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Working Paper Series

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NOVEMBER 2019

CEEPR WP 2019-019

MASSACHUSETTS INSTITUTE OF TECHNOLOGY

Driving Behavior and the Price of Gasoline: Evidence from Fueling-Level Micro Data*

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November 2019

Abstract

We use novel microdata on on-road fuel consumption and prices paid for fuel in Japan to estimate short-run price elasticities of demand for gasoline consumption. We have three main findings. First, our elasticity estimates of roughly -0.37 are in orders of magnitude larger than previously estimated using more aggregate data. Second, we are one of the first papers to separately estimate both the price elasticities of kilometers driven (-0.30) *and* on-road fuel economy (0.07). Lastly, we find that on-road fuel economy is determined by recent prices than distant past prices paid, suggesting limited habit formation of fuel-conserving driving behaviors.

Keywords: price elasticity of gasoline consumption, energy efficiency, learning

JEL Codes: Q31, Q41, R48, D12, L71

*We thank comments from Kyle Emerick, Federico Esposito, Laura Gee, Kenneth Gillingham, Kelsey Jack, Yoshifumi Konishi, Ashley Langer, Shomon R. Shamsuddin, Richard L. Sweeney, Koichi Ushijima, Arthur A. Van Benthem, Catherine Wolfram, Hidefumi Yokoo, and participants at 2019 AERE Summer Conference and Kyoto Summer Workshop on Applied Economics. We also appreciate the IID, Inc. Group for sharing the data on on-road fuel consumption. This research was assisted by a grant from the Abe Fellowship Program administered by the Social Science Research Council in cooperation with funds provided by the Japan Foundation Center for Global Partnership. The views expressed here are those of the author and do not reflect those of the data provider or the funding agencies. This paper was written in part while Tanaka was visiting the MIT's Center for Energy and Environmental Policy Research (CEEPR). He is grateful to CEEPR for its hospitality. The usual disclaimer applies.

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I. Introduction

Automobile usage imposes substantial social costs, including the greenhouse gas emissions, local pollution that is harmful to human health, traffic congestion and accidents, and oil dependency (Parry et al. 2007, Currie and Walker 2011, and Knittel et al. 2016). While economists often advocate gasoline taxes to address these externalities, policy makers often rely on more costly fuel economy standards (Austin and Dinan 2005 and Jacobsen 2013). A major source of the inefficiency of fuel economy standards is that they reduce marginal cost of driving. This leads to two inefficiencies on the intensive margin. The first has been well documented: drivers will drive too many miles compared to the social optimum. This is known as rebound. Reducing the marginal cost of driving leads to a second effect, the magnitude of which is less well known. In particular, on-road fuel economy will suffer through changes in either driving style or vehicle maintenance. Despite the potential importance of these behavioral responses, we know little about this latter effect. A major difficulty in estimating this effect is the lack of extensive and systematic data on fuel consumption at the micro level. Instead, most existing studies rely on imperfect and often highly aggregated panel data, such as monthly gasoline consumption at the state level (see, for example, Hughes et al. (2008)).

In this study, we investigate the short-run price elasticity of demand for gasoline consumption using innovative, high-frequency data, collected from a mobile phone application. The data report detailed micro-level information on gasoline consumption, vehicle distance traveled, and gasoline prices paid at the refueling level over 90,000 drivers for 10 years. The use of such micro data allows us to make unique contributions in three aspects. First, by observing actual prices paid by individual drivers for fuel at every refueling level, we can estimate the own-price elasticity of demand for gasoline at the driver-vehicle level. Second, we can decompose the impact on fuel consumption into those behavioral changes that capture changes in vehicle distance traveled and adjustments in driving style and vehicle maintenance, as reflected in actual on-road fuel economy. Lastly, we can explore the extent to which drivers adjust their actual fuel economy in response to a series of past gasoline prices to understand habit formation of fuel-conserving driving behaviors from past events. In addition to these, we also investigate asymmetric price effects across price increases and decreases.

We estimate an average elasticity of around -0.37. This is larger than conventional estimates of -0.02 to -0.04 in the macroeconomic forecast analysis (U.S. Energy Information Administration 2018) or -0.034 to -0.077 from 2001 to 2006 in Hughes et al. (2008).[1] Our

[1]See the similar estimates summarized in Lin and Prince (2013). Also note that Li et al. (2014), and indirect so does Davis and Kilian (2011), documents evidence that changes in gasoline taxes are more salient

estimate is similar to recent work by Levin et al. (2017) which uses daily expenditure data from credit card receipts.

