Fueling Electrification: The Impact of Gas Prices on Hybrid Car Usage*

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Abstract

We use micro-level data on fuel consumption, mileage, and travel mode to study how plug-in hybrid drivers respond to fuel prices. When fuel prices rise, plug-in hybrids reduce fuel consumption more than gasoline and diesel cars. They do not proportionally reduce their mileage; instead, they increase electric charging. Since plug-in hybrids drive in electric mode for only half the distance suggested by official test cycle values, fuel prices are effective in improving the environmental performance of these vehicles.

Keywords: fuel price elasticity, automobiles, carbon emissions

JEL codes: D12, L91, Q31

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1 Introduction

Automobile usage imposes substantial negative environmental externalities, accounting for approximately 25 percent of global oil use and around 10 percent of global energy-related CO_2 greenhouse gas emissions in 2023 (International Energy Agency, 2023). The pressure to address climate change has led major economies to encourage the adoption of cleaner vehicles, including battery and plug-in hybrid electric vehicles.

Plug-in hybrids, in particular, have been heralded by policymakers as a transition technology to aid in the electrification of the transportation sector. Their crossover characteristics (internal combustion engine combined with a battery) make them attractive to consumers hesitant to switch to a fully electric car due to concerns about range and the availability of charging infrastructure. From a policy perspective, plug-in hybrids may represent a "slower but more plausible path" (The Washington Post, 2024) to mass electrification, allowing for partial electrification of travel without requiring a full shift in consumer behavior or infrastructure. In contexts where charging networks are underdeveloped or long-distance travel is common, plug-in hybrids can achieve emissions reductions while mitigating range anxiety. By familiarizing consumers with electric drivetrains and encouraging early adoption of charging habits, plug-in hybrids can potentially serve as a stepping stone toward full electrification.

Reflecting their appeal, plug-in hybrid sales are now growing at a fast pace in key markets, including the US and Asia, leading automakers such as GM and Toyota to invest in plug-in hybrid models.[1] In the U.S. and Europe, plug-in hybrids account for around half of the stock of electric vehicles, largely thanks to substantial purchase subsidies. These incentives target adoption, while usage subsidies primarily aim to support the development of charging infrastructure. Usage incentives are generic in their scope; currently, there are no

[1] According to the U.S. Energy Information Administration, plug-in hybrid sales outpaced battery vehicle growth in 2023 (eia.gov), a trend echoed in Asia (Asia Pacific). General Motors and Toyota, for instance, have announced renewed investments in plug-in hybrid models (GM, Toyota).

direct policies affecting the intensity of use for plug-in hybrids, such as encouraging driving in electric mode or penalizing driving in internal combustion mode. Real-world usage data reveal a striking discrepancy: many plug-in hybrids are driven primarily in internal combustion mode, resulting in fuel consumption and emissions far above official test-cycle figures (Chakraborty et al., 2020; Plötz et al., 2021; European Commission, 2024). Ironically, these optimistic official values are used to justify purchase subsidies and calculate manufacturers' compliance with emission standards.[2]

In this study, we evaluate how plug-in hybrid usage responds to gasoline prices in the short run. In a stylized conceptual framework, we show that, unlike drivers of traditional internal combustion engines, plug-in hybrid drivers can reduce gasoline consumption not only by driving less but also by charging more and increasing electric-mode mileage. Reliable estimates of both fuel consumption and mileage elasticities are therefore crucial for understanding the response of carbon emissions to fuel prices and for designing effective regulatory policies to promote plug-in hybrids in electric mode, specifically.

We use detailed micro-level data from a German mobile phone application where users record fuel consumption, distance traveled, and the price paid for each refueling. The dataset spans six years (from 2016 to 2021) and comprises 49,443 drivers, around 3 percent of whom drive a plug-in hybrid. Our sample accounts for about one percent of Germany's total stock of plug-in hybrids. Since our data comprises drivers voluntarily engaging with the application, we assess representativeness using external survey data.

In the first step, we quantify the discrepancy between real-world fuel consumption and manufacturer-reported values. While gasoline and diesel cars consume 30 to 40 percent more fuel in real-world driving conditions than reported by manufacturers during controlled testing cycles, plug-in hybrids feature a striking difference between official and on-road fuel economy

[2]In the U.S., federal tax incentives available for plug-in hybrids can reach $7,500, depending on the vehicle price, assembly location, battery component sourcing, and the buyer's income (US incentives). In Europe, various incentives are available in the form of purchase subsidies and tax benefits (European incentives).

ratings, with an on-road-to-NEDC fuel economy ratio of 2.93, indicating a higher reliance on combustion mode. The observed share of electric-mode driving is 0.32, compared to the official NEDC utility factor of 0.67, a gap of 35 percentage points. This lower electric-mode share increases fuel consumption, implying that real-world CO_2 emissions are approximately twice as high as official estimates when applying the type-approval formula. We provide a descriptive analysis of the implications and determinants of the low utility factor for plug-in hybrids.

In the second step, we assess the impact of fuel prices on fuel demand, focusing on travel mode (electric versus combustion) for plug-in hybrids. Using detailed vehicle-driver data and an instrumentation strategy that addresses the endogeneity of fuel prices with respect to driving behavior, we estimate the elasticities of mileage and fuel consumption. A one percent price increase reduces fuel consumption by 0.22 percent for gasoline and 0.22 to 0.25 percent for diesel. Our estimates fall within the range of elasticities (-0.16 to -0.37) reported in prior studies. Most of the reduction in fuel consumption stems from decreased driving, with fuel-conserving behavior accounting for 12 to 29 percent of the total effect.

Zooming in on plug-in hybrids, we find that the average fuel consumption elasticity is larger in magnitude than that of gasoline and diesel drivers, ranging between -0.33 and -0.41. In contrast, the elasticity of mileage is not significantly different from zero. The elasticity of on-road fuel economy is an order of magnitude larger for plug-in hybrids than gasoline and diesel vehicles, suggesting that the observed change in fuel consumption is unlikely to result solely from fuel-conserving behavior, particularly given the null effect on mileage. Instead, the evidence points to increased electric-mode usage as the main driver. Specifically, a 10 percent increase in fuel prices raises the share of kilometers driven in electric mode by 1.5 percentage points. We calculate that around 89 percent of the improvement in on-road fuel economy (liters/km) comes from increased charging (shifting to electric driving), while 11 percent comes from fuel-conserving behavior in fuel mode. Higher fuel prices, therefore, lead plug-in hybrid drivers to shift toward electric mode without reducing total driving, thereby enhancing the environmental effectiveness of these vehicles.

However, this effect appears to be short-lived. Estimating a distributed lag model including recent past prices, we find no evidence of habit changes in charging behavior in response to fuel price shocks. This is consistent with experimental findings that electric vehicle drivers do not form new charging routines in response to price signals Bailey et al. (2023).

Finally, building on the finding that the average electric-mode share is only 32 percent, we examine the disutility of charging. Focusing on the distribution of drivers' fixed preferences for gasoline over electric mode after netting out price effects, we show substantial heterogeneity in charging preferences ("hassle costs") across drivers.

Our results have important policy implications. First, policies to support the adoption of plug-in hybrids and calculate compliance with emission regulations by manufacturers should reflect real-world electric driving shares and emissions.[3] Second, financial incentives matter. In particular, policies raising the carbon price on transportation fuels paid by drivers of plug-in hybrids are an effective tool for increasing the electrification of miles driven without a significant impact on mileage. Our findings bolster recommendations for rationalizing carbon prices presented by Rapson and Muehlegger (2023).[4] Third, financial incentives are proving to be much more critical in encouraging drivers to recharge due to

[3]For instance, the discrepancy between real-world and official fuel consumption has prompted the European Commission to require the installation of onboard fuel consumption monitoring devices since 2021 (European Commission, 2024). The data collected so far shows that, for new plug-in hybrid electric vehicles registered in 2021, the real-world CO_2 emissions were, on average, 3.5 times higher than the type-approval values (100 gram CO_2/km). The report discusses that the discrepancy is largely due to the fact that these vehicles are not being charged and driven fully electrically as frequently as assumed. As a consequence, the Commission has introduced changes to the calculation of the utility factor (the expected share of distance driven electrically) used to determine emissions during the official test procedure starting in 2025 (Commission Regulation (EU) 2023/443).

[4]Road fuels currently face lower carbon pricing than electricity in terms of embedded carbon costs per unit of energy. Under Germany's national Emissions Trading System, the CO_2 price is fixed at €55/tonne in 2025 (https://www.bmuv.de/fileadmin/Daten_BMU/Download_PDF/Gesetze/behg_en_bf.pdf). In contrast, power generators under the EU Emissions Trading System face a market-determined allowance price, projected to average around €70/tonne in 2025 based on 2024 trends (https://www.ice.com/products/197/EUA-Futures/data?marketId=5474739).

the absence of habit changes. Finally, the high and highly heterogeneous "hassle cost" of charging underscores that time-saving investments in charging infrastructure can amplify the effect of fuel price policies. Our findings are complementary to those of Gessner et al. (2024), who show that increased access to charging (specifically, home charging) substantially boosts electric charging among hybrid drivers in a company setting, where financial incentives are irrelevant since the employer covers fuel and electricity costs.

Related literature Our work contributes to four strands of literature.

First, we relate to the work of economists documenting the large discrepancies between ex-ante estimates produced by engineering models and real-world energy savings: Allcott and Greenstone (2017), Fowlie et al. (2018), and Reynaert and Sallee (2021). We demonstrate that monetary incentives play a crucial role in ensuring that plug-in hybrids contribute to environmental improvements. Ignoring usage incentives to encourage electric driving can significantly undermine the anticipated reductions in emissions. Specific to plug-in hybrids, Plötz et al. (2021) provide a systematic review of real-world usage and fuel consumption of 100,000 vehicles in North America, China, and Europe; they show that the share of kilometers driven in electric mode by plug-in hybrids is only half the official test cycle values for private vehicles and even lower for company cars because of the low charging frequency. The real-world electric range is also lower than estimated from test cycles; these factors raise tailpipe CO_2 emissions by two to four times. We confirm their findings in our study, adding an analysis of the determinants of the low share of electric driving. Tsanko (2023) studies the environmental benefits of subsidizing plug-in hybrids when emissions are higher than officially estimated.[5]

Second, we contribute to the literature discussing consumers' behavioral biases regard-

[5]Dong and Lin (2012) is an early study based on survey data looking at the charging network's impact on plug-in hybrids' fuel consumption. Raghavan and Tal (2022) also use survey data to investigate the variables influencing the charging choices of plug-in hybrid owners. Our study uses micro-level data with more extensive coverage to understand the response of fuel consumption and charging choices to fuel prices.

ing fuel consumption: Allcott and Knittel (2019). The literature has mainly studied the relationship between fuel prices, fuel economy, and automobile purchases (the adoption margin): Busse et al. (2013); Allcott and Wozny (2014); Sallee et al. (2016); Grigolon et al. (2018); Levinson and Sager (2023). Beresteanu and Li (2011) investigate environmental policies targeting the adoption of hybrid vehicles. Salvo and Huse (2013) study the usage margin for flex-fuel cars, analysing the discrete choice between ethanol and gasoline at each refueling and documenting limited switching even when prices approach energy-equivalent parity. We document a systematic bias in operational usage. Plug-in drivers underutilize electric mode, despite clear cost savings, indicating behavioral barriers that extend beyond rational cost-benefit calculations. In a study complementing our work, Gessner et al. (2024) quantify the impact of home-charging availability on energy use and emissions; specifically, lowering the hassle cost of charging by providing access to home charging increases electricity consumption and decreases emissions by 39 percent.

Third, our paper complements a growing literature on the usage of battery vehicles. Davis (2019), Burlig et al. (2021), and Nehiba (2024) show that electric vehicles tend to be driven less than other vehicles. Johansen and Munk-Nielsen (2022) and Davis (2022) provide context for these findings, showing the importance of portfolio complementarities in the adoption and usage of electric vehicles. While our dataset does not contain information on multi-vehicle ownership, we leverage its unique high-frequency and panel features to identify plug-in-hybrid usage patterns, mileage, and charging responses to fuel prices, as well as habit behavior.

Fourth, we relate to the sizable number of studies investigating how fuel consumption and mileage respond to fuel prices. Earlier studies mainly relied on aggregate gasoline expenditure data and cross-sectional variation. Aggregation creates an endogeneity issue, as movements in demand cause fuel prices and consumption to shift in the same direction. Such correlation results in an upward bias of the estimated elasticities (Kilian and Zhou, 2023). Table A.I in the Appendix summarizes selected price elasticity estimates of gasoline demand from the most recent studies developed in the last decade. These studies mostly use individual-level data (thus avoiding aggregation biases) or panel-level data at the monthly and state levels (addressing the endogeneity concerns using instrumental variable techniques); their elasticity estimates are an order of magnitude larger than earlier ones, ranging between -0.16 and -0.37. Our estimates are consistent with these studies, yielding a gasoline price elasticity of approximately -0.22. We contribute to the empirical debate on fuel elasticity by looking at different fuel and engine types in addition to gasoline (diesel and plug-in hybrids). Furthermore, we estimate how plug-in hybrid charging responds to fuel prices, which has not been investigated in the literature so far.

2 Data

Our primary dataset comes from Spritmonitor, an application where users record their refuelings and track their effective on-road fuel consumption. Our records range between 2016 and 2021 and refer to cars built in 2016 or thereafter. We observe the refueling date, the amount fueled, the distance traveled since the previous refueling, the total amount paid, and whether the users completely or partially filled up their tanks. Figure A.1 in the Appendix provides a sample screenshot of the application used by drivers to track themselves. The number of plug-in hybrid models increases toward the end of our sample, as shown in Panel (a) of Figure A.2, from 22 in 2018 to 49 in 2020. Likewise, the number of drivers in our panel increases with the build year, from 273 in 2018 to 398 in 2020, as shown in Panel (b) of Figure A.2. The average number of refuelings per driver-month is around 1.5–1.8 for diesel cars and 1.4–1.6 for gasoline cars (Figure A.3). Plug-in hybrids shadow gasoline cars throughout the pre-COVID period. All three series dip in early 2020, reflecting COVID-related travel slowdowns.

We match the observed vehicle nameplate, engine type (gasoline, diesel, or plug-in hybrid), and engine power with additional car characteristics scraped from the General German Automobile Club (ADAC), adding information on the official fuel economy, emission values, the driving ranges and charging times (for battery cars). The official fuel economy and emission values are based on the New European Driving Cycle (NEDC).[6]

We obtain average daily fuel prices from Tankerkönig (for gasoline grades normal E10, super, and standard diesel) and fuelo.net (for gasoline grades super plus and premium, and for diesel premium). We use the prices of different fuel grades to investigate drivers' switching behavior across grades; this level of detail is usually unavailable in other studies. Electricity prices are sourced from the German Federal Statistical Office (Statistisches Bundesamt); Figure A.4 in the Appendix shows that household electricity prices remained stable throughout the sample.[7] Finally, we collect information from the Federal Network Agency (Bundesnetzagentur) on the number and type of charging points.

Prior to analysis, we process and aggregate the data in several steps. We remove unrepresentative or inconsistent entries, outliers, and vehicles that fall outside the scope of our analysis. In particular, we require at least 365 days between a user's first and last log entry, ensuring sufficiently long and consistent reporting, and use the Interquartile Range method to exclude outliers based on kilometers traveled, price per liter, fuel economy, duration of the fill-up interval, and total fuel quantity consumed. Additionally, to mitigate the influence of long-distance trips, the primary analysis excludes records corresponding to the top 30 percent of the distribution of daily distance traveled by fuel and engine type, which corresponds to 90 km/day for plug-in hybrids. This exclusion removes only 6 percent of the observations

[6] In September 2018, the European Union gradually adopted the Worldwide harmonized Light vehicles Test Procedure (WLTP). Using our extensive set of car attributes, we impute the NEDC values for the vehicles whose fuel economy is expressed in WLTP to harmonize the measure of fuel economy across all cars in our sample.

[7] Although no publicly available dataset provides granular data on public EV-charging prices across Germany, Figure A.5 in the Appendix summarizes the annual charges reported by the German energy provider LichtBlick for 2017–2021.

from the final sample.[8] A detailed description of the data-cleaning protocol is available in Appendix B.

We aggregate our data to the monthly level for two main reasons. First, aggregation helps minimize the impact of typing errors when labeling a refueling as partial or full; such mislabeling would limit our ability to analyze data at the refueling level. Second, we compare elasticities across different fuel and engine types (gasoline, diesel, and plug-in hybrids). Aggregating data monthly is helpful in interpreting our estimated elasticities consistently.

As travel logs are self-reported by users, the precision of monthly aggregates may vary depending on the number of entries. To reduce the influence of sparsely reported months, we weight each observation by the number of travel logs recorded in that month. This precision-weighting approach follows Solon et al. (2015), recommending weights when observation reliability varies systematically.[9]

2.1 Sample representativeness

As our sample includes only drivers engaging with the app, one may suspect that these drivers could be either more motivated to save fuel than the general population or could drive company cars and, therefore, be required to track their mileage and fuel consumption. Before removing long-distance trips, our sample's average annual mileage is 13,360 km for gasoline cars and 21,180 km for diesel cars. We study how representative our sample is by comparing these numbers with the averages reported by the German Federal Highway and Transport Research Institute (Bundesanstalt für Straßenwesen, BASt). The reported average annual mileage is between 10,400 km (private) and 15,300 km (company) for gasoline cars and 17,400 km (private) and 29,100 km (company) for diesel cars. Accounting for the

[8]In Section 5.2, we show that the results remain robust after extending the cutoff to the top 20 percent of the distribution, corresponding to a maximum daily mileage of 112 km/day for plug-in hybrids. This cutoff removes only 3 percent of the observations from the final sample.

[9]In Section 5.2, we show that our results are robust to the use of OLS instead of weighted linear regressions.

fact that our sample includes only recent cars, our sample averages are very close to the ones reported for the general population. To further confirm our sample's representativeness, we compare mean annual mileage across vehicle segments between BASt private and company cars and our Spritmonitor sample. We find that, in each segment, the Spritmonitor mean lies squarely between the BASt private and BASt company means, consistent with our sample mixing both private and company vehicles.[10]

Finally, we use complementary data from the German Mobility Panel, which surveys a representative sample of the German population once a year to monitor their mobility patterns. The monthly mileage of vehicles driven in normal circumstances (excluding, for example, vacation trips) reported in the German Mobility Panel is within the range of the averages reported in our sample after excluding long-distance trips: 709 km for gasoline cars and 1,240 km for diesel cars. The monthly mileage in our sample is 669 km for gasoline and 1,024 km for diesel cars.[11]

3 The Utility Factor Gap

Our granular data allow us to quantify the discrepancy between real-world fuel consumption and manufacturer-reported values. Plug-in hybrids combine an internal combustion engine with an electric motor, allowing the vehicle to switch between or simultaneously use both

[10]For small and mini cars, the BASt private average is 10,343 km, the BASt company average is 16,283 km, and our sample average is 12,747 km. For compact to upper midsize cars, the corresponding values are 12,933 km, 28,003 km, and 17,162 km. For luxury and sports cars, they are 10,573 km, 19,636 km, and 13,403 km, and for vans and SUVs, they are 13,519 km, 26,135 km, and 15,435 km.

[11]We also compare the calculated share of electric driving for the plug-in hybrids we observe in our sample with other studies. As explained in Section 3, such share is approximately equal to 32 percent. We confirm that our sample appears to include both private and company vehicles. Plötz et al. (2020) report an average share of electric driving of 18 percent for German company cars and 43 percent for private vehicles. Gessner et al. (2024) report a similar utility factor (21 percent) for a sample of 3,519 hybrid company cars; in their data, fuel and charging expenditures are covered by the employer. This is not often the case in Germany; for some companies, drivers might not even have a choice but to pay privately to charge their vehicles at home (while the employer covers fuel costs). Company cars constitute 10 to 15 percent of the total passenger car fleet in Germany (Kraftfahrt-Bundesamt, 2023).

power sources based on driving conditions and needs. Typically, plug-in hybrids operate primarily on electric power during city driving (below 50 to 80 km/h, depending on the car model). For highway travel, rapid acceleration, low battery charge, driving mode (for example, sport mode), or in cold weather, the gasoline engine engages simultaneously to provide additional power and conserve battery life. Blending fuel use is governed by software. To study the usage behavior of drivers of plug-in hybrids, we introduce the utility factor. We define the utility factor as the share of kilometers driven in electric mode. Because of the simultaneous use of both power sources, the utility factor of hybrids needs to be calculated, as it cannot be directly inferred from the data, even when observing drivers' recharging and refueling patterns. Specifically, the utility factor (UF) is defined as follows:

$$\mathrm{UF} = 1 - \frac{\text{On-road fuel economy}}{\text{Fuel economy}_{CS}}, \tag{1}$$

where fuel economy values are measured in liters per 100 km. The variable "On-road fuel economy" is calculated using the driver's logs of fuel consumption and mileage and is therefore directly observable. The variable "Fuel economy$_{CS}$" refers to the hypothetical fuel economy measured while the plug-in hybrid operates in charge-sustaining (CS) mode, that is, when the battery is depleted and the car behaves like a conventional hybrid, mainly relying on the internal combustion engine. The denominator of Equation (1) is therefore not directly observable because of the simultaneous engagement of electric and internal combustion modes.

To calculate the denominator, existing studies (Plötz et al., 2020; Tietge et al., 2019) use the official fuel economy in charge-sustaining mode from the NEDC test cycles, adjusted by a factor that addresses the discrepancy between NEDC values, calculated in a controlled environment, and the real-world fuel consumption of a plug-in hybrid operating like a conventional hybrid. Accordingly, they approximate the utility factor as:

$$\text{UF} \approx 1 - \frac{\text{On-road fuel economy}}{\phi \cdot \text{Fuel economy}_{CS}^{\text{NEDC}}},$$

where ϕ is a correction factor accounting for the gap between NEDC and real-world performance in charge-sustaining mode.[12] These studies approximate the correction factor ϕ at around 1.5 (that is, a 50% increase), based on the discrepancy between on-road and official fuel economy values for hybrid electric vehicles that are not externally chargeable and therefore operate exclusively in charge-sustaining mode. This assumption is optimistic, as a 50% deviation exceeds the average gap observed for conventional vehicles.[13] Additionally, it does not account for variation in discrepancy due to specific driving conditions, such as weather or vehicle age.

To improve on this, we use non-chargeable hybrids in our dataset to directly approximate the denominator of Equation (1). In particular, we regress the on-road fuel economy of non-chargeable hybrids on: (i) the month in which we observe the refueling activity (to account for the weather conditions), (ii) the vehicle's official fuel economy, (iii) the vehicle's class, (iv) body type, (v) power (kW), (vi) curb weight, and (vii) build year. We then use the regression coefficients to obtain the predicted on-road fuel economy in charge-sustaining mode for plug-in hybrids. Those predicted values become our denominator, $\text{Fuel }\widehat{\text{economy}}_{CS_{it}}$, in Equation (1), so that

$$\widehat{\text{UF}}_{it} \;=\; 1 - \frac{\text{On-road fuel economy}_{it}}{\text{Fuel }\widehat{\text{economy}}_{CS_{it}}}.$$

This approach eliminates any reliance on a single, fixed "gap" factor and instead allows the

[12] Technically, the NEDC fuel economy in charge-sustaining mode is calculated as follows (Plötz et al., 2022):

$$\text{Fuel economy}_{\text{CS}}^{\text{NEDC}} = \frac{\text{Fuel economy}^{\text{NEDC}}}{1 - \left(\frac{\text{electric range}}{\text{electric range}+25}\right)}.$$

[13] Tietge et al. (2019) find that non-rechargeable hybrids consistently exhibit average divergence values above the levels of conventional power train vehicles.

data to speak for themselves. Table A.II in the Appendix shows the estimation results. The linear specification delivers statistically strong predictive accuracy, halving the unexplained variance relative to a naive average and reducing absolute error to well below one liter per 100 km.[14]

To assess the robustness of the utility-factor calculation, we recompute this measure using a wide range of deviation values $\phi \in \{1.3; 1.5; 1.7\}$; the lower end (1.3, corresponding to a 30 percent deviation) reflects the mean deviation for conventional vehicles in our data, while the upper end (1.7, corresponding to a 70 percent deviation) assumes that hybrid car drivers exhibit less fuel-conserving driving style than conventional car drivers.

Figure A.6 illustrates the monthly average utility factor (UF) that results from our prediction exercise. The line "UF(HEV)" is calculated using the regression-based, month-specific correction derived from non-chargeable hybrids; the other three lines apply fixed correction factors $\phi \in \{1.3; 1.5; 1.7\}$ for comparison. Our regression-based utility factor closely follows the series based on the lower deviation value ($\phi = 1.3$).

Some plug-in hybrids allow drivers to manually switch between electric and internal combustion modes (in low-speed driving conditions), giving them more control over their driving preferences. More generally, drivers need to recharge the battery for hybrids to operate efficiently in electric mode. Without regular charging, the vehicle will default to using the internal combustion engine more frequently, even at lower speeds, thereby reducing the share of electric kilometers and lowering the utility factor. Hence, the utility factor is closely linked to driver behavior, particularly the decision to recharge.

Table 1 presents the summary statistics. On-road fuel consumption for vehicles of all fuel types exceeds official NEDC estimates, consistent with previous studies (Reynaert and

[14]We re-estimated the specification using two machine-learning algorithms: random forest and extreme-gradient boosting, using the same set of covariates and five-fold cross-validation. The out-of-sample root-mean-square error for OLS averages 0.65 liter/100 km, while Random Forest and XGBoost yield an economically negligible difference. Given the absence of predictive gains and the easier interpretability of OLS, we retain the linear model in the main analysis.

Sallee, 2021; Plötz et al., 2018). The ratio of on-road to NEDC fuel economy is 1.31 for gasoline and 1.41 for diesel vehicles, implying that real-world fuel use is 31 to 41% higher than reported under controlled test cycles. Plug-in hybrids (PHEVs) exhibit the largest discrepancy, with an on-road-to-NEDC fuel economy ratio of 2.93, indicating a higher reliance on combustion mode. The observed utility factor (share of electric-mode driving) is 0.32, compared to the official NEDC utility factor of 0.67, a gap of 35 percentage points. This lower electric-mode share increases fuel consumption and implies that real-world CO_2 emissions are approximately 2.1 times higher than official estimates when applying the type-approval formula, contributing to the elevated fuel economy ratio.[15]

Panel (a) of Figure 1 plots the histogram of monthly utility factors for each driver–vehicle; the mass point at zero indicates that many drivers never charge their plug-in hybrid. In addition, only 23 percent of drivers achieve electric-mode shares above 50 percent in any given month. Panel (b) shows each driver's average utility factor for each vehicle-driver throughout the sample period. Here, the zero mass diminishes. Still, a substantial share of drivers charge only occasionally.

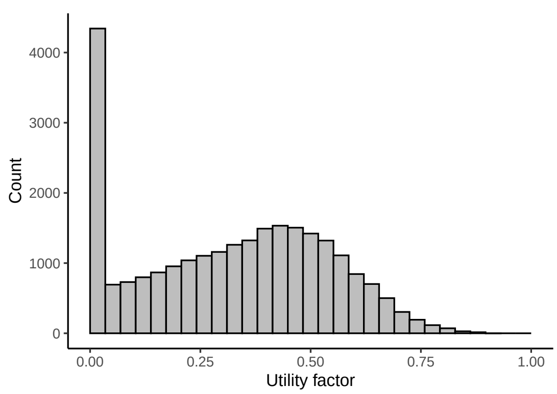
[15]The official NEDC utility factor assumes that 67% of driving is in electric mode with near-zero tailpipe CO_2 emissions, while the observed utility factor indicates only 32% electric-mode driving. Using the type-approval formula, actual CO_2 emissions are $0.67/0.32 \approx 2.1$ times higher than official estimates. The on-road/NEDC fuel economy ratio of 2.93 (4.70 vs. 1.67 liters/100 km) is higher because it reflects both the lower utility factor and less efficient real-world driving in fuel mode.

Table 1: Summary statistics

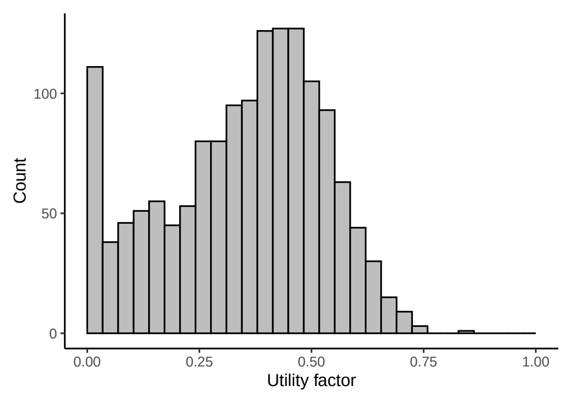
	PHEV		Gasoline		Diesel	
	Mean	SD	Mean	SD	Mean	SD
Fueling level data						
Fuel usage (liter/month)	41.96	26.29	49.31	25.53	65.62	33.73
Monthly Mileage (km)	909	468	669	333	1,024	520
Annual Mileage (km)	10,914	5,611	8,025	3,999	12,289	6,245
On-road fuel economy (liter/100km)	4.70	1.84	7.50	1.62	6.51	1.16
NEDC fuel economy (liter/100km)	1.67	0.37	5.74	1.08	4.62	0.68
On-road/NEDC fuel economy	2.93	1.32	1.31	0.21	1.41	0.19
Utility factor (Official - NEDC)	0.67	0.05				
Utility factor (HEV data)	0.32	0.22				
Fuel price (€/liter)	1.313	0.140	1.296	0.138	1.154	0.123
Fuel price (IV1, €/liter)	1.345	0.116	1.358	0.112	1.185	0.108
Fuel price (IV2, €/liter)	1.343	0.116	1.357	0.113	1.183	0.109
Sample sizes						
Number of observations	25,426		784,212		357,731	
Number of drivers	1,494		33,027		14,922	

The table reports summary statistics of the main variables. Mean and standard deviation (SD) of fuel use, mileage, fuel-economy metrics, utility factors, and fuel prices for plug-in hybrids (PHEVs), gasoline cars, and diesel cars; the unit of observation is a driver-month, with sample sizes reported at the bottom.

Figure 1: Utility factor analysis



(a) Monthly utility factor



(b) Vehicle/driver utility factor

The figure reports: in Panel (a), the histograms of monthly utility factors for each vehicle-driver; in Panel (b), the average utility factors for each vehicle-driver throughout the sample period.

3.1 Implications of the utility factor gap

The discrepancy between official and real-world utility factors weakens emission-based policy instruments for plug-in hybrids. As actual tailpipe carbon dioxide emissions are approximately twice as high as the official estimates, a plug-in hybrid rated at 40 g/km CO_2 would in reality emit on the order of 80 g/km CO_2. Such a level exceeds the 50 g/km CO_2 to 60 g/km CO_2 thresholds that condition purchase subsidies and favourable taxation in Belgium, France, and Germany, implying that a large share of the current hybrid fleet would forfeit these benefits if real-world emissions were used. Additionally, the European Union's Regulation (EU) 2019/631 sets fleet-wide targets for the average CO_2 emissions from all new passenger cars. Manufacturers rely on the low official emissions ratings of plug-in hybrids to comply with these stringent targets. Acknowledging the issue, the European Commission plans to revise the utility-factor schedule in 2025 to reflect on-road behavior more accurately (European Commission, 2024).

In the United States, up to 2022 federal tax credits for plug-in hybrid electric vehicles are not directly tied to emissions (Internal Revenue Service, 2023), sidestepping the issue of misreported emissions. However, the approach still does not account for the environmental impact of plug-in hybrids when operated predominantly in gasoline mode.

3.2 Sources of the Utility Factor Gap

Why do drivers charge their plug-in hybrids infrequently? We provide two descriptive facts to answer this question. First, we establish that recharging plug-in hybrids is cheaper than refilling the tank. We calculated the difference in usage cost per 100 km for all plug-in hybrid users in our sample, assuming a fuel price of €1.37 per liter (the average fuel price in 2021) and an electricity price of €0.30 per kWh.[16] Figure A.7 in the Appendix plots the

[16]The electricity price of €0.30 per kWh is higher than what most households paid in Germany in 2021 to reflect that some charging may occur at higher prices at public chargers.

kernel density of cost differences (€ per 100 km) between using fuel and electricity across users. On average, using electricity is €2.9 per 100 km cheaper. For a driver traveling 10,000 km annually, exclusively using the electric mode would imply cost savings of about €290 relative to combustion-mode driving. The dashed line shows an adjusted calculation that accounts for deviations from official fuel economy values, which slightly increases the estimated savings.

Second, we provide further descriptive evidence on the determinants of the utility factor. Analyzing the charging behavior of a sample of plug-in hybrid drivers for 30 days, Chakraborty et al. (2020) find that vehicle characteristics (driving range) and the availability and cost of charging impact charging decisions. We estimate a regression model for fractional dependent variables (Papke and Wooldridge, 1996) and regress the monthly utility factor on: (i) an indicator identifying that the average daily kilometers in a month exceeding twice the electric range; (ii) an indicator identifying drivers whose mileage is above the 95^{th} percentile of the mileage distribution to capture heavy users (potentially, company car drivers); and (iii) the monthly density (in km^2) of public charging points suitable for plug-in hybrid charging.

Column 1 of Table A.III shows that the utility factor is lower when: (i) car owners frequently drive beyond the car's range (by 10.3 percentage points); (ii) the car is, in general, heavily driven (by 2.1 percentage points). A 0.01 increase in charging-point density (roughly one additional station per 100 km^2) is associated with a 1.7 percentage-point increase in the utility factor. In column 2 of Table A.III, we add driver-specific fixed effects; the effect of the availability of charging points persists.

These descriptive regressions help explain the variation in the utility factor across drivers and the relatively small share of electric charging. Although our sample is unique for the level of detail, the current data cannot fully reveal the importance of these drivers and disentangle them from other behavioral aspects, as we do not have driver-specific attributes. While electricity is a cheaper input than conventional fuel, drivers still prefer internal-combustion mode, suggesting significant "hassle costs" associated with charging (and, as a consequence, using electricity as an input to drive). In Section 6, we extend the analysis to quantify these hassle costs. Our findings reveal substantial heterogeneity across drivers.

4 Conceptual Framework

We develop a stylized framework to explore why the elasticity of fuel consumption and mileage with respect to fuel prices may differ between drivers of internal combustion engines and plug-in hybrids. We show that plug-in hybrid vehicle drivers can substitute toward electric mileage as gasoline prices increase, thereby mitigating the need to reduce total mileage; in contrast, combustion engine drivers can only respond by cutting mileage.

We model the choice of mode (electric or gasoline) and mileage within a continuous-discrete framework (Dubin and McFadden, 1984), reflecting the fact that these choices are interrelated. A plug-in hybrid driver is assumed to choose the mode (electric or gasoline) and the mileage that, in combination, provide the greatest utility. The mode and mileage choices are made jointly to maximize utility, reflecting that mileage is conditional on mode and mode affects the marginal cost of driving.

Consider the following indirect utility specification for a driver choosing alternative $j = E, G$, that is, electric E or gasoline G mode:

$$U_j = y - V_j(p_j) + \varepsilon_j,$$
$$V_j(p_j) = \frac{A_j}{1-\eta_j} p_j^{1-\eta_j},$$

where y denotes income (additive and separable), $V_j(p_j)$ the disutility from operating costs, increasing in price p_j, and ε_j a mode-specific random utility component; the term η_j denotes the price elasticity of consumption for mode j (gasoline or electricity) and A_j a preference parameter.[17]

The conditional demand for mileage in mode j is obtained via Roy's identity:

$$\theta_j = -\frac{\partial U_j(p_j, y)/\partial p_j}{\partial U_j(p_j, y)/\partial y} = A_j p_j^{-\eta_j}.$$

We now turn to the mode choice probabilities. Assuming that ε_j is i.i.d. according to a Type 1 Extreme Value distribution, we can write the mode j choice probability as:

$$s_j = \frac{\exp(-V_j(p_j))}{\sum_{k=E,G}\exp(-V_k(p_k))}.$$

Total mileage θ is given by the weighted average of conditional demands with the choice probabilities as weights:

$$\theta(p_E, p_G) = s_E\theta_E + s_G\theta_G.$$

4.1 Mileage Elasticity to Gasoline Prices

The elasticity of total mileage with respect to gasoline price is defined as:

$$\eta_\theta = \frac{\partial \theta}{\partial p_G} \cdot \frac{p_G}{\theta},$$

which can be expressed as follows:

$$\eta_\theta = \underbrace{-\eta_G\frac{s_G\theta_G}{\theta}}_{\text{Within-mode effect}} + \underbrace{\frac{s_G(1-s_G)\theta_G p_G(\theta_E - \theta_G)}{\theta}}_{\text{Cross-mode substitution}}$$

The elasticity can be decomposed into two components: (i) within-mode effect: even if the plug-in driver continues to use gasoline mode, a higher gasoline price reduces the conditional

[17] Price p_j is expressed in utility units.

mileage demand θ_G through standard price sensitivity η_G. Since only a fraction s_G of total trips (and only the conditional mileage θ_G on those trips) are affected, the within-mode response is scaled by $\frac{s_G\theta_G}{\theta} < 1$. When gasoline prices rise, the conditional demand reacts only to the fraction of trips taken in combustion mode. This effect unambiguously makes the mileage elasticity less negative; (ii) cross-mode substitution effect: higher gasoline prices also shift the probability of choosing gasoline mode s_G downward, increasing the likelihood of choosing electric mode s_E. If *conditional* mileage demands (which we do not observe in the data) differ between modes ($\theta_E \neq \theta_G$), this substitution affects total mileage. If $\theta_E > \theta_G$, a positive substitution effect further mitigates mileage reduction. If $\theta_E < \theta_G$, substitution could amplify mileage reduction.

Comparison with an internal combustion engine driver For a driver restricted to gasoline mode ($s_G = 1$, $s_E = 0$):

$$\theta = s_G\theta_G,$$

Therefore, the elasticity of mileage with respect to gasoline prices is simply:

$$\eta_\theta = -\eta_G$$

Compared to internal combustion engine drivers, plug-in hybrid drivers may exhibit a muted response in total mileage to rising gasoline prices because they can substitute toward electric driving rather than solely reducing mileage. This substitution channel is absent for combustion-only vehicles, where the elasticity is driven entirely by the within-mode response.

4.2 Fuel consumption elasticity to gasoline prices

Define gasoline consumption as the liters used in gasoline mode (assuming constant fuel efficiency):

$$F = s_G \theta_G,$$

where we assume θ_G implicitly adjusts the unit to account for constant fuel economy (liters per kilometer).

The elasticity of gasoline consumption with respect to p_G is:

$$\eta_F = \frac{\partial F}{\partial p_G} \cdot \frac{p_G}{F}$$

The elasticity of fuel consumption with respect to gasoline prices can be expressed as follows:

$$\eta_F = \underbrace{-\eta_G}_{\text{Demand response}} - \underbrace{(1 - s_G)\theta_G p_G}_{\text{Mode switching}}$$

Again, the elasticity can be decomposed into two terms: (i) the first term ($-\eta_G$) is the standard price elasticity of gasoline demand conditional on mode choice; (ii) the second term is the additional reduction in fuel consumption from drivers switching to electric mode.

Comparison with an internal combustion engine driver For a pure gasoline driver ($s_G = 1$, $s_E = 0$), the elasticity of fuel consumption η_F reflects only the direct effect:

$$\eta_F = -\eta_G \tag{2}$$

4.3 Numerical Example

We propose a simple numerical example to illustrate our framework. We assign parameter values that result in a share of electric driving of approximately 0.37, reflecting the low use of plug-in hybrid in electric mode observed in the data (Section 2).

Results are summarized in Table 2. Plug-in hybrid drivers exhibit an inelastic mileage response ($\eta_\theta = -0.03$) compared to internal combustion engine drivers ($\eta_\theta = -0.30$). Fuel consumption elasticity is more negative for plug-in vehicles ($\eta_F = -0.33$) than for internal combustion engine drivers ($\eta_F = -0.30$), as mode switching amplifies the reduction in gasoline use.

Table 2: Numerical example: parameters and computed values

	PHEV	**ICE**
Parameters		
A_E	4.00	–
A_G	0.50	0.50
η_E	0.30	–
η_G	0.30	0.30
p_G (\$/km)	1.00	1.00
p_E (\$/km)	0.50	–
Mileage		
Share electric ($\frac{s_E \theta_E}{\theta}$)	0.37	0.00
Elasticities		
Mileage (η_θ)	-0.03	-0.30
Fuel Consumption (η_F)	-0.33	-0.30

The table reports a numerical example, including parameters, the share of electric driving, and elasticities of mileage and fuel consumption with respect to gasoline prices for plug-in hybrid electric vehicles (PHEV) and internal combustion engine vehicles (ICE).

5 Empirical Elasticity Estimates

5.1 Empirical design

To study the impact of fuel prices on fuel demand, we regress measures of fuel consumption, travel distance, and travel mode (electric versus fuel) on fuel prices. We begin with the following specification:

$$y_{it} = \alpha + \beta \times \ln(P_{it}) + \gamma_t + \eta_i + \varepsilon_{it}, \tag{3}$$

where $\ln(P_{it})$ represents the log of per-liter fuel price paid by driver i in month t, γ_t are time fixed effects (year and month) controlling for unobserved time-varying effects, and η_i are driver fixed effects controlling for any unobserved driver-specific characteristics affecting the relationship between our variables of interest and fuel prices. Each driver is associated with only one vehicle, so the unit of observation is driver-vehicle-month.

We define four outcome variables, y_{it}: (i) the log of per-month fuel consumption (in liters); (ii) the log of per-month mileage (in km); (iii) the log of per-month on-road fuel economy; and (iv) the per-month utility factor for plug-in hybrids, namely the share of kilometers driven in electric mode. In all specifications, we cluster the standard errors at the driver level and weight by the number of fueling logs recorded by each user in month t. We do not include the electricity prices as a control because they exhibit very little variation throughout the sample period: see Figure A.4 in the Appendix.[18]

Identification Thanks to the granularity of our data, our coefficient of primary interest is identified by the within-driver deviations in fuel prices from their own average. Our fixed

[18] In robustness checks, we include logged electricity prices and the logged number of charging stations as controls. The inclusion of these additional covariates does not substantially alter our results. Nehiba (2024) finds that a 10% increase in electricity prices results in a modest 0.82% reduction in mileage for electric vehicles. Bushnell et al. (2022) document that gasoline prices have a larger effect on electric vehicle adoption than electricity prices, as the link between vehicle use, home charging, and electricity bills appears to be less well understood by consumers.

effects at the month and year levels absorb persistent differences in fuel prices. Similarly to Knittel and Tanaka (2021), heterogeneity across drivers generating a correlation between fuel consumption and fuel prices does not threaten identification.

While posted fuel prices are exogenous for drivers, an endogeneity concern remains, as the fuel prices drivers pay may be endogenous to their individual fuel consumption and mileage. First, consumers may adjust their search behavior in response to increased fuel prices, resulting in a downward bias in elasticity estimates.[19]

In addition, gasoline and diesel are offered in different grades or quality levels. Modern cars can use any quality level without resulting in engine damage, and most gas stations in Germany offer at least standard and premium grades of gasoline.[20] Much like search intensity, drivers can switch to a cheaper, lower-grade fuel when prices increase. In our setting, we find empirical evidence of consumers switching fuel grades when prices change. Among gasoline users, including drivers of gasoline plug-in hybrids, around 40 percent use more than one fuel grade during the sample period, and 11.0 percent switch fuel grades within a quarter. We regress the driver's quarterly shares of fuel grades on the prices of the fuel grades. We observe four grades of gasoline (normal, super, super plus, and premium) and two grades of diesel (normal and premium). Table A.IV in the Appendix shows that price changes are associated with switching across fuel grades. For instance, column 1 of the table shows that drivers reduce their share of normal grade when the price of normal gasoline increases (holding the price of other grades fixed). The same pattern holds for the other grades.

Finally, long-distance travel, such as highway or rural driving, may expose drivers to

[19]This concern is probably not of particular importance in our setting. Using data on search queries in 2015 from a German smartphone application that enables users to compare fuel prices across stations, Montag et al. (2023) find that online search intensity did not correlate with price levels. In addition, Figure A.8 in the Appendix shows that self-reported fuel prices closely match average posted fuel prices, and the discrepancy between effective and posted fuel prices does not systematically increase when prices rise.

[20]Using a lower-grade fuel when the premium is recommended slightly affects the fuel economy and the car's performance.

higher fuel prices due to limited competition or availability, introducing an upward bias.

To address potential endogeneity in consumer-level fuel prices, we construct two instrumental variables. First, following Knittel and Tanaka (2021), we instrument each driver's reported fuel price with the daily national average price of the same fuel grade on the purchase date. For each refueling transaction, we replace the self-reported price with the corresponding national average for that fuel grade on that day, and then aggregate to the monthly level by computing a volume-weighted average, using liters purchased in each transaction as weights. Because refueling dates differ across consumers, this instrument retains cross-sectional variation in price exposure even after aggregation to monthly data. Second, to account for endogenous fuel-grade switching, we construct an alternative instrument based on each driver's predominant fuel grade, defined as the one used in more than 50% of that driver's refueling transactions. For each refueling event, we assign the national average price of the driver's predominant grade on that day, regardless of which grade was actually purchased in that instance, and then aggregate these assigned prices to the monthly level using the same volume-weighted procedure.[21]

After accounting for year, month, and driver fixed effects, the identifying variation in both instruments comes from within-month-year differences across drivers in assigned national average prices. These differences arise from variation in refueling days and fuel grade composition. For plug-in hybrids, around 70 percent of the variation in reported prices is absorbed by the fixed effects, and between 69 and 73 percent of the variation in the instruments (that is, national fuel prices) is absorbed by the fixed effects, leaving the remaining share available for identification.

[21] Further details are provided in Appendix B.

5.2 Results

Table 3 reports the estimation results of Equation (3). The first three columns of Table 3 report the WLS estimates; columns 4 to 6 ("IV 1") report the IV results using the average fuel prices of the corresponding fuel grade to instrument for the actual price paid; columns 7 to 9 ("IV 2") report the IV results using the average price of the most used fuel grade as instrument. The first stage of the IV specifications is reported in Table A.V in the Appendix. Our two instrumentation strategies produce similar results for estimated elasticities of fuel consumption and mileage, reflecting the strong correlation between the instruments.

The estimated IV1 and IV2 coefficients are substantially larger than the WLS estimates and statistically significant at the one percent level. This suggests that WLS estimates are attenuated: fuel consumption is positively correlated with prices, likely reflecting driving in more expensive refueling contexts rather than the causal effects of price. At the same time, our estimates suggest a limited role for systematic search behavior and grade switching. This result aligns with findings from previous studies (Knittel and Tanaka, 2021).

For gasoline car drivers, we estimate an elasticity of fuel consumption of approximately -0.22 and an elasticity of mileage of -0.20. For diesel car drivers, the elasticity of fuel consumption ranges from -0.22 to -0.25, and the elasticity of mileage ranges from -0.15 to -0.18.

The elasticity of fuel economy (columns 6 and 9) is -0.02 to -0.03 for gasoline and -0.07 for diesel. These elasticities imply that, for gasoline cars, approximately 88 percent of the reduction in fuel consumption stems from a decrease in mileage; the remaining 12 percent originates from fuel-conserving measures, such as improved driving and maintenance behavior. The magnitude is consistent with the findings of Knittel and Tanaka (2021). For diesel cars, the percentage of reduction in fuel consumption attributable to fuel-conserving behavior is slightly higher (roughly 29 to 31 percent).

For plug-in hybrid drivers, the estimated elasticity of fuel consumption is substantially larger than for gasoline and diesel car users, ranging between −0.33 and −0.41 (we do not reject the hypothesis that the coefficients are equal in the two specifications). However, these drivers do not seem to reduce their mileage in response to fuel price increases (their elasticity of mileage is estimated noisily and close to zero). Notably, a one percent rise in fuel prices is associated with a 0.25 percent decrease in fuel economy. Given the on-road/NEDC fuel economy ratio of 2.93, indicating that these vehicles consume nearly three times more fuel than expected, this decrease is substantial. The elasticity of the fuel economy deviation ratio is an order of magnitude larger for plug-in hybrids than for gasoline and diesel vehicles, suggesting that such a significant effect is unlikely to stem solely from fuel-conserving behavior, especially given the null effect on mileage.

When comparing plug-in hybrids to traditional internal combustion vehicles, plug-in hybrids offer an additional margin of adjustment through recharging behavior. Table 4 suggests that a one percent rise in fuel prices leads to a utility factor increase of 0.15 percentage points.[22] Higher fuel prices encourage plug-in hybrid drivers to increase the use of their vehicles in electric mode through charging. In particular, we calculate that around 89 percent of the improvement in on-road fuel economy (liters/km) comes from increased charging (shifting to electric driving), while 11 percent comes from fuel-conserving behavior in fuel mode.[23]

[22] At the mean UF of 0.32, this corresponds to a 46% increase in the share of electric driving (0.148/0.32).

[23] The decomposition follows from the UF identity:

$$\mathrm{UF} = 1 - \frac{\mathrm{FE}_{\text{on-road}}}{\mathrm{FE}_{\mathrm{CS}}} \implies \mathrm{FE}_{\text{on-road}} = \mathrm{FE}_{\mathrm{CS}}(1 - \mathrm{UF})$$

Taking log derivatives with respect to fuel price:

$$\frac{\partial \ln \mathrm{FE}_{\text{on-road}}}{\partial \ln P} = \frac{\partial \ln \mathrm{FE}_{\mathrm{CS}}}{\partial \ln P} + \frac{\partial \ln(1 - \mathrm{UF})}{\partial \ln P}$$

$$-0.245 = \beta_{\mathrm{FE}_{\mathrm{CS}}} - \frac{1}{1 - 0.32} \times 0.148$$

$$-0.245 = \beta_{\mathrm{FE}_{\mathrm{CS}}} - 0.217 \implies \beta_{\mathrm{FE}_{\mathrm{CS}}} = -0.028$$

Table 3: Results

	WLS			IV 1			IV 2		
	ln(Fuel Use)	ln(VKT)	ln(FE)	ln(Fuel Use)	ln(VKT)	ln(FE)	ln(Fuel Use)	ln(VKT)	ln(FE)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
PHEVs									
ln(Price)	-0.230**	-0.157*	-0.073*	-0.405***	-0.159	-0.245***	-0.329**	-0.084	-0.245***
	(0.101)	(0.095)	(0.039)	(0.142)	(0.139)	(0.052)	(0.137)	(0.131)	(0.049)
R^2	0.319	0.213	0.702	0.319	0.213	0.702	0.319	0.213	0.702
Observations	25,426	25,426	25,426	25,426	25,426	25,426	25,426	25,426	25,426
Gasoline									
ln(Price)	-0.069***	-0.059***	-0.010***	-0.220***	-0.197***	-0.023***	-0.225***	-0.198***	-0.027***
	(0.018)	(0.018)	(0.002)	(0.024)	(0.024)	(0.003)	(0.023)	(0.024)	(0.003)
R^2	0.242	0.209	0.904	0.242	0.209	0.904	0.242	0.209	0.904
Observations	784,212	784,212	784,212	784,212	784,212	784,212	784,196	784,196	784,196
Diesel									
ln(Price)	-0.117***	-0.082***	-0.035***	-0.220***	-0.151***	-0.070***	-0.252***	-0.178***	-0.074***
	(0.023)	(0.023)	(0.003)	(0.029)	(0.029)	(0.003)	(0.029)	(0.029)	(0.003)
R^2	0.240	0.228	0.878	0.240	0.228	0.878	0.240	0.228	0.878
Observations	357,731	357,731	357,731	357,731	357,731	357,731	357,722	357,722	357,722
Fixed effects									
Driver	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

The table reports the estimation results of Equation (3). The dependent variables are: (i) the log of fuel consumption (in liters) in columns 1, 4, and 7; (ii) the log of vehicle kilometers traveled (VKT) in columns 2, 5, and 8; and (iii) the log of fuel economy (FE, in liters/100km) in columns 3, 6, and 9. Columns 1, 2, and 3 present the WLS parameter estimates. Columns 4 to 9 are estimated using the instrumental variable approach. PHEVs: plug-in hybrid electric vehicles. All specifications include driver, year, and month fixed effects. Standard errors are clustered at the driver level and reported in parentheses. ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively.

Contribution shares:

$$\text{Charging effect} = \frac{0.217}{0.245} = 89.0\% \quad \text{and} \quad \text{Fuel-mode effect} = \frac{0.028}{0.245} = 11.0\%$$

All coefficients are from IV2 specifications in Table 3.

Table 4: Results – utility factor

	WLS (1)	IV 1 (2)	IV 2 (3)
PHEVs			
ln(Price)	0.047**	0.148***	0.148***
	(0.023)	(0.030)	(0.028)
R^2	0.664	0.663	0.663
Observations	25,426	25,426	25,426
Fixed effects			
Driver	Yes	Yes	Yes
Year	Yes	Yes	Yes
Month	Yes	Yes	Yes

The table reports the estimation results of Equation (3) for plug-in hybrid electric vehicles (PHEVs). The dependent variable is the utility factor UF (the share of driving in electric mode) calculated according to Equation (1) using the empirical estimation of Fuel economy$_{CS}$ based on non-rechargeable HEVs (UF HEV). All specifications include driver, year, and month fixed effects. Standard errors are clustered at the driver level and reported in parentheses. ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively.

Implications on CO_2 emissions As fuel consumption maps approximately one-to-one to CO_2 emissions, the fuel use elasticities can also be interpreted as CO_2 elasticities.[24] Increased electrification, driven by a 0.15 percentage point increase in the utility factor (Table 4, IV2), accounts for approximately 66.2% of the CO_2 emission reduction for plug-ins. Additionally, hybrid owners face lower costs in absorbing fuel price shocks, as they can switch to electric mode without significantly reducing mileage, unlike gasoline and diesel vehicle owners. Together, these results suggest that fuel prices are indeed effective at improving the environmental benefits of plug-in hybrids as they determine a more pronounced reduction in fuel demand for drivers; at the same time, absorbing fuel shocks is less costly for these drivers.

[24] Burning one liter of gasoline emits 2,390g of CO_2 while burning one liter of diesel emits 2,640g of CO_2. The greenhouse-gas calculations refer exclusively to tailpipe CO_2. Charging emissions from electricity production are outside the scope of this paper and are regulated under the EU ETS.

Robustness We conduct an extensive set of robustness checks on these results. Our results are robust to: (i) the use of a range of deviation values (1.3, 1.5, and 1.7) in the denominator of Equation (1) to calculate the utility factor (Table A.VI in the Appendix); (ii) the inclusion of observations with long-distance traveled, with a maximum daily mileage of 105.4 km for plug-in hybrids (Table A.VII and Table A.VIII in the Appendix); (iii) the use of unweighted regression methods (Tables A.IX and A.X in the Appendix); (iv) the use of a linear time trend (Tables A.XI and A.XII) [25]; and (v) impact of the COVID-19 pandemic (Tables A.XIII and A.XIV).

In particular, related to (v), we estimate the following augmented specification:

$$y_{it} \;=\; \alpha \;+\; \beta_1 \ln(P_{it}) \;+\; \beta_2 \left[\ln(P_{it}) \times I_t\right] \;+\; \delta\, I_t \;+\; \gamma_t \;+\; \eta_i \;+\; \varepsilon_{it}\,, \tag{4}$$

where $\ln(P_{it})$ is the log of the per-liter fuel price paid by driver i in month t, $I_t = I(t >$ March 2020) is the COVID-period indicator, γ_t are year-and-month fixed effects, and η_i are driver (vehicle) fixed effects.

In this formulation, the coefficient β_2 captures any change in price-sensitivity after March 2020. Across both WLS and IV estimations, β_2 is rather small and statistically indistinguishable from zero, confirming that our main estimates are not driven by changes in the fleet composition that overlap with the pandemic. Similarly, in the utility factor regressions (Table A.XIV), the post-2020 interactions are again insignificant.

[25] When using a linear time trend, Table A.XI shows that R^2 values are lower, indicating that the linear trend captures less of the time-specific variation in fuel prices and driving behavior compared to year and month fixed effects. This reduced explanatory power is consistent with Figure A.8, which highlights significant within-month price fluctuations, such as those during the COVID-19 lockdown in 2020, that a linear trend may not fully account for, unlike the fixed effects approach. Nevertheless, the results confirm the direction of the effects.

5.3 Changes in recharging habits

The evidence thus far suggests that fuel prices have a contemporaneous effect on electric recharging behavior. To test for the presence of changes in recharging habits, we estimate a distributed lag model that includes in Equation (3) past fuel prices:

$$\mathrm{UF}_{it} = \alpha + \sum_{j=0}^{t} \beta_j \ln P_{it-j} + \gamma_t + \eta_i + \varepsilon_{it}, \tag{5}$$

where P_{it-j} represents the log of per-liter fuel price paid by driver i in month $t-j$, and the outcome variable of interest is the utility factor. Table 5 reports the coefficients of the six most recent past refueling prices paid by the driver; these prices are instrumented using monthly average prices. The estimates indicate no empirical evidence of habit modifications due to past price shocks; even the most recent past fuel price does not influence the current charging behavior. Our findings thus align with evidence from Knittel and Tanaka (2021) on fuel economy and Bailey et al. (2023) on charging times for electric vehicles.

Table 5: Changes in recharging habits

Dependent variable	Utility factor (HEV)					
	(1)	(2)	(3)	(4)	(5)	(6)
PHEVs						
$\ln(\text{Price}_t)$	0.173***	0.159***	0.175***	0.159**	0.131*	0.181**
	(0.050)	(0.054)	(0.062)	(0.065)	(0.073)	(0.074)
$\ln(\text{Price}_{t-1})$	-0.029	-0.018	-0.060	-0.074	-0.055	-0.097
	(0.045)	(0.063)	(0.072)	(0.075)	(0.080)	(0.082)
$\ln(\text{Price}_{t-2})$		-0.020	-0.041	-0.027	0.006	0.037
		(0.050)	(0.072)	(0.074)	(0.073)	(0.069)
$\ln(\text{Price}_{t-3})$			0.048	0.091	0.055	0.019
			(0.057)	(0.077)	(0.074)	(0.071)
$\ln(\text{Price}_{t-4})$				-0.040	-0.023	-0.017
				(0.055)	(0.082)	(0.077)
$\ln(\text{Price}_{t-5})$					-0.033	0.011
					(0.063)	(0.076)
$\ln(\text{Price}_{t-6})$						-0.062
						(0.060)
R^2	0.690	0.704	0.713	0.718	0.728	0.736
Observations	21,177	17,425	14,697	12,578	10,887	9,503
Fixed effects						
Driver	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
Month	Yes	Yes	Yes	Yes	Yes	Yes

The table reports the coefficients of the six most recent prices paid based on the distributed lag model as specified by Equation (5). The dependent variable is the utility factor. All specifications are estimated using the instrumental variable approach, where monthly average prices are used as the instrument. All specifications include fixed effects for driver, year, and month. Standard errors are clustered at the driver level and reported in parentheses. ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively.

6 The hassle cost of charging

In Section 2, we showed that the share of electric driving is only 32%. While electricity is a cheaper input than conventional fuel, drivers still prefer internal-combustion mode, suggesting significant "hassle costs" associated with charging (and, as a consequence, using electricity as an input to drive). We specify and estimate a simple discrete choice model of electric charging versus fueling choice to approximate the distribution of drivers' hassle costs associated with charging. Since our data do not support estimating the continuous–discrete framework in Section 4 (for example, we do not observe the conditional mileage demand by mode), we instead focus on a simpler discrete choice model of powertrain mode.

On a given trip r, a driver i has the choice j to drive in electric mode, namely charge the battery ($j = E$), or in internal combustion mode, namely use fuel because the battery is empty ($j = G$). Trips are conducted during a period t. The utility that a driver receives from choice j is given by:

$$U_{ijr} = \alpha_1 p_{ijt} + \eta_{ij} + \xi_{ijt} + \varepsilon_{ijr}, \tag{6}$$

where p_{ijt} is driver i's expenditure per kilometer associated with charging or refueling in period t. The driver's utility also depends on η_{ij}, denoting individual and mode-specific unobservables, ξ_{ijt}, period-specific unobservables, as well as ε_{ijr}, an idiosyncratic trip-specific preference shock. The driver chooses to charge and drive electric if $U_{iEr} > U_{iGr}$. Assuming that ε_{ijr} is i.i.d. according to a Type 1 Extreme Value distribution, we can write the choice probability of recharging as follows:

$$s_{iEr} = \frac{1}{1 + \exp(\underbrace{\alpha_1 \Delta p_{it} + \Delta\eta_i + \Delta\xi_{it}}_{\delta_{it}})},$$

where $\Delta x_{it} = x_{iGt} - x_{iEt}$. Let $\delta_{it} = \alpha_1 \Delta p_{it} + \Delta\eta_i + \Delta\xi_{it}$.

We aggregate at the period t (month) level. Let R_{it} denote the total number of trips conducted by driver i within the period t and θ_{ir} the trip distance. We set s_{iEt}, the choice probability of charging for period t, equal to the observed share of driving in electric mode, which is the utility factor per period t:

$$s_{iEt} = \frac{\sum_{r=1}^{R_{it}} s_{iEr}\theta_{ir}}{\sum_{r=1}^{R_{it}} \theta_{ir}} = \mathrm{UF}_{it}.$$

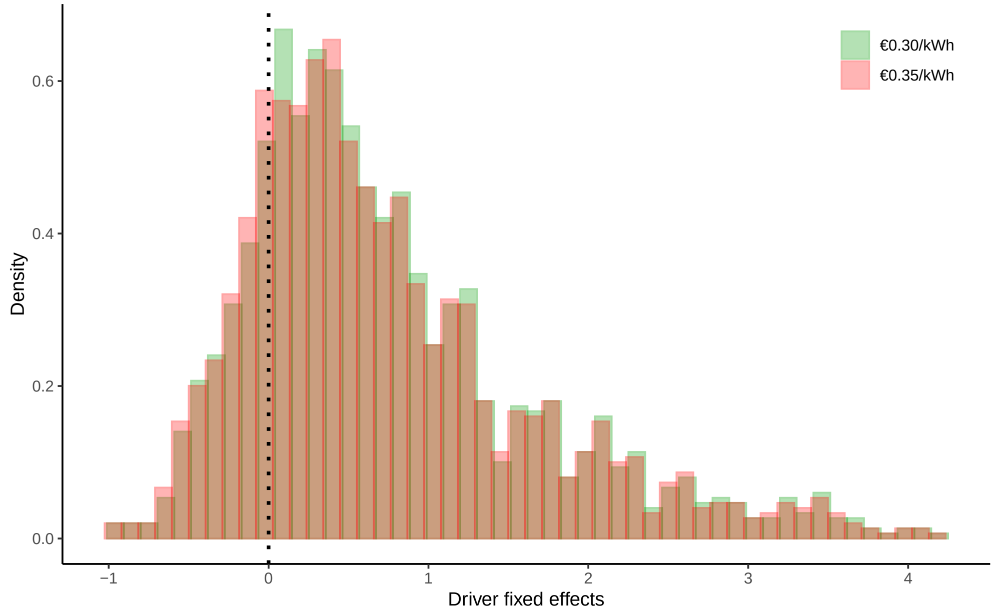
Aggregation allows the model to capture the share of electric driving, which reflects non-binary behaviors such as partial charging. We solve for $\delta_{it} = \ln\left(\frac{1-\mathrm{UF}_{it}}{\mathrm{UF}_{it}}\right)$, and use the value in the linear regression:

$$\delta_{it} = \alpha_1 \Delta p_{it} + \Delta\eta_i + \Delta\xi_{it}. \tag{7}$$

To compute Δp_{it}, we use information on the fuel price per liter, the fuel economy in internal combustion mode, the electricity price, and the fuel economy in electric mode, and calculate the price of fueling and electric charging per kilometer. As for electricity prices, we use €0.30 and €0.35 per kWh. We assume that $\Delta\xi_{it}$ is mean-zero and account for possible correlation with reported prices using national average prices as instruments.

Figure 2 reports the distribution of the driver-specific fixed effects $\Delta\eta_i$, representing the drivers' fixed preference for gasoline over electric mode after netting out price effects. The distribution is right-skewed with a mass above zero ($\eta_{iG} > \eta_{iE}$), revealing substantial heterogeneity in charging preferences across drivers. This heterogeneity explains the inelastic response of the utility factor to fuel prices: for drivers with large $\Delta\eta_i$, even significant price swings are offset by charging inconvenience. These results suggest that policies targeting charging convenience, along with fuel prices, are crucial to shifting behavior among charging-reluctant drivers, as also shown in Gessner et al. (2024).

Figure 2: Distribution of the (dis)utility of charging versus refueling



The figure plots the distribution of driver-specific fixed effects representing the driver (dis)utility of charging relative to refueling. The coefficients are obtained after regressing δ_{it}, specified in Equation (7), on the price differences Δp_{it} and fixed effects at the driver level.

7 Conclusion

Plug-in hybrids combine an internal combustion engine with an electric battery. These cars can deliver critical environmental benefits by acting as bridge technology toward fully electrified private transport, but only if used to maximize electric driving. In this paper, we investigate the usage behavior of plug-in hybrid cars and the extent to which fuel prices influence such usage.

Using detailed micro-level data, we document that plug-in hybrids are only occasionally used in electric mode, with only 32 percent of their mileage driven on an electric motor on average. This is a problem because the assumed utility factor used to determine the official fuel economy rating suggests that plug-in hybrids are clean vehicles and allow car manufacturers to comply more easily with fuel economy standards. In reality, the environmental benefits of plug-in hybrids are overstated if they are not used in electric mode as much as expected.

We study the extent to which the usage of plug-in hybrids responds to fuel prices. Unlike combustion engine car drivers, who can only reduce their mileage to absorb fuel price shocks, drivers of plug-in vehicles can also change their charging behavior and increase the share of mileage driven in electric mode. We find that a ten percent increase in fuel prices leads to an increase in the utility factor of around 1.5 percentage points. We find no evidence of habit modifications in charging behavior. Finally, we estimate substantial heterogeneity in charging preferences across drivers.

Our results suggest that fuel prices are effective at promoting the use of plug-in hybrids in electric mode, ultimately contributing to the goal of reducing greenhouse gas emissions and mitigating climate change.

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Appendix A

Tables

Table A.I: Selected elasticity estimates

Paper	**Market/time**	**Temporal/cross-sectional variation**	**Type of price elasticity**	**Elasticity**
Panel A: Literature				
Kilian and Zhou (2023)	US 1989-2022	Month/state	Fuel use	-0.20 (post 2014)
Gelman et al. (2023)	US 2013-2016	Week/individual	Fuel spending	-0.16
Knittel and Tanaka (2021)	Japan 2005-2014	Day/individual	Fuel use VMT	-0.37 -0.30
Gillingham and Munk-Nielsen (2019)	Denmark 1998-2011	Biennial/vehicle	VMT	-0.30
Coglianese et al. (2017)	US 1989-2008	Month/state	Fuel use	-0.37
Levin et al. (2017)	243 US cities 2006-2009	Day/metropolitan area	Fuel use	-0.27 to -0.35
Gillingham (2014)	California 2006-2009	Biennial/vehicle	VMT	-0.22
Panel B: This paper				
	Germany 2016-2021	Month/individual	Fuel use - PHEV VMT - PHEV Fuel use - gasoline VMT - gasoline Fuel use - diesel VMT - diesel	-0.41 to -0.33 -0.16 to -0.09 (n.s.) -0.22 -0.20 -0.25 to -0.22 -0.18 to -0.15

The table summarizes the elasticity of fuel prices to fuel demand estimated in prior studies from the last decade (panel A) and our own estimated elasticities (panel B). For each study, the table lists the relevant market and time frame, the temporal and cross-sectional variation, the type of elasticity, and the estimated values. VMT: Vehicle Miles Traveled; PHEV: Plug-in Hybrid Electric Vehicle

Table A.II: Regression of non-chargeable hybrids on-road fuel economy

Dependent Variable:	On-road fuel economy
	(1)
Constant	1.408*** (0.106)
February	-0.122*** (0.026)
March	-0.322*** (0.026)
April	-0.485*** (0.026)
May	-0.644*** (0.026)
June	-0.707*** (0.025)
July	-0.702*** (0.025)
August	-0.677*** (0.024)
September	-0.654*** (0.024)
October	-0.499*** (0.024)
November	-0.237*** (0.024)
December	-0.026 (0.025)
Official fuel economy	0.469*** (0.024)
Power (100 kW)	0.331*** (0.031)
Weight (tonne)	1.284*** (0.092)
Build year: 2017	-0.172*** (0.019)
Build year: 2018	-0.170*** (0.020)
Build year: 2019	-0.354*** (0.018)
Build year: 2020	-0.350*** (0.019)
Build year: 2021	-1.541*** (0.188)
Body: light	-0.012 (0.014)
Body: medium	0.242*** (0.017)
Class: small	0.066*** (0.021)
RMSE	0.645
R^2	0.475
Adjusted R^2	0.475
Observations	18,432

The table reports OLS estimates from a regression of on-road fuel economy for non-chargeable hybrids on the following covariates: (i) the month of refueling activity (to account for weather conditions), (ii) the vehicle's official fuel economy, (iii) vehicle class, (iv) body type, (v) power (kW), (vi) curb weight, and (vii) build year. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table A.III: Determinants of utility factor

Dependent variable:	Utility factor (HEV)	
	(1)	(2)
Trip length exceed range	-0.317*	0.050
	(0.134)	(0.081)
Charging points density	4.828*	3.731***
	(1.948)	(1.178)
Heavily driven car	-0.059**	
	(0.022)	
Observations	25,426	24,713
Fixed effects		
Year	Yes	Yes
Month	Yes	Yes
Driver		Yes

The table reports the parameter estimates of a fractional response model and robust standard errors (in parentheses). The dependent variable in each specification is the utility factor, the share of driving in electric mode. Column 1 includes year and month fixed effects. Column 2 includes driver, year, and month fixed effects. ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% level, respectively.

Table A.IV: Switching between fuel grades

Dependent variables: Share	Normal	Super	Super Plus	Premium	Diesel Normal	Diesel Premium
	(1)	(2)	(3)	(4)	(5)	(6)
ln(Price Normal)	-1.450***	1.029***	-0.156	0.577***		
	(0.160)	(0.197)	(0.109)	(0.121)		
ln(Price Super)	0.778***	-0.456***	0.089	-0.411***		
	(0.133)	(0.166)	(0.095)	(0.103)		
ln(Price Super Plus)	0.240***	-0.067	-0.024	-0.149***		
	(0.041)	(0.052)	(0.031)	(0.032)		
ln(Price Premium)	0.702***	-0.595***	0.051	-0.158*		
	(0.120)	(0.148)	(0.086)	(0.089)		
ln(Price Diesel Normal)					-0.009	0.009
					(0.055)	(0.055)
ln(Price Diesel Premium)					0.113	-0.113
					(0.074)	(0.074)
R^2	0.828	0.810	0.783	0.788	0.782	0.782
Observations	332,211	332,211	332,211	332,211	143,752	143,752
Fixed effects						
Driver	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
Quarter	Yes	Yes	Yes	Yes	Yes	Yes

The table reports the parameter estimates of an OLS model showing switching across fuel grades. The dependent variables are the share of each fuel grade Normal, Super, Super Plus, Premium, Diesel Normal, and Diesel Premium over the total fuel pumped in a quarter, as shown in columns 1–6. All specifications include driver, year, and quarter fixed effects. Standard errors are clustered at the driver level and reported in parentheses. ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively.

Table A.V: First stage results for IV estimates

Dependent variable	ln(Price paid)					
	PHEV		Gasoline		Diesel	
	IV1	IV2	IV1	IV2	IV1	IV2
	(1)	(2)	(3)	(4)	(5)	(6)
ln(Posted Price)	0.846***	0.927***	0.861***	0.909***	0.899***	0.952***
	(0.013)	(0.010)	(0.002)	(0.010)	(0.003)	(0.005)
R^2	0.844	0.850	0.879	0.876	0.868	0.867
F-test	476.036	496.263	14,164.560	13,784.497	5,756.691	5,698.389
Observations	25,426	25,426	784,212	784,196	357,731	357,722
Fixed effects						
Driver	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
Month	Yes	Yes	Yes	Yes	Yes	Yes

The table reports the first stage results for the IV estimates, including the F-statistics of the excluded instruments. All specifications include driver, year, and month fixed effects. Standard errors are clustered at the driver level and reported in parentheses. ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively.

Table A.VI: Robustness check – alternative deviation ranges

	WLS			IV 1			IV 2		
	UF(1.3)	UF(1.5)	UF(1.7)	UF(1.3)	UF(1.5)	UF(1.7)	UF(1.3)	UF(1.5)	UF(1.7)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
PHEVs									
ln(Price)	0.042*	0.046**	0.045**	0.137***	0.141***	0.135***	0.140***	0.143***	0.137***
	(0.023)	(0.022)	(0.021)	(0.030)	(0.029)	(0.027)	(0.028)	(0.027)	(0.025)
R^2	0.686	0.714	0.723	0.685	0.713	0.723	0.685	0.713	0.723
Observations	25,426	25,426	25,426	25,426	25,426	25,426	25,426	25,426	25,426
Fixed effects									
Driver	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

The table reports the estimation results of Equation (3) for plug-in hybrid electric vehicles (PHEVs) using a range of deviation values for the calculation of the utility factor. The dependent variable is the utility factor (UF; the share of driving in electric mode) calculated according to Equation (1) using the deviation value of 1.3 (in columns 1, 4, and 7), 1.5 (in columns 2, 5, and 8), and 1.7 (in columns 3, 6, and 9). Columns 1, 2, and 3 present the WLS parameter estimates. Columns 4 to 9 are estimated using the instrumental variable approach. All specifications include driver, year, and month fixed effects. Standard errors are clustered at the driver level and reported in parentheses. ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively.

Table A.VII: Robustness check – incl. long-distances

	WLS			IV 1			IV 2		
	ln(Fuel Use)	ln(VKT)	ln(FE)	ln(Fuel Use)	ln(VKT)	ln(FE)	ln(Fuel Use)	ln(VKT)	ln(FE)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
PHEVs									
ln(Price)	-0.061	-0.045	-0.016	-0.359**	-0.122	-0.237***	-0.235*	-0.020	-0.215***
	(0.104)	(0.097)	(0.038)	(0.145)	(0.139)	(0.051)	(0.139)	(0.131)	(0.049)
R^2	0.346	0.257	0.697	0.346	0.257	0.696	0.346	0.257	0.696
Observations	26,231	26,231	26,231	26,231	26,231	26,231	26,231	26,231	26,231
Fixed effects									
Driver	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

The table reports the estimation results of Equation (3) for plug-in hybrid electric vehicles (PHEVs) including observations with long-distance traveled, with a maximum daily mileage of 105.4 km. The dependent variables are: (i) the log of fuel consumption (in liters) in columns 1, 4, and 7; (ii) the log of vehicle kilometers traveled (VKT) in columns 2, 5, and 8; and (iii) the log of fuel economy (FE, in liters/100km) in columns 3, 6, and 9. Columns 1, 2, and 3 present the WLS parameter estimates. Columns 4 to 9 are estimated using the instrumental variable approach. PHEVs: plug-in hybrid electric vehicles. All specifications include driver, year, and month fixed effects. Standard errors are clustered at the driver level and reported in parentheses. ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively.

Table A.VIII: Robustness check – incl. long-distances (Utility Factor)

	WLS	IV 1	IV 2
		UF(HEV)	
	(1)	(2)	(3)
PHEVs			
ln(Price)	0.013	0.142***	0.130***
	(0.022)	(0.030)	(0.029)
R^2	0.653	0.652	0.652
Observations	26,231	26,231	26,231
Fixed effects			
Driver	Yes	Yes	Yes
Year	Yes	Yes	Yes
Month	Yes	Yes	Yes

The table reports the estimation results of Equation (3) for plug-in hybrid electric vehicles (PHEVs) including observations with long-distance traveled, with a maximum daily mileage of 111.4 km. The dependent variable is the utility factor UF (the share of driving in electric mode) calculated according to Equation (1) using the empirical estimation of Fuel economy$_{CS}$ based on non-rechargeable HEVs (UF HEV). All specifications include driver, year, and month fixed effects. Standard errors are clustered at the driver level and reported in parentheses. ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively.

Table A.IX: Robustness check – unweighted regressions

	OLS			IV 1			IV 2		
	ln(Fuel Use)	ln(VKT)	ln(FE)	ln(Fuel Use)	ln(VKT)	ln(FE)	ln(Fuel Use)	ln(VKT)	ln(FE)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
PHEVs									
ln(Price)	-0.260***	-0.141*	-0.118***	-0.359***	-0.095	-0.265***	-0.315***	-0.035	-0.280***
	(0.086)	(0.080)	(0.034)	(0.123)	(0.116)	(0.048)	(0.120)	(0.112)	(0.047)
R^2	0.309	0.209	0.711	0.309	0.209	0.711	0.309	0.209	0.710
Observations	25,426	25,426	25,426	25,426	25,426	25,426	25,426	25,426	25,426
Fixed effects									
Driver	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

The table reports the estimation results of Equation (3) for plug-in hybrid electric vehicles (PHEVs) using IV regressions without weights. The dependent variables are: (i) the log of fuel consumption (in liters) in columns 1, 4, and 7; (ii) the log of vehicle kilometers traveled (VKT) in columns 2, 5, and 8; and (iii) the log of fuel economy (FE, in liters/100km) in columns 3, 6, and 9. Columns 4 to 9 are estimated using the instrumental variable approach. All specifications include driver, year, and month fixed effects. Standard errors are clustered at the driver level and reported in parentheses. ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively.

Table A.X: Robustness check – unweighted regressions (Utility Factor)

	OLS	IV 1	IV 2
		UF(HEV)	
	(1)	(2)	(3)
PHEVs			
ln(Price)	0.065***	0.146***	0.155***
	(0.019)	(0.027)	(0.026)
R^2	0.681	0.680	0.680
Observations	25,426	25,426	25,426
Fixed effects			
Driver	Yes	Yes	Yes
Year	Yes	Yes	Yes
Month	Yes	Yes	Yes

The table reports the estimation results of Equation (3) for plug-in hybrid electric vehicles (PHEVs) using IV regressions without weights. The dependent variable is the utility factor UF (the share of driving in electric mode) calculated according to Equation (1) using the empirical estimation of Fuel economy$_{CS}$ based on non-rechargeable HEVs (UF HEV). All specifications include driver, year, and month fixed effects. Standard errors are clustered at the driver level and reported in parentheses. ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively.

Table A.XI: Robustness check – linear trend

	WLS			IV 1			IV 2		
	ln(Fuel Use)	ln(VKT)	ln(FE)	ln(Fuel Use)	ln(VKT)	ln(FE)	ln(Fuel Use)	ln(VKT)	ln(FE)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
PHEV									
ln(Price)	-0.184*	-0.103	-0.081**	-0.322**	-0.050	-0.272***	-0.242*	0.028	-0.270***
	(0.100)	(0.095)	(0.039)	(0.140)	(0.137)	(0.054)	(0.134)	(0.129)	(0.050)
R^2	0.311	0.210	0.677	0.311	0.210	0.676	0.311	0.210	0.676
Observations	25,426	25,426	25,426	25,426	25,426	25,426	25,426	25,426	25,426
Gasoline									
ln(Price)	-0.028	-0.022	-0.006**	-0.150***	-0.131***	-0.019***	-0.146***	-0.125***	-0.021***
	(0.018)	(0.018)	(0.002)	(0.024)	(0.024)	(0.003)	(0.023)	(0.023)	(0.003)
R^2	0.240	0.208	0.898	0.240	0.208	0.898	0.240	0.208	0.898
Observations	784,212	784,212	784,212	784,212	784,212	784,212	784,196	784,196	784,196
Diesel									
ln(Price)	-0.072***	-0.098***	0.026***	-0.136***	-0.169***	0.033***	-0.158***	-0.193***	0.035***
	(0.022)	(0.022)	(0.003)	(0.027)	(0.028)	(0.003)	(0.027)	(0.027)	(0.003)
R^2	0.239	0.227	0.871	0.239	0.227	0.871	0.239	0.227	0.871
Observations	357,731	357,731	357,731	357,731	357,731	357,731	357,722	357,722	357,722
Fixed effects									
Driver	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

All specifications include driver and year fixed effects. Standard errors are clustered at the driver level and reported in parentheses. ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively.

Table A.XII: Robustness check – linear trend (Utility Factor)

	WLS	IV 1	IV 2
	(1)	(2)	(3)
PHEV			
ln(Price)	0.047**	0.150***	0.150***
	(0.023)	(0.030)	(0.028)
R^2	0.657	0.657	0.657
Observations	25,426	25,426	25,426
Fixed effects			
Driver	Yes	Yes	Yes
Year	Yes	Yes	Yes

All specifications include driver and year fixed effects. Standard errors are clustered at the driver level and reported in parentheses. ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively.

Table A.XIII: Robustness check – COVID-19

	WLS			IV 1			IV 2		
	ln(Fuel Use)	ln(VKT)	ln(FE)	ln(Fuel Use)	ln(VKT)	ln(FE)	ln(Fuel Use)	ln(VKT)	ln(FE)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
PHEV									
ln(Price)	-0.330**	-0.338**	0.008	-0.941***	-0.717**	-0.224	-0.775**	-0.541	-0.234*
	(0.154)	(0.135)	(0.064)	(0.344)	(0.333)	(0.136)	(0.358)	(0.332)	(0.135)
Post	-0.037	-0.097**	0.059***	-0.189*	-0.195*	0.006	-0.154	-0.153	0.000
	(0.052)	(0.047)	(0.021)	(0.104)	(0.100)	(0.042)	(0.111)	(0.104)	(0.043)
ln(Price) × Post	0.184	0.141	0.042	0.579	0.422	0.157	0.523	0.328	0.195
	(0.179)	(0.161)	(0.067)	(0.415)	(0.395)	(0.159)	(0.446)	(0.418)	(0.164)
R^2	0.319	0.213	0.703	0.318	0.213	0.702	0.319	0.213	0.702
Observations	25,426	25,426	25,426	25,426	25,426	25,426	25,426	25,426	25,426
Fixed effects									
Driver	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

The table reports the estimation results of Equation (4) for plug-in hybrid electric vehicles (PHEVs). "Post" indicates the period after March 2020. The dependent variables are: (i) the log of fuel consumption (in liters) in columns 1, 4, and 7; (ii) the log of vehicle kilometers traveled (VKT) in columns 2, 6, and 8; and (iii) the log of fuel economy (FE, in liters/100km) in columns 3, 6, and 9. All specifications include driver, year, and month fixed effects. Standard errors are clustered at the driver level and reported in parentheses. ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively.

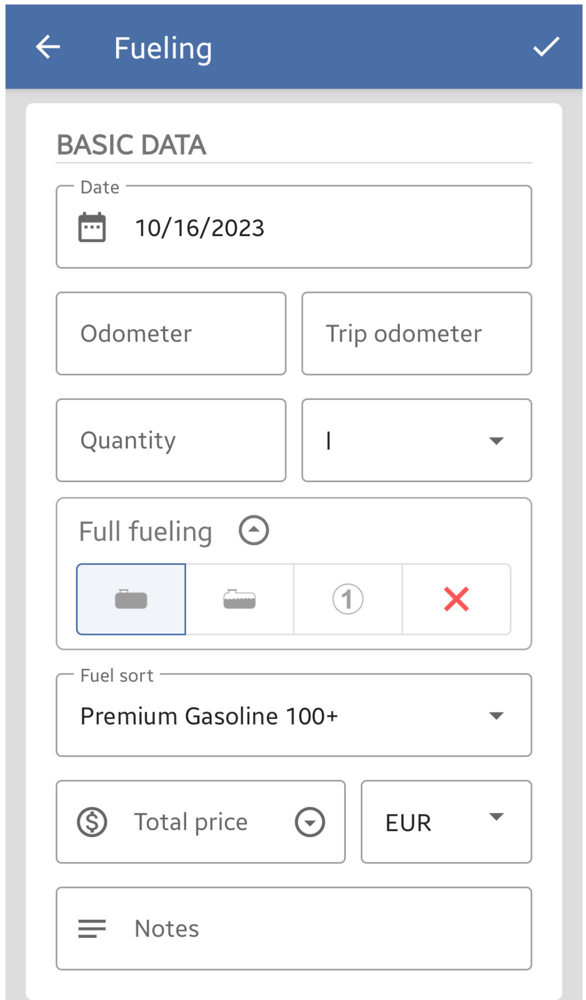
Table A.XIV: Robustness check – COVID-19 (Utility Factor)

	WLS	IV 1	IV 2
	(1)	(2)	(3)
PHEV			
ln(Price)	0.004	0.147**	0.156**
	(0.038)	(0.073)	(0.078)
Post	-0.032**	0.001	0.005
	(0.013)	(0.023)	(0.025)
ln(Price) $\times$ Post	-0.027	-0.098	-0.122
	(0.041)	(0.088)	(0.095)
R^2	0.664	0.664	0.664
Observations	25,426	25,426	25,426
Fixed effects			
Driver	Yes	Yes	Yes
Year	Yes	Yes	Yes
Month	Yes	Yes	Yes

All specifications include driver, year, and month fixed effects. Standard errors are clustered at the driver level and reported in parentheses. ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively.

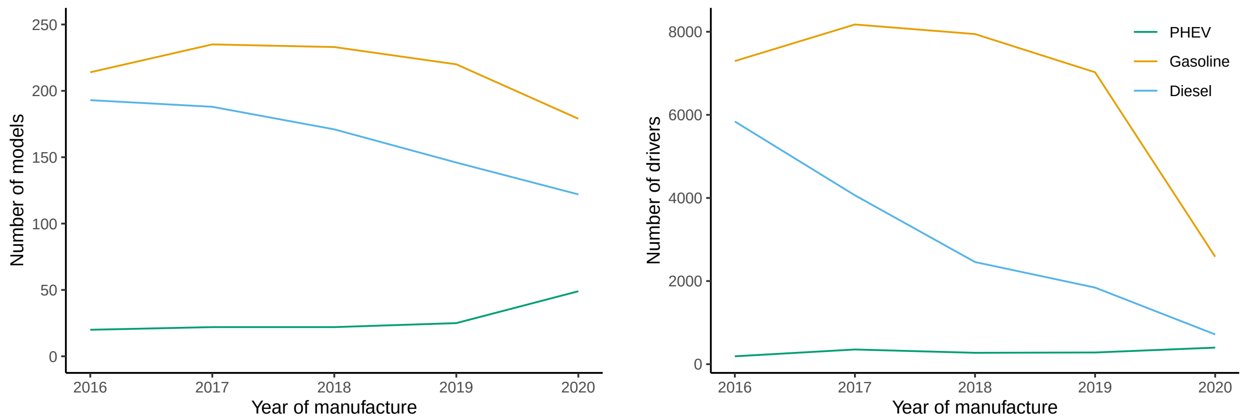
Figures

Figure A.1: Sample screenshot of the application Spritmonitor



This picture illustrates how the application users record their travel logs in the application Spritmonitor.

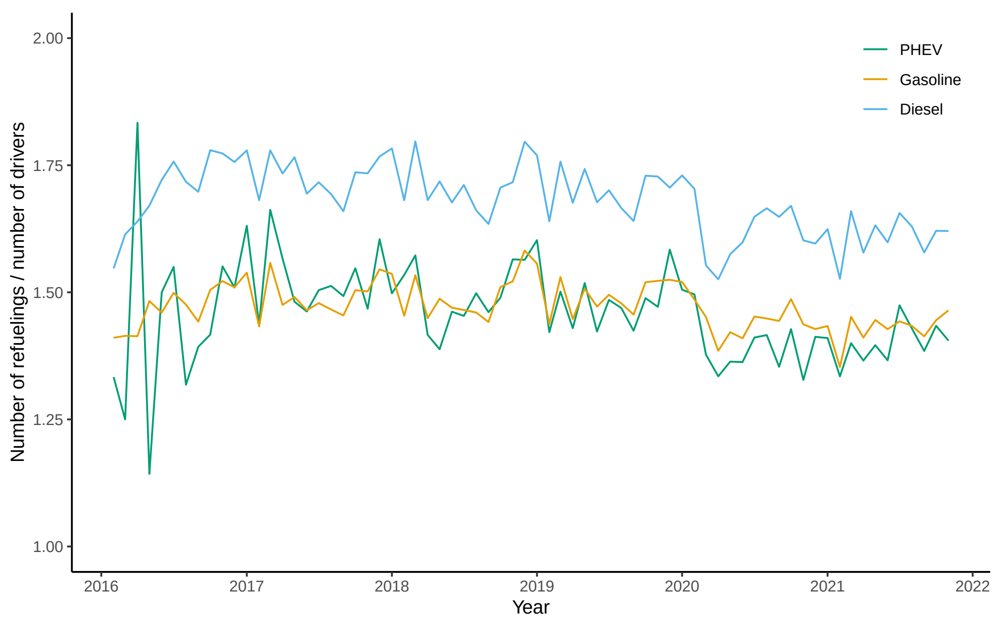
Figure A.2: Number of models and drivers by year of manufacture



(a) Model (b) Driver

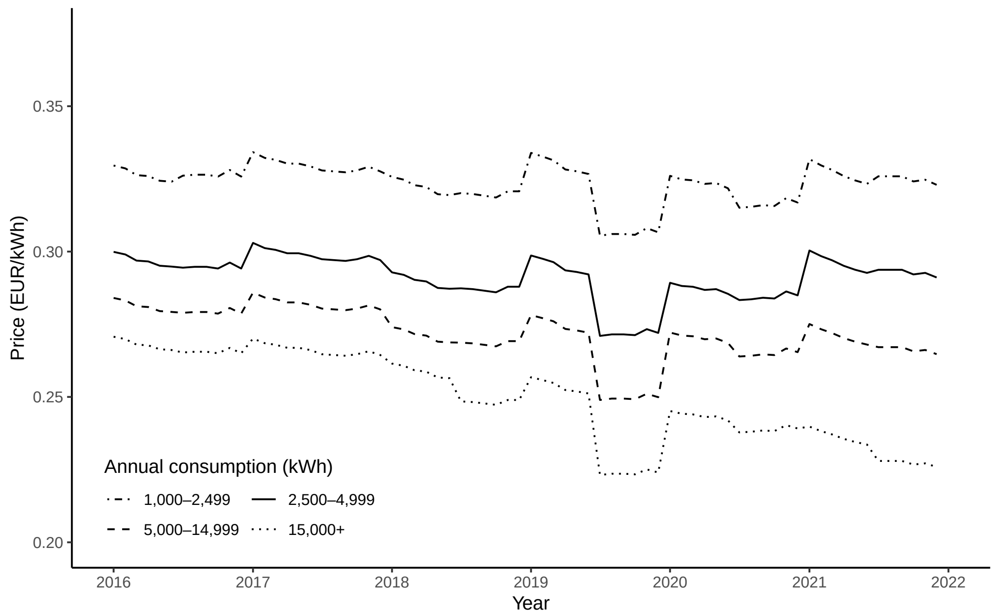
The figure shows: in Panel (a) the number of vehicle models by year of manufacture, and in Panel (b) the number of drivers by year of manufacture in our sample.

Figure A.3: Number of refuelings per number of drivers by month



The figure shows the average number of refuelings per driver by month for each fuel type in our sample.

Figure A.4: Household electricity prices

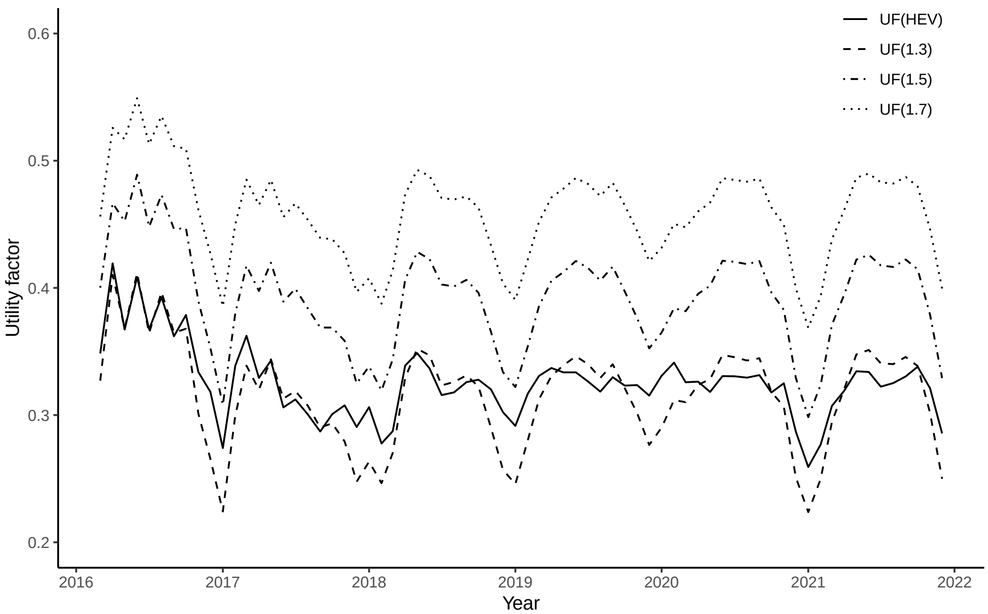


The figure plots household electricity prices, including taxes, levies, and VAT, adjusted by the consumer price index (CPI) with 2015 as the base year. The unit is € per kWh. Source: Statistisches Bundesamt.

Figure A.5: Average public charging prices in Germany (2017–2021).

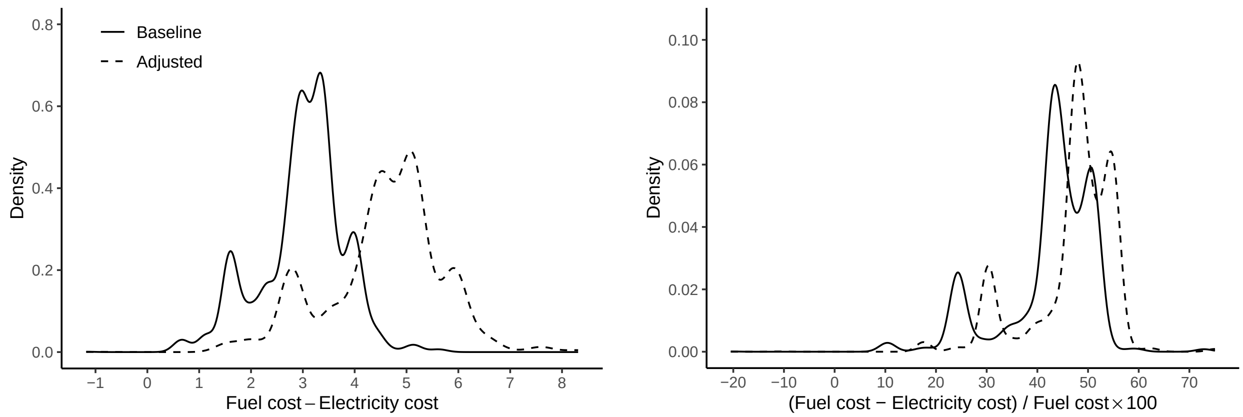
The figure shows the average price of charging an electric vehicle (EV) at public charging stations in Germany, broken down by major operator, for each year. The unit is € per kWh. Source: LichtBlick

Figure A.6: Utility factor over time



The figure shows the monthly average utility factor (UF) for plug-in hybrid electric vehicles (PHEVs) in our sample. The solid line (HEV) is calculated using the regression-based, month-specific correction factors derived from non-chargeable hybrids (HEVs) as described in Section 3. The other lines are calculated using fixed correction factors (1.3, 1.5, and 1.7).

Figure A.7: Cost differences refueling versus recharging

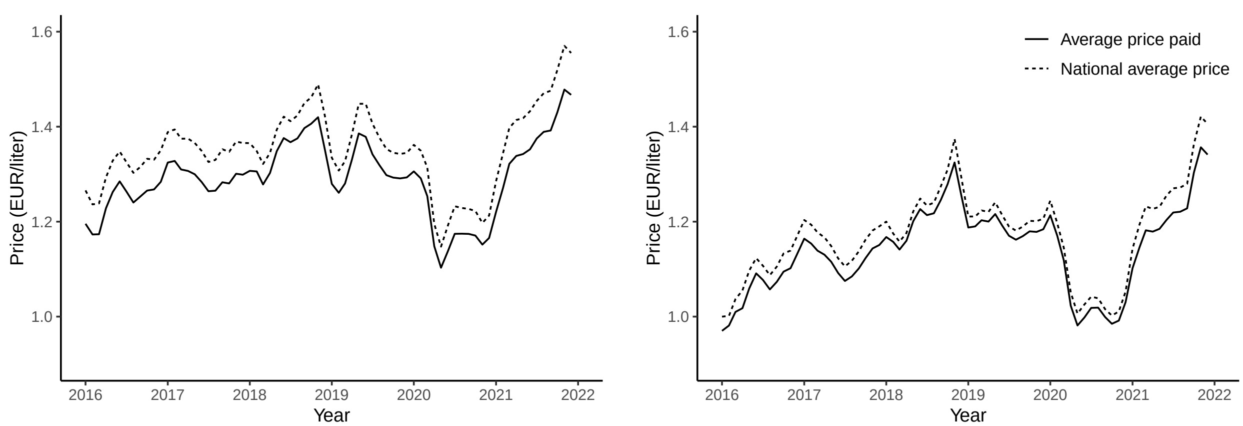


(a) Cost differences

(b) Cost difference as % of fuel cost

The figure shows the kernel density of the cost difference between fuel and electricity for each PHEV in our sample, expressed in €/100 km in Panel (a), and the kernel density of the cost difference as a percentage of the total fuel cost in Panel (b). In the baseline calculation, we assume a fuel price of €1.37 per liter (the average in 2021) and an electricity price of €0.30 per kWh. In the adjusted calculation, we account for average deviations from official fuel economy values, applying adjustment factors of 1.38 to gasoline consumption and 1.27 to electricity consumption.

Figure A.8: Reported and posted fuel prices



(a) Gasoline

(b) Diesel

The figure plots: in Panel (a) the national average prices of normal gasoline in Germany (dotted line) and average actual price paid as reported by the application user (solid line); in Panel (b) the national average prices of diesel in Germany (dotted line) and average actual price paid as reported by the application user (solid line). The unit is € per liter.

Appendix B

B.1 Data processing process

To prepare the vehicle logbook data for analysis, we follow the cleaning procedure in Plötz et al. (2020), excluding users with (i) fewer than seven distinct days of travel logs and (ii) less than 1,500 km of total mileage or 50 liters of total fuel consumption. In addition, we introduce a stricter filter by requiring at least 365 days between a user's first and last log entry, ensuring sufficiently long and consistent reporting. Table B.I summarizes the number of refuelings per driver after cleaning, by vehicle type (Gasoline, Diesel, PHEV) and refueling type (Total, Full, Partial). Gasoline vehicles provide the largest sample (33,027 drivers) with the highest mean number of total refuelings (31.97), while PHEVs yield the smallest sample (1,494 drivers) with a mean of 21.68. Across all vehicle types, full refuelings are more frequent than partial ones.

Figure B.1 shows the distribution of driver-level panel lengths in the cleaned sample. Most drivers are observed for relatively short periods, with the modal panel length around 12–18 months. The long right tails indicate that a smaller share of drivers contribute multi-year records. The pattern is consistent across vehicle types.

To accurately calculate real-world fuel economy from this logbook data, we apply the full-to-full method, also known as the tank-to-tank method, or full tank method. In this method, fuel economy is computed over fill-up intervals, which are defined as the period between two consecutive full-tank refueling events. Since partial refuelings do not allow for an exact calculation of fuel economy relative to distance traveled, the quantities of fuel added and odometer readings recorded during any partial refuelings are accumulated and assigned to the subsequent full-tank event. The total fuel quantity consumed within a fill-up interval is the sum of all fuel quantities purchased since the previous full refueling, while the distance traveled is determined by the difference in odometer readings between the two full-tank events. Fuel economy is then calculated as the total fuel quantity consumed per 100 kilometers driven within each fill-up interval.

After constructing the fill-up intervals, we apply an outlier removal procedure separately for each engine type (gasoline, diesel, and plug-in hybrid electric vehicles). Specifically, we use the Interquartile Range (IQR) method to exclude outliers based on the following variables: kilometers traveled, price per liter, fuel economy, duration of the fill-up interval, and total fuel quantity consumed. Additionally, we exclude records corresponding to the top 30 percent of the distribution of daily distance traveled to remove unusually long-distance trips. For plug-in hybrids, this cutoff corresponds to 90 km per day. Overall, this procedure eliminates approximately 6 percent of observations from the final sample.

For each fill-up interval, total fuel expenditure is calculated in two ways: (i) as the sum of fuel quantities purchased multiplied by the actual price per liter paid by the driver at each refueling event, and (ii) as the hypothetical total expenditure the driver would have incurred if all fuel had been purchased at the national average price prevailing on each refueling date. The second measure is used to construct the instrumental variable for the actual price paid.

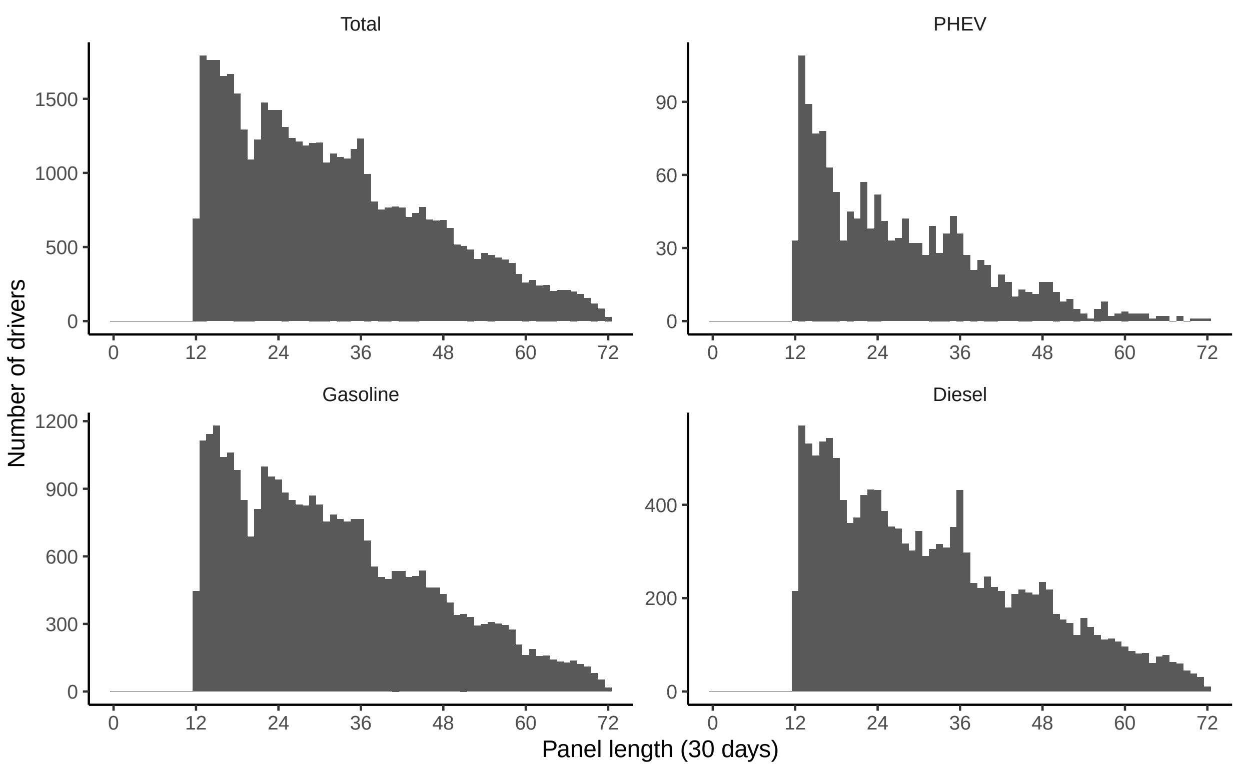
From the fill-up interval data, we then calculate daily averages of fuel quantity purchased, total fuel cost (actual and hypothetical), distance traveled, and fuel quantity consumed. Finally, these daily values are aggregated to the monthly level. At this monthly frequency, we derive the variables used in the analysis: total fuel quantity consumed (in liters), total kilometers traveled, fuel economy (in liters per 100 kilometers), and both actual and instrumented fuel prices (calculated as total expenditure divided by total fuel quantity purchased).

Table B.I: Number of refuelings per driver before aggregation

		Total		Full		Partial	
Type	N	Mean	SD	Mean	SD	Mean	SD
PHEV	1,494	21.68	19.10	21.49	18.95	0.19	0.68
Gasoline	33,027	31.97	21.87	31.55	21.63	0.42	1.24
Diesel	14,922	37.20	26.66	36.73	26.36	0.47	1.41
Total	49,443	33.24	23.56	32.81	23.30	0.43	1.28

The table reports the number of refuelings per driver after data cleaning, disaggregated by vehicle type (PHEV, gasoline, and diesel cars) and by refueling type (full and partial). Reported values are means and standard deviations (SD). Sample sizes correspond to the number of drivers (N).

Figure B.1: Distribution of driver-level panel lengths



The figure plots histograms showing the distribution of the panel lengths of drivers in our sample. The panel length is defined as the time period between the first and last month of data for each driver in our sample. The four panels correspond to: upper left – total (gasoline, diesel, and PHEV); upper right – PHEV; bottom left – gasoline; bottom right – diesel.