl. Quarterly Pmt)	270.63	251.04	65067
Fuel Cost	-208.29***	12.09	65067
Maintenance Cost	-56.82***	15.79	65067
Administrative Cost	63.27	50.85	65067
Quarterly Payment	780.09**	329.12	17313
Net Purchase Price*	15626.63***	4495.81	18299
Downpayment*	5128.96*	2888.43	9864
Additional Spending Categories			
Electricity Bill Spending	41.77	27.46	65067
Overall Utilities Spending	92.59	66.50	65067
Discretionary Spending Categories			
Total Discretionary Spending	-14.51	172.46	65067
Food Away From Home Spending	3.54	75.54	65067
Entertainment Spending	-9.03	9.78	65067
Personal Care Spending	-38.44	50.15	65067
Vacation Spending	62.53	71.70	65067

*p < 0.10, **p < 0.05, *** p < 0.01

These are results for the EV model with no entropic balancing, regressed on full controls. This is to test if the entropic balancing is adjusting groups significantly when compared to a fully equipped OLS model. Coefficients remain similar in sign and significance like the main specification with larger magnitudes as expected due to bias adjustment from bias present between groups.

Within-HH EV Switcher Results:

Switcher Outcome	Δ Mean	SE	p-value	N
Gasoline -> Electric Vehicle				
Fuel Cost	-496.553	301.3309	0.3472	2
Discretionary Spend	-1699.15	1011.585	0.3419	2
Electricity Bill	45.16523	82.53371	0.6812	2
Electric Vehicle -> Gasoline				
Fuel Cost	725.4533	.	.	1
Discretionary Spend	3619.662	.	.	1
Electricity Bill	112.2537	.	.	1

*p < 0.10, **p < 0.05, *** p < 0.01

Statistical power is heavily limited for within HH switchers, as very few exist in a rotating panel structure. However, directionally, results are expected of a real world switch. Fuel prices fall by similar magnitudes as the entropic model. Electricity costs are higher. Discretionary results in the main model were null, but these two households experienced decreases. It can be inferred that while it is unclear if EV households upon adoption decrease or hold spending constant, they do not experience increases. The reverse happens when switching away from an electric vehicle. Interestingly this household experiences increases in electricity consumption. This is primarily due to this specific observation winding down, as their household lost an earner, switched from a luxury EV sedan to an economy gasoline van/truck, and began spending more on medical costs.

A Consideration on Mechanisms:

Contrary to the common belief that hybrid vehicles act as a “stepping-stone” toward electric vehicles, AUC & common overlap analysis revealed only marginally better matching with EV-to-hybrid compared to EV-to-gasoline. This aligns with the findings presented by Xing et al. (2021), noting that EVs do not significantly replace hybrid vehicles, but gasoline vehicles. These findings suggest that policy shouldn’t be aimed at getting already fuel-efficient households (hybrid-owning households) to upgrade to being fully electric. However, they also suggest that the wider market (gasoline households) have significantly improved matching to hybrid vehicles. The barriers to electric vehicles are simply too high for the market to populate and bridge the gap to the far-removed island they sit on. The barriers to hybrids are much lower, meaning if fuel-efficiency for environmental or economic benefits is the goal, hybrid vehicles should be prioritized over electric vehicles as long as the inherent cost of EVs is high. Thus, policymakers should consider that the realistic path to fuel-efficiency for households is through hybrids, not electric vehicles. EVs will remain confined to a high-income, luxury, and almost as a form of novelty, for as long as their acquisitional costs are high.

Notably, maintenance and administrative costs remained null throughout cross-sectional studies of the treatment group and the wider market (the weighted gasoline counterfactual). This challenges common views on both sides of the aisle. Fuel-efficient vehicles do not significantly benefit from less visits to the mechanic, nor do they suffer from increased complexity in their components. Thus, if an average American is considering purchasing something like a hybrid but is worried that more moving parts with the battery will be costlier to repair, they shouldn’t experience any significant increases. However, if an average American is considering an EV to take advantage of the decreased maintenance costs from the “no mechanic visits” story, they will

be quickly disappointed. The benefit to these vehicles is purely contained within their fuel-efficiency, nothing more, nothing less.

However, the story changes if the person is a participant in the luxury market. When electric vehicles are confined to the luxury vehicle market, they find significant cost competitiveness. As discussed within the paper, the acquisitional burdens practically disappear, but maintenance savings manifest, along with increased insurance premiums. The decreased maintenance cost can be practically explained: luxury vehicles are generally more costly to repair with more expensive components and specialized parts. Electric vehicles have far less moving parts, so their maintenance savings can significantly manifest in the luxury segment where cars are significantly more expensive to repair and service. At the same time, electric vehicles are also significantly more fragile: their fragile batteries cause them to be totaled easier. Thus, in a luxury segment, where all insurance and registration costs are higher, the marginal cost to insure an electric vehicle becomes detectable instead of potentially being drowned out by the noise of a wider distribution when compared to the rest of the market. Regardless, EVs become worth it in the luxury segment, further cementing them as far removed from the average American household.

A Note:

Thanks for reading my paper!!!

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