We next split our elasticity estimate into the elasticity of vehicle-kilometer traveled (VKT) to gasoline prices and the price elasticity of actual on-road fuel economy achieved. Our VKT elasticity is -0.30. The magnitude is also greater than the short-run elasticities estimated in other studies (e.g., the one month elasticity in the 2000s is -0.07 in Hughes et al. (2008) and -0.02 between 1997 and 2001 in Small and Dender (2007)), and our estimates are even larger than the medium-run or long-run elasticities of around -0.123 over two years in Knittel and Sandler (2018) and -0.15 in Gillingham (2011).

We also find meaningful response of on-road fuel economy to changes in gasoline prices, likely manifesting itself through changes in driving style and/or changes in vehicle maintenance behavior. The price elasticity of actual fuel economy is roughly 0.07. We are one of the first, if not the first, to estimate this key parameter.[2] Yet, growing discussions in the energy efficiency gap suggest great potential for behavioral adjustments on the energy cost savings (Allcott and Greenstone 2012). We shed a new light on driving behavioral adjustments drivers make for given distance in response to price changes. The existing literature on the price effect on fuel economy is exclusively limited to the extrinsic margin, in which high gasoline prices incentivize consumers to switch to high fuel efficient vehicles (Li et al. 2009, Klier and Linn 2010, Busse et al. 2013). In contrast, evidence on the intrinsic margin, in which consumers respond to day-to-day fluctuations in gasoline prices, is remarkably absent. Our evidence highlights a relatively unexploited channel through which fuel consumption responds to prices.

We further investigate whether the price effects on on-road fuel economy persist or fade away over time; are these effects capturing drivers learning how to drive better or a short-term response to price changes? By relating the current actual fuel economy to all past prices paid by the drivers, we find that the recent prices have greater explanatory power than distant past prices, suggesting that there is little learning or habit formation from the past events that persists over time.

Additional analysis shows substantial asymmetry in the price elasticity of demand for gasoline consumption when gasoline prices rise or fall. The neoclassical economics theory predicts that comparable price changes have similar effects regardless of the direction of

to consumers than day-to-day fluctuations in the tax-exclusive gasoline prices. Both papers find elasticity estimates in line with our own when focusing on variation in gasoline prices coming from changes in gasoline even when using more aggregate data.

[2]While not the focus of the paper, Langer and McRae (2017) includes regressions of trip-level fuel consumption for 108 drivers that were loaned a set of identical Honda Accords over forty days. They find that increases in gas prices increased fuel consumption, but do not untangle why this is. Given the short time period it may be the case that gas prices varied little making it difficult to identify the true response.

its change. In contrast, the behavioral model of loss aversion proposed by Kahneman and Tversky (1979) suggests that consumers perceive a price increase more greatly than an equivalent price decrease. While a growing body of studies document evidence in favor of the behavioral model (DellaVigna 2009), little is known about whether this asymmetric price effects holds for gasoline, a product for which price has been extremely volatile, and demand is found to be relatively price inelastic (Lin and Prince 2013). The order of the magnitude when price goes up from the previous purchase is -0.42, nearly twice greater than that for falling prices of -0.22, suggesting that consumers are highly more sensitive to increasing prices than decreasing prices. The magnitude of our estimated short-run elasticity for price increase is close to the range of the long-run elasticities in other studies (e.g., -0.11 in Small and Dender (2007) from 1997 to 2001, -0.35 in Bento et al. (2009), and similar estimates summarized in Graham and Glaister (2002)).

This article proceeds as follows. Section II describes the primary data we use for the analysis. Section III examines the price elasticity of demand for gasoline consumption, vehicle distance traveled, and actual fuel economy. Section IV examines the learning effect of a history of prices paid on the current driving behavior. Section V explores the heterogenous price elasticities across various dimensions. Section VI concludes.

II. Data[3]

The primary data on the on-road fuel consumption are collected by a private company through a unique mobile phone application. Drivers can freely download and use the application to learn about their own real-world fuel economy relative to that of other drivers driving the same configuration of vehicles[4] and tips to improve driving behaviors to save fuel costs. For this purpose, drivers report the amount of fuel purchased to fill the tank completely and the odometer value at every refueling level, from which fuel consumption and the distance traveled can be obtained.

For each observation, we can also identify the date and time of the purchase, the price of gasoline paid,[5] and prefecture of the gasoline station where the purchase was made. The average daily (i.e. 24-hour) fuel consumption and distance traveled are computed using the date and time for the two consecutive refuels. The actual fuel-economy figures are computed by dividing the distance traveled by the gasoline consumption.

[3]See Online Appendix A for more detailed description of the data and the variables construction.

[4]The vehicle configurations can be uniquely matched at the detailed level of model, manufacturing year and month, displacement size