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

Laura Grigolon† Eunseong Park‡ Kevin Remmy§

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Abstract

We use micro-level data on fuel consumption, mileage, and travel mode to study plug-in hybrid drivers' response to fuel prices. When fuel prices rise, plug-in hybrids reduce fuel consumption more than gasoline and diesel cars. They do not reduce their mileage but increase electric recharging, without evidence of habit formation. As the share of kilometers driven in electric mode by plug-in hybrids is only half the official test cycle value, fuel prices are effective in improving the environmental performance of these vehicles. We estimate drivers' value of charging time at €15 to €41/hour.

Keywords: fuel price elasticity, automobiles, carbon emissions

JEL codes: D12, L91, Q31

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†Email: grigolon@uni-mannheim.de, University of Mannheim, MaCCI, and CEPR.

‡Email: eunseong.park@uni-mannheim.de, University of Mannheim and ZEW Mannheim.

§Email: remmy@uni-mannheim.de, University of Mannheim and MaCCI.

1 Introduction

Automobile usage imposes substantial negative externality costs. It accounts for around 28 percent of global greenhouse gas emissions and significantly contributes to outdoor air pollution. The pressure to address climate change has brought 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 cross-over 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.[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; presently, there are no direct policies affecting the intensity of use for plug-in hybrids, encouraging driving in electric mode, or penalizing driving in internal combustion mode. Evidence from real-world usage data (Plötz et al., 2021) suggests that plug-in hybrids tend to be used mainly in internal combustion mode, so actual fuel consumption and emissions of those vehicles are much higher than indicated by official figures. Ironically, official emissions (based on test cycles) 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. Unlike drivers of traditional internal combustion engines, who can reduce gasoline consumption mainly through mileage, drivers of plug-in hybrids can charge their vehicles

[1] According to the U.S. Energy Information Administration (eia.gov), plug-in-hybrid sales are currently growing at a rate that outpaces electric vehicle growth. The same trend is observed in Asia (Asia Pacific). Automakers are also increasing their offer of plug-in-hybrid models to consumers (GM and Toyota).

[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).

more frequently and increase the share of mileage driven in electric mode. Reliable estimates of both elasticities are crucial for understanding the response of fuel consumption and carbon emissions to fuel prices and for designing effective regulatory policies to promote plug-in hybrids in electric mode, specifically.

To answer our research question, we use detailed micro-level data from a German mobile phone application that allows users to record fuel consumption, distance traveled, and the price paid for each refueling. The dataset spans six years (from 2016 to 2021) and comprises 71,040 drivers; around 4 percent of users drive a plug-in hybrid, 65 percent drive a gasoline car, and 31 percent a diesel car. Our sample accounts for about one percent of Germany's total stock of plug-in hybrids. Our data comprises drivers voluntarily engaging with the application. Using additional data from a representative sample, we validate the representativeness of our sample and the external validity of our results.

In the first step, we document that the share of mileage driven in electric mode (the utility factor) by plug-in hybrids is, on average, only 39 percent. This is well below the official percentage adopted by international and European standards (WLTP and NEDC) for determining the level of pollutants emitted by plug-in hybrids, which is around 70 to 85 percent (Plötz et al., 2022). Consequently, the fuel consumption of plug-in hybrids is, on average, double that of official estimates. We provide a descriptive analysis of the 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 the travel mode (electric versus combustion) for plug-in hybrids. We exploit the detailed data to estimate the elasticity of fuel consumption and mileage to fuel prices at the vehicle-driver level. We address endogeneity concerns related to the actual price drivers pay by using an innovative instrumentation strategy that accounts for consumer switching across fuel grades. We estimate an elasticity of fuel consumption of around -0.23 for gasoline car drivers and between -0.25 and -0.22 for diesel car drivers. Our estimates are consistent with the most recent studies investigating how fuel consumption responds to gasoline prices, which find elasticity estimates between -0.16 and -0.37.

Zooming in on plug-in hybrids, we have three main findings. First, the average estimated fuel consumption elasticity is larger than that of gasoline and diesel drivers (between -0.29 and -0.40). In contrast, the elasticity of mileage is not significantly different from zero. Notably, the share of mileage driven in electric mode increases as fuel prices rise: a ten percent rise in fuel price increases the share of kilometers driven in electric mode by 1.6 percentage points. Higher fuel prices thus encourage plug-in hybrid drivers to increase the use of their vehicles in electric mode without substantially sacrificing their driving capability. That improves the environmental benefits of plug-in hybrids. Around 53 percent of CO_2 savings generated by higher fuel prices derive from the increase in the utility factor.

Second, we estimate a distributed lag model including recent past prices and do not find evidence of habit formation in recharging due to past fuel shocks. Our findings are consistent with the results of a recent field experiment by Bailey et al. (2023), showing the absence of habit formation in the timing of charging for electric vehicles.

Third, building on the finding that the share of electric driving is only 39 percent, we focus on drivers' disutility of charging. Drivers may find charging costly because of the limited battery range (especially when traveling long distances), the lack of access to charging points (especially when at-home charging is unavailable), the lack of financial incentives (when the car is company-owned and fuel is paid by the employer), and multiple unobserved sources of behavioral barriers, such as limited attention or imperfect information about fuel and charging costs. To obtain an approximation of drivers' cost of charging, we specify and estimate a simple model of recharging and fueling choice based on the charging time. For a reasonable range of electricity prices, we find that drivers' value of charging time is between €15 and €41/hour; this value is high considering the German average wage rate of €22.6/hour but aligns with the median wage rate of buyers of battery vehicles (€35/hour). The high value is unsurprising given the prevalent disutility of electric recharging shown by drivers in our sample; at the same time, our estimates align with Dorsey et al.'s (2022) estimates of drivers' value of time (around $28/hour). These numbers are essential to evaluate the benefits of time-saving investments, such as expanding the charging network.

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 account for real-world electric driving shares and emissions. Second, financial incentives matter. In particular, policies increasing the carbon price paid by drivers of plug-in hybrids would be an effective tool to increase 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). Third, financial incentives are proving to be much more important in encouraging drivers to recharge due to the absence of habit formation. Finally, the estimated value of charging time (between €15 and €41/hour) is an essential input for policymakers when evaluating the cost-benefits of making time-saving investments in the charging infrastructure for drivers of battery vehicles.

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.[3]

[3] Dong and Lin (2012) is an early study based on survey data looking at the charging network's impact

Second, we contribute to the literature discussing consumers' behavioral biases regarding fuel consumption: Allcott and Knittel (2019). The literature has extensively studied the relationship between fuel prices, fuel economy, and automobile purchases: Busse et al. (2013); Allcott and Wozny (2014); Sallee et al. (2016); Grigolon et al. (2018). Beresteanu and Li (2011) investigate environmental policies targeting the adoption of hybrid vehicles. Similar to our study, Salvo and Huse (2013) look at the usage of flex-fuel cars (ethanol and gasoline), documenting a low rate of switching between fuels.

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 to 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 pin down plug-in-hybrid usage patterns, mileage and charging responses to fuel prices, and habit formation.

Fourth, we relate to the sizeable 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 recent studies developed in the last decade. These studies mostly use individual-level data (thus avoiding aggregation biases) or panel-level data at the month and state level (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; we find a gasoline price elasticity of around

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.

-0.23. 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 so far in the literature.

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 sample screenshots of the application used by drivers to track themselves. 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, the 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).[4]

We obtain the 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 the behavior of drivers switching from premium to less-expensive mid and regular-grade fuel when prices are high; this level of detail is usually unavailable in other studies. Electricity prices are sourced from the German Federal Statistical Office (Statistisches Bundesamt). Figure A.2 in the Appendix shows that electricity prices remained stable throughout the sample; the rates

[4] 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.

depend on each household's contract (which, in turn, depends on their consumption level). Finally, we collect information from the Federal Network Agency (Bundesnetzagentur) on the number and type of charging points.

We aggregate our data to the monthly level for two 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 and in avoiding issues of anticipatory behavior regarding fuel purchases in response to fuel tax fluctuations (Coglianese et al., 2017). We also remove records corresponding to the top 30 percent of the distribution of daily distance traveled by fuel and engine type, as long-distance trips (for example, holiday travel) are assumed to reflect exceptional driving circumstances for German drivers.

As the travel logs are self-reported by users, drivers may change their recording behavior according to the price level. Thus, we follow Solon et al. (2015) and account for the possibility of endogenous sampling by weighing each observation by the inverse probability of selection, based on the number of travel logs recorded in a month.[5]

To study the usage behavior of drivers of plug-in hybrids, we construct the utility factor, namely the share of kilometers driven in electric mode. Because many drivers do not report electric recharges or do so only irregularly, we follow Plötz et al. (2021) and calculate the utility factor based on the on-road and official fuel economy. Specifically, we calculate the utility factor as follows:

$$\mathrm{UF} = 1 - \frac{\text{On-road fuel economy}}{1.5 \times \text{Official fuel economy}}, \tag{1}$$

where the official and on-road 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

[5] In Section 3.2, we show that our results are robust to the inclusion of observations with long-distance traveled (with a maximum daily mileage of 111.4 km for plug-in hybrids) and the use of OLS instead of weighted linear regressions.

and mileage. The variable "Official fuel economy" is provided by ADAC and refers to the official fuel economy of plug-in hybrid vehicles in charge-sustaining mode (a combination of engine and motor management to maintain the battery state of charge). The denominator of Equation (1) approximates the fuel economy in charge-sustaining mode; the 50 percent addition accounts for the discrepancy between real-world fuel economy and actual fuel economy. This method is optimistic as a 50 percent deviation is above the mean deviation for conventional vehicles; in our data, the mean deviation for conventional vehicles turns out to be 30 to 40 percent, which would imply a lower utility factor. We test the robustness of our results using a range of deviation values (1.3 to 1.7).

Table 1 presents the summary statistics. As our sample includes only drivers who engage with the app, we 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. In our sample, before removing long-distance trips, the average annual mileage is 14,389 km for gasoline cars and 22,333 km for diesel cars. We study how representative our sample is by comparing these numbers with the averages reported by the German Federal Highway Research Institute (Bundesanstalt für Straßenwesen). 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 fact that our sample includes only recent cars, our sample averages are very close to the ones reported for the general population. As a further test, we use complementary data from the German Mobility Panel (MOP), 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 MOP 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 670 for gasoline and 1,018 for diesel cars.

Table 1 shows that the on-road emissions for cars of all fuel types exceed the official fuel economy rating measured by standard test cycles; this result aligns with previous studies

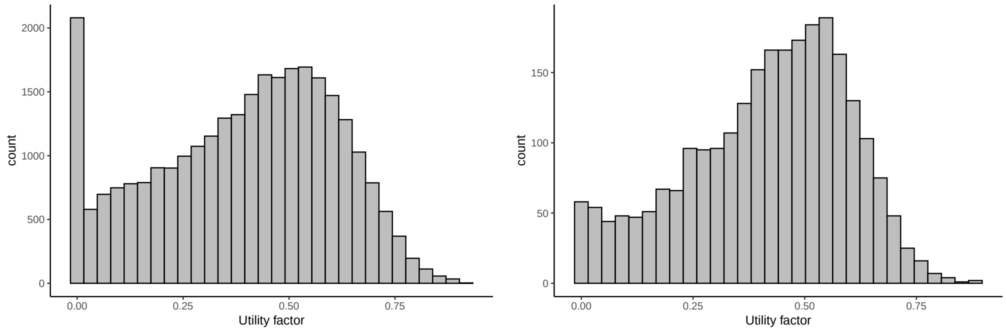
(Reynaert and Sallee, 2021; Plötz et al., 2018). Plug-in hybrids feature the most striking difference between official and on-road fuel economy ratings because they are used predominantly in combustion mode: the average utility factor (electric driving share) in our sample is 39 percent. Panel (a) of Figure 1 plots the histogram of monthly utility factors for each vehicle-driver; the histogram displays a mass point at zero: drivers often do not charge their plug-in hybrid at all. In addition, only 25 percent of drivers use the car in electric mode for more than 50 percent of the mileage. Panel (b) of Figure 1 plots the average utility factors for each vehicle-driver throughout the sample period. Compared to Panel (a), the mass point at zero shrinks; drivers charge their cars some months but not every month. Still, a substantial share of users never charge their cars.

Table 1: Summary statistics

	Gasoline		Diesel		PHEV	
Fueling level data	Mean	SD	Mean	SD	Mean	SD
Fuel usage (liter/month)	49.45	25.94	65.19	33.84	42.80	26.97
Mileage (km/month)	669.72	338.93	1,017.80	523.69	928.22	491.56
Mileage (km/year)	8,036.67	4,067.13	12,213.61	6,284.30	11,138.63	5,898.71
On-road fuel economy (liter/100km)	7.52	1.62	6.51	1.16	4.71	1.78
Official fuel economy (liter/100km)	5.74	1.08	4.62	0.68	1.67	0.36
Utility factor					0.39	0.22
Fuel price (€/km)	1.30	0.14	1.16	0.12	1.33	0.14
Sample sizes						
Number of refuelings	841,065		393,518		29,934	
Number of drivers	46,071		22,290		2,679	

The table reports summary statistics of the main variables. The total number of observations (refuelings by each driver/vehicle) is 1,264,517.

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.

2.1 Usage patterns for plug-in hybrids

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.[6] Figure A.3 in the Appendix plots the histogram of cost differences (€ per 100 km) between using fuel and electricity across users. Using plug-in hybrids in electric mode is cheaper than using them in combustion mode, with the average cost difference equal to €2.9 per 100 km. For a user driving 10,000 km per year, using the plug-in hybrid exclusively in electric mode would generate cost savings of €290 compared to solely using the car in combustion mode. Notably, these financial incentives do not play a role for drivers of company cars in Germany; the employer often bears the fuel costs, and company car drivers might not even have a choice but to pay privately to charge their vehicles at home.

[6] 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.

Second, we use data from the MOP survey to monitor their mobility patterns. The latest survey waves (2021/2022 and 2022/2023) collect fueling and charging logs for 42 plug-in hybrids; we also obtain information on whether the owner can charge at home and if the car is privately owned. Notwithstanding the small sample size, Table A.II in the Appendix reveals interesting usage patterns. Consistent with the financial incentives illustrated above, privately owned plug-in hybrids are more often operated electrically; the share of mileage driven in electric mode is almost double that of company cars. The utility factor is lower for owners frequently driving long-distance (routes over 100 km), as the car requires a longer break to recharge the battery during the journey, and for drivers that cannot recharge their vehicle at home.

Guided by the complementary evidence provided by the German Mobility Panel, we turn to our dataset to obtain further descriptive evidence on the determinants of the utility factor. 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 more than half of the trips of a user exceed the electric range of the car by 50 percent; (ii) an indicator identifying drivers whose mileage is above the 90^{th} percentile of the mileage distribution to capture the most likely drivers of company cars; and (iii) the monthly density (in km^2) of public charging points suitable for plug-in hybrid charging.

The patterns emerging from the German Mobility Panel are confirmed in our sample. 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 3.0 percentage points); (ii) the car is most likely a company car (by 2.6 percentage points); and (iii) the density of public charging points decreases by 0.01 units (by 2.1 percentage points). In column 2 of Table A.III, we add driver-specific fixed effects; the sign of the parameter estimates does not change; the coefficient of the indicator for frequent trips above the range is noisy as we exploit only within-driver variation for the identification, while the effect of the availability of charging points persists. These descriptive regressions help explain the variation in the utility factor across drivers and the 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 behavioral aspects as we do not have driver-specific attributes.

3 Estimation and Results

3.1 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:

$$y_{it} = \alpha + \beta \times \ln(P_{it}) + \gamma_t + \eta_i + \varepsilon_{it}, \tag{2}$$

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 three dependent variables, y_{it}: (i) the log of per-month fuel consumption (in liters); (ii) the log of per-month mileage (in km); and (iii) 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.2 in the Appendix.[7]

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 effects at

[7] 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.

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 fuel prices that drivers pay might be endogenous to the individual's fuel consumption and mileage. First, consumers may change their search behavior when fuel prices increase, leading to a downward bias in elasticity estimates. 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.4 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. Second, gasoline and diesel are offered in different grades or quality levels; modern cars can use any quality level without resulting in engine damage.[8] Most gas stations in Germany offer at least standard and premium grades of gasoline, allowing consumers to 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, 39.8 percent use more than one fuel grade over the sample period, and 11.0 percent switch within a quarter. We regress the quarterly shares of fuel grades defined at the driver level on the prices of the fuel grades. We define four grades of gasoline: (i) normal; (ii) super; (iii) super plus; and (iv) premium. Table A.IV in the Appendix shows that price changes are associated with switching across fuel grades. For instance, column 1 of Table A.IV 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, as well.

We build two sets of instruments to address endogenous switching between fuel grades and, more generally, to tackle any concern about the endogeneity of actual prices drivers

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

pay. First, following Knittel and Tanaka (2021), we instrument the user-reported fuel price using the national average fuel prices for the corresponding fuel grade in the same period. Second, after determining each driver's most used fuel grade, we reconstruct the per-period national average price of their most used fuel grade.[9]

After accounting for year, month, and driver fixed effects, our two sources of identifying variation are month of the year and within-driver variation. The within-driver variation, after accounting for the month of the year, originates from variation in the grade mix that drivers use over time. Before presenting the coefficient estimates, we assess the importance of each source of variation. A variance decomposition reveals that, for plug-in-hybrids, around 78 percent of the variation in prices is absorbed by year, month, and driver-fixed effects. The month of the year accounts for around 19 percent of the residual variance, while individual variation accounts for around 3 percent, conditional to a certain month of the year. The variance decomposition provides similar results for all prices used in the analysis (the price paid by the drivers and the instruments).

3.2 Results

Table 2 reports the estimation results of Equation (2). The first three columns of Table 2 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; the estimated coefficients are over three times larger than the WLS estimates and statistically significant at the one percent level. While our focus is on plug-in hybrids, we estimate the elasticity for other fuel types, as well. For gasoline car drivers, we estimate an elasticity of fuel consumption of around -0.23 and an elasticity of

[9]Specifically, we use the national average fuel price of the fuel grade most used by users whose share of said fuel grade is greater than 50%, which suggests strategic switching.

mileage of -0.21. For diesel car drivers, the elasticity of fuel consumption is between -0.22 and -0.25, and the elasticity of mileage is between -0.16 and -0.18.

The estimated elasticities for plug-in hybrid car drivers are the most interesting. Their elasticity of fuel consumption is substantially greater in magnitude than gasoline and diesel car users (between -0.29 and -0.40). 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). Compared to traditional internal combustion vehicles, plug-in hybrids offer an additional margin of adjustment in one's recharging behavior. Columns 6 and 9 suggest that a one percent rise in fuel prices leads to a utility factor increase of 0.15 to 0.16 percentage points. Higher fuel prices encourage plug-in hybrid drivers to increase the use of their vehicles in electric mode.

Table 2: Results

	WLS			IV 1			IV 2		
	ln(Fuel Use)	ln(VKT)	UF	ln(Fuel Use)	ln(VKT)	UF	ln(Fuel Use)	ln(VKT)	UF
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
PHEVs									
ln(Price)	-0.1033	-0.0683	0.0200	-0.4023***	-0.1295	0.1545***	-0.2860**	-0.0239	0.1501***
	(0.0945)	(0.0900)	(0.0209)	(0.1421)	(0.1370)	(0.0290)	(0.1370)	(0.1314)	(0.0280)
R^2	0.33820	0.25481	0.72538	0.33780	0.25479	0.72417	0.33805	0.25480	0.72425
Observations	29,242	29,242	29,242	29,242	29,242	29,242	29,242	29,242	29,242
Gasoline									
ln(Price)	-0.0723***	-0.0628***		-0.2331***	-0.2101***		-0.2348***	-0.2065***	
	(0.0175)	(0.0176)		(0.0238)	(0.0239)		(0.0232)	(0.0234)	
R^2	0.25457	0.22474		0.25443	0.22463		0.25444	0.22464	
Observations	832,330	832,330		832,330	832,330		832,300	832,300	
Diesel									
ln(Price)	-0.1241***	-0.0909***		-0.2221***	-0.1549***		-0.2507***	-0.1792***	
	(0.0224)	(0.0226)		(0.0286)	(0.0288)		(0.0280)	(0.0282)	
R^2	0.25343	0.24389		0.25337	0.24386		0.25333	0.24385	
Observations	393,204	393,204		393,204	393,204		393,190	393,190	
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 (2). 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 utility factor (UF; the share of driving in electric mode) 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 fixed effects for driver, year, and month. PHEVs: plug-in hybrid electric vehicles. 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.[10] In our setting, a change in fuel price has a stronger impact on CO_2 emissions for plug-in hybrids than for conventional fuel cars. The additional CO_2 savings deriving from the increased electrification of driving account for roughly 52 percent of the CO_2 reduction. In addition, the cost of absorbing fuel price shocks is lower for plug-in hybrid owners thanks to their ability to switch to their vehicle's electric power source when fuel prices rise. 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.

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 and 1.7) in the denominator of Equation (1) in order 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 111.4 km for plug-in hybrids (Table A.VII in the Appendix); and (iii) the use of OLS instead of WLS (Table A.VIII in the Appendix).

3.3 Habit formation

The evidence thus far suggests that fuel prices have a contemporaneous effect on electric recharging behavior. To test for the presence of habit formation, we estimate a distributed lag model that includes in Equation (2) past fuel prices:

$$\mathrm{UF}_{it} = \alpha + \sum_{j=0}^{t} \beta_j \ln P_{it-j} + \gamma_t + \eta_i + \varepsilon_{it}, \tag{3}$$

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 3 reports the coefficients of the six most recent past refueling prices paid by the driver; these prices are instrumented using

[10]Burning one liter of gasoline emits 2,390g of CO_2 while burning one liter of diesel emits 2,640g of CO_2.

monthly average prices. The estimates indicate no empirical evidence of habit formation as a result of 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 electric vehicles charging times.

4 Value of charging time

In section 2, we showed that the share of electric driving is only 39%. Drivers may find charging costly because of the limited battery range (especially when traveling long distances), the lack of access to charging points (especially when at-home charging is unavailable), the lack of financial incentives (when the car is company-owned and fuel is paid by the employer), and multiple possible sources of behavioral barriers, such as limited attention or imperfect information about fuel and charging costs. To quantify drivers' cost of charging, we specify and estimate a simple model of recharging versus fueling choice based on the charging time. On a given trip s, a driver i has the choice j to drive in electric mode, namely charge the battery ($j = C$), or in internal combustion mode, namely use fuel because the battery is empty ($j = F$). Trips are conducted during a period t; the term θ_s denotes the mileage of each trip s. The utility that a driver receives from choice j is given by:

$$U_{ijs} = (\alpha_1 p_{ijt} + \alpha_2 d_{ij} + \xi_{ijt} + \varepsilon_{ijs})\theta_s,$$

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 the d_{ij}, the charging or fueling time per kilometer, ξ_{ijt}, which denotes period-specific unobservables, as well as ε_{ijs}, an idiosyncratic trip-specific preference shock. The driver chooses to charge if $U_{iCs} > U_{iFs}$. Assuming that ε_{ijs} is i.i.d. according to a Type 1 Extreme Value distribution, we can write the choice probability of recharging as follows:

$$s_{iCs} = \frac{1}{1 + \exp(\underbrace{\alpha_1 \Delta p_{it} + \alpha_2 \Delta d_i + \Delta \xi_{it}}_{\delta_{it}})},$$

Table 3: Habit formation

Dependent variable	Utility factor					
	(1)	(2)	(3)	(4)	(5)	(6)
PHEVs						
ln(Price$_t$)	0.1720***	0.1876***	0.1969***	0.1841***	0.1285*	0.1922***
	(0.0482)	(0.0536)	(0.0600)	(0.0636)	(0.0740)	(0.0736)
ln(Price$_{t-1}$)	-0.0280	-0.0906	-0.0848	-0.1177	-0.0636	-0.0916
	(0.0457)	(0.0618)	(0.0708)	(0.0771)	(0.0831)	(0.0846)
ln(Price$_{t-2}$)		0.0278	-0.0279	0.0170	-0.0223	-0.0217
		(0.0488)	(0.0726)	(0.0756)	(0.0809)	(0.0825)
ln(Price$_{t-3}$)			0.0503	0.0032	0.0412	0.0389
			(0.0591)	(0.0813)	(0.0888)	(0.0966)
ln(Price$_{t-4}$)				0.0218	-0.0074	0.0482
				(0.0597)	(0.0985)	(0.1085)
ln(Price$_{t-5}$)					-0.0197	-0.0905
					(0.0713)	(0.0932)
ln(Price$_{t-6}$)						-0.0062
						(0.0629)
R^2	0.74350	0.75192	0.76405	0.77121	0.77964	0.78306
Observations	23,067	18,091	14,658	12,090	10,078	8,509
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 (3). 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.

where $\Delta p_{it} = p_{iFt} - p_{iCt}$, and $\Delta d_i = d_{iF} - d_{iC}$. Let $\delta_{it} = \alpha_1 \Delta p_{it} + \alpha_2 \Delta d_i + \Delta \xi_{it}$.

We aggregate at the period t (month) level and set the choice probabilities of charging equal to the observed shares as follows:

$$\sum_{s=1}^{S_t} s_{iCs}\theta_{is} = s_{iCt}\theta_{it} = \theta_{iCt}, \tag{4}$$

$$s_{iCt} = \frac{\theta_{iCt}}{\theta_{it}} = UF_{it}. \tag{5}$$

We solve for δ_{it} and use the value in the linear regression:

$$\delta_{it} = \alpha_1 \Delta p_{it} + \alpha_2 \Delta d_i + \Delta \xi_{it}. \tag{6}$$

By taking the ratio of the estimated coefficients on time and price differences (α_2/α_1), we obtain estimates of drivers' value of charging time, which is determined by the marginal rate at which drivers trade off time savings and the expected (negative) dollar savings in terms of fueling versus recharging. To calculate Δd_i, we set the time of fueling at zero and use data on the battery size (in kWh), the battery efficiency (in km/kWh), and charging time (in hours) to calculate the vehicle-specific charging time in hour/km. 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 charging per kilometer. As for electricity prices, we use €0.30 and €0.35 per kWh.

Table 4 reports the OLS and IV coefficients of the estimation of Equation (6); prices are instrumented using monthly average prices. Our estimates are based on the time cost associated with recharging; drivers, on average, tend not to recharge their vehicles often, which means they prefer saving the time costs associated with recharging. The IV estimates show that drivers' value of charging time is between €15 and €41/hour. Our estimates align with Dorsey et al.'s (2022) estimates of drivers' value of time (around $28/hour).

Finally, Figure A.5 in the Appendix reports the distribution of the driver-specific fixed effects. These estimates are obtained after regressing δ_{it} on the price differences Δp_{it} and fixed effects at the driver level; they show the individual level (dis)utility of charging relative to refueling. The distribution is left-skewed with a mass below zero, revealing strong heterogeneity in charging preferences across drivers. The strong disutility of charging exhibited by some drivers also explains the inelastic response of the utility factor to fuel prices.

Table 4: Value of Charging Time

Electricity price	€0.30/kWh		€0.35/kWh	
	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)
Δ Price (Δp_{it})	0.211***	0.285***	0.213***	0.286***
	(0.006)	(0.007)	(0.006)	(0.007)
Δ Charging time (Δd_i)	12.455***	11.601***	6.985***	4.293***
	(1.304)	(1.353)	(1.328)	(1.390)
R^2	0.054	0.049	0.057	0.051
Observations	26,850	26,658	26,850	26,658
	Implied value of time (€/hour)			
	59.05	40.65	32.75	15.00
	(6.58)	(5.00)	(6.48)	(4.97)

The table reports the estimation results of Equation (6) for plug-in hybrid electric vehicles (PHEVs) using OLS and IV. The dependent variable is δ_{it}, which is defined in Section 4. Electricity price is €0.30/kWh in columns 1 and 2, and €0.35/kWh in columns 3 and 4. The IV specifications are estimated using the instrumental variable approach, where monthly average prices are used as the instrument. Standard errors are reported in parentheses. ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively.

5 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 39 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 1.6 percentage points. We find no evidence of habit formation in charging behavior. Finally, we estimate a drivers' value of time between €15 and €41/hour.

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

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	-0.40 to -0.29 0.13 to -0.02 -0.23 -0.21 -0.22 -0.16

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: Utility factor by driver characteristic

Driver charascteristics	Average utility factor
Private car	0.67
Company car	0.38
Frequent use on routes > 100km	0.37
Occasional use on routes > 100 km	0.56
Charging availability at home	0.53
No charging availability at home	0.38
Overall	0.52
Observations	42

The table reports summary statistics of usage patterns for 42 plug-in hybrids. The data comes from the 2021-2022 German Mobility Panel.

Table A.III: Determinants of utility factor

Dependent variable	Utility factor	
	(1)	(2)
Trip lengths exceed range	-0.0802***	-0.0133
	(0.0247)	(0.0150)
Charging points density	5.467***	4.157***
	(1.061)	(0.717)
"Company car"	-0.0685***	
	(0.0137)	
Observations	29,934	29,934
Fixed effects		
Driver	No	Yes
Year	Yes	Yes
Month	Yes	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 gasoline grades

Dependent variables: Share	Normal (1)	Super (2)	Super Plus (3)	Premium (4)
ln(Price Normal)	-1.572***	1.119***	-0.1069	0.5595***
	(0.1562)	(0.1921)	(0.1061)	(0.1194)
ln(Price Super)	0.9076***	-0.6072***	0.0800	-0.3803***
	(0.1297)	(0.1614)	(0.0935)	(0.1010)
ln(Price Super Plus)	0.2738***	-0.0923*	-0.0118	-0.1697***
	(0.0396)	(0.0497)	(0.0292)	(0.0310)
ln(Price Premium)	0.6667***	-0.4879***	-0.0172	-0.1616*
	(0.1244)	(0.1527)	(0.0849)	(0.0941)
R^2	0.84050	0.82302	0.79541	0.80399
Observations	371,596	371,596	371,596	371,596
Fixed effects				
Driver	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Quarter	Yes	Yes	Yes	Yes

The table reports the parameter estimates of an OLS model showing switching across fuel grades. The dependent variables are: (i) the share of fuel grade Normal over the total fuel pumped in a quarter in column 1; (ii) the shares of fuel grade Super over the total fuel pumped in a quarter in column 2; (iii) the shares of fuel grade Super Plus over the total fuel pumped in a quarter in column 3; and (iv) the shares of fuel grade Premium over the total fuel pumped in a quarter in column 4. 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
log(Posted price)	0.8416***	0.9233***	0.8590***	0.9261***	0.9002***	0.9576***
	(0.0119)	(0.0098)	(0.0023)	(0.0019)	(0.0032)	(0.0022)
R^2	0.85195	0.85671	0.88339	0.88311	0.87295	0.87234
F-test	906.48	941.83	20,530.2	20,474.7	9,008.2	8,959.0
Observations	29,242	29,242	832,330	832,300	393,204	393,190
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 using a range of deviation values

	WLS			IV 1			IV 2		
Deviation value	1.3	1.5	1.7	1.3	1.5	1.7	1.3	1.5	1.7
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
PHEVs									
ln(Price)	0.0176	0.0200	0.0198	0.1529***	0.1545***	0.1497***	0.1504***	0.1501***	0.1459***
	(0.0218)	(0.0209)	(0.0192)	(0.0302)	(0.0290)	(0.0265)	(0.0290)	(0.0280)	(0.0255)
R^2	0.70053	0.72538	0.73314	0.69934	0.72417	0.73183	0.69939	0.72425	0.73191
Observations	29,242	29,242	29,242	29,242	29,242	29,242	29,242	29,242	29,242
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 (2) 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 by 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 including observations with long distance traveled

	WLS			IV 1			IV 2		
	ln(Fuel Use)	ln(VKT)	UF	ln(Fuel Use)	ln(VKT)	UF	ln(Fuel Use)	ln(VKT)	UF
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
PHEVs									
ln(Price)	-0.0160	-0.0059	0.0042	-0.3793***	-0.0876	0.1660***	-0.2389*	0.0266	0.1523***
	(0.0970)	(0.0902)	(0.0206)	(0.1358)	(0.1288)	(0.0287)	(0.1348)	(0.1269)	(0.0284)
R^2	0.36865	0.29465	0.72129	0.36807	0.29461	0.71952	0.36843	0.29464	0.71981
Observations	30,191	30,191	30,191	30,191	30,191	30,191	30,191	30,191	30,191
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 (2) for plug-in hybrid electric vehicles (PHEVs) including observations with long-distance traveled, with a maximum daily mileage of 111.4 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 utility factor (UF; the share of driving in electric mode) in columns 3, 6, and 9. Columns 1, 2, and 3 present the WLS parameter estimates. Columns 4 to 9 are estimated by 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.

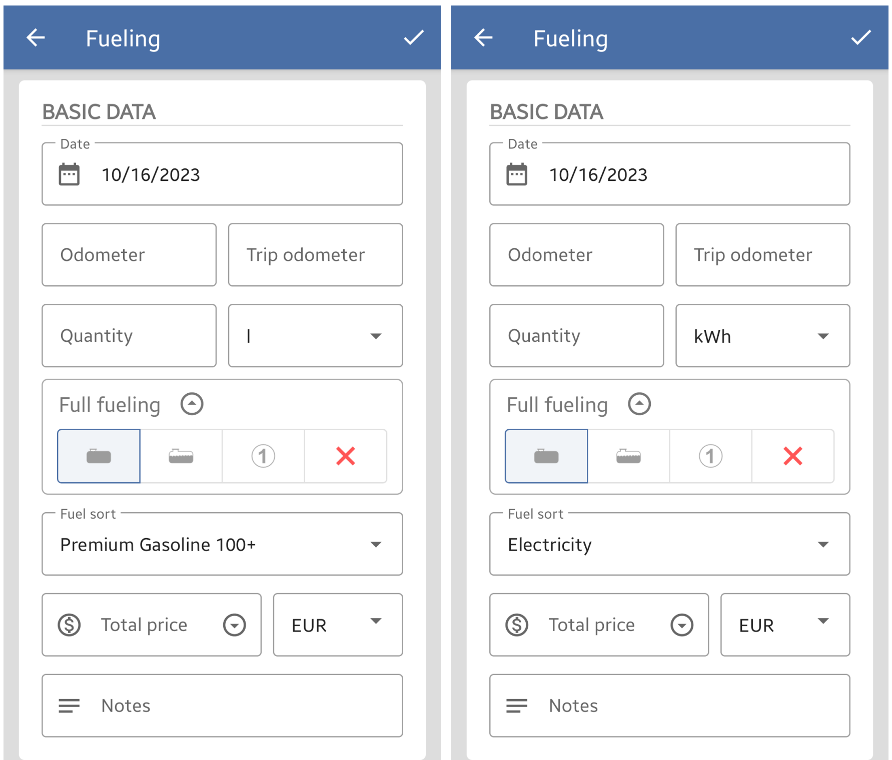
Table A.VIII: Robustness check using OLS

	OLS			IV 1			IV 2		
	ln(Fuel Use)	ln(VKT)	UF	ln(Fuel Use)	ln(VKT)	UF	ln(Fuel Use)	ln(VKT)	UF
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
PHEVs									
ln(Price)	-0.1592*	-0.0625	0.0489***	-0.2867**	-0.0194	0.1435***	-0.2044*	0.0802	0.1538***
	(0.0827)	(0.0782)	(0.0171)	(0.1212)	(0.1154)	(0.0250)	(0.1181)	(0.1117)	(0.0244)
R^2	0.31598	0.23584	0.73617	0.31591	0.23583	0.73556	0.31598	0.23573	0.73542
Observations	29,934	29,934	29,934	29,934	29,934	29,934	29,934	29,934	29,934
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 (2) for plug-in hybrid electric vehicles (PHEVs) using OLS. 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 utility factor (UF; the share of driving in electric mode) in columns 3, 6, and 9. Columns 1, 2, and 3 present the OLS parameter estimates. Columns 4 to 9 are estimated by 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.

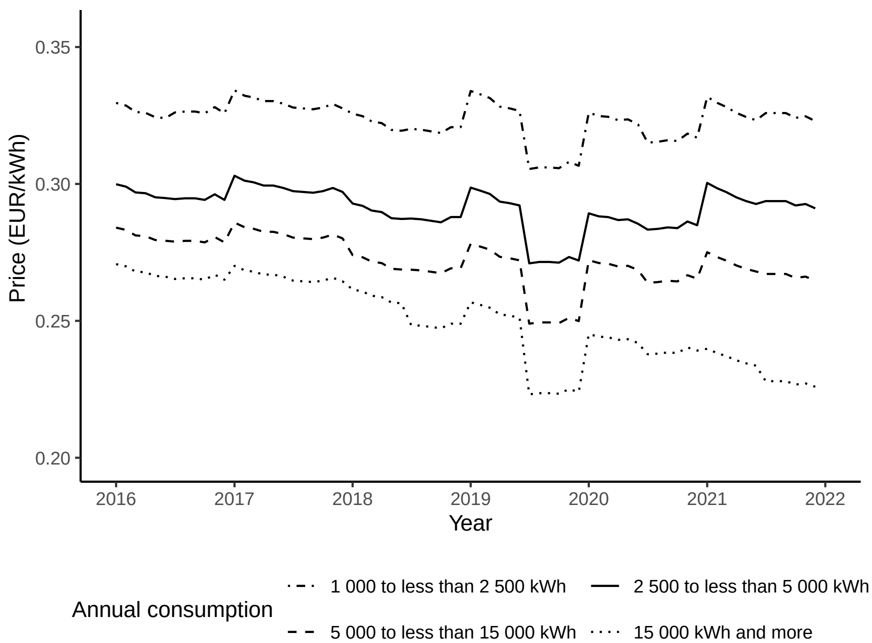
Figures

Figure A.1: Sample screenshots of the application Spritmonitor



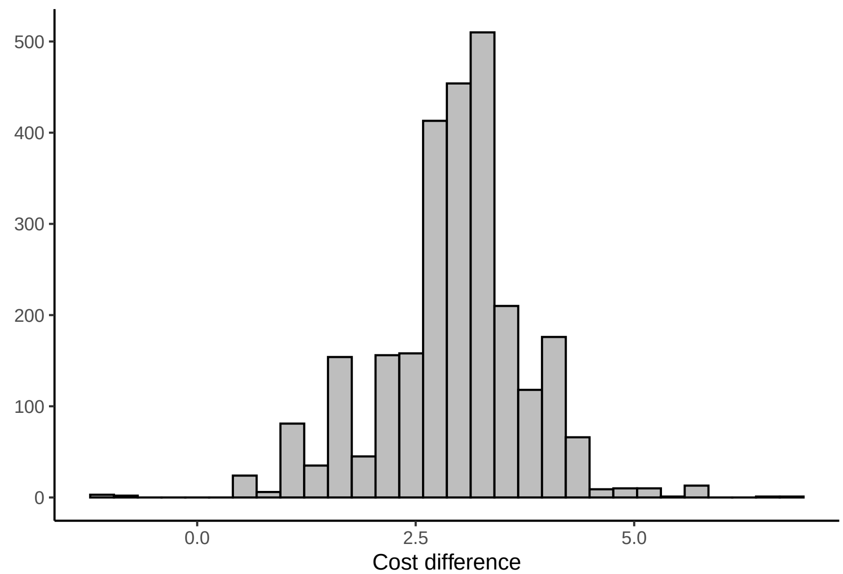
These pictures illustrate how the application users record their travel logs in the application Spritmonitor.

Figure A.2: Electricity Prices



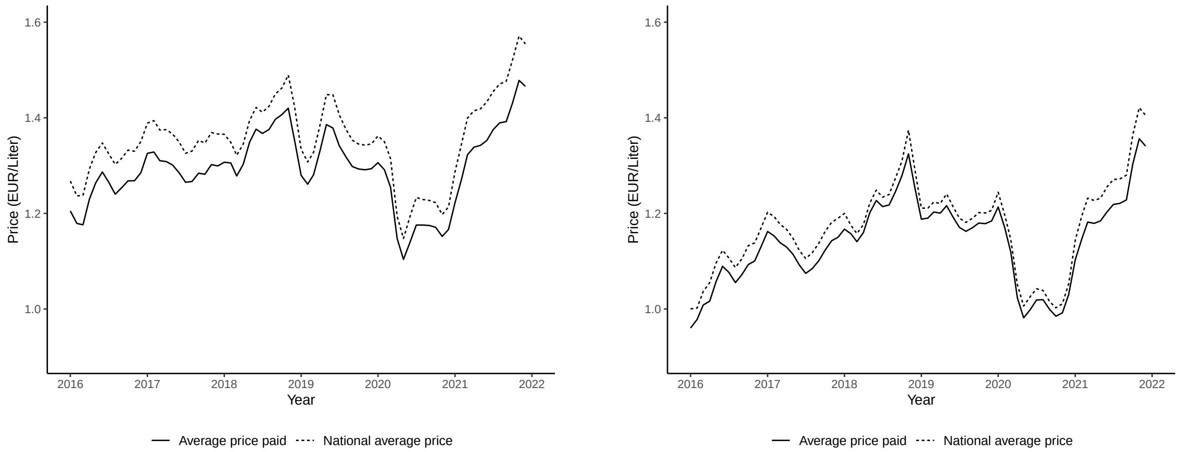
The figure plots household electricity prices, including taxes, levies, and VAT, adjusted by the consumer price index (CPI) with 2015 as the base year. The unit is € per kWh. Source: Statistisches Bundesamt.

Figure A.3: Cost differences refueling versus recharging



The figure reports the histogram of cost difference (fuel cost - electricity cost) for each vehicle in our sample in € per 100km. We assume a fuel price of €1.37 per liter (the average fuel price in 2021) and an electricity price of €0.30 per kWh.

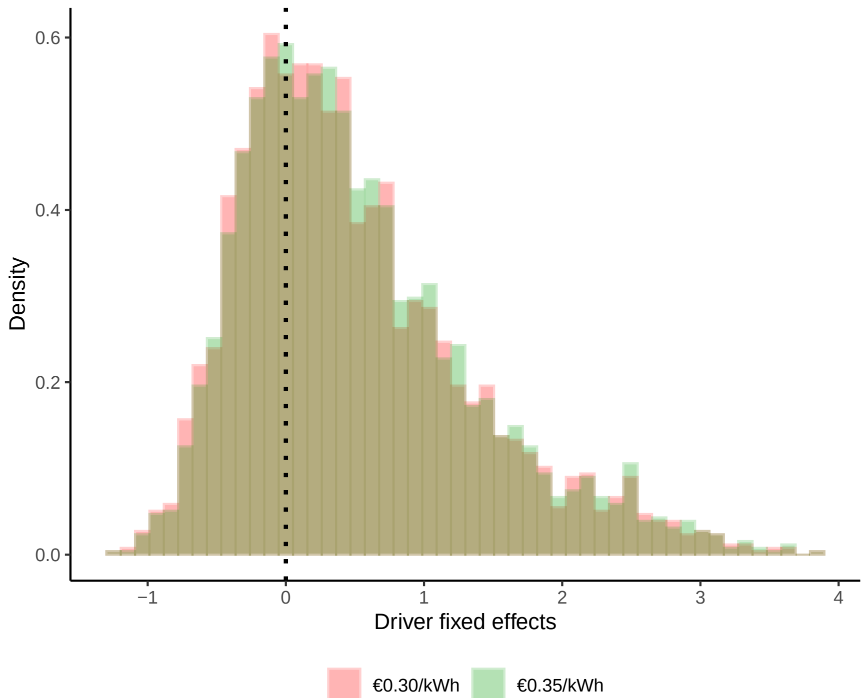
Figure A.4: Reported and posted fuel prices



Panel (a): Gasoline Panel (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.

Figure A.5: 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 (4), on the price differences Δp_{it} and fixed effects at the driver level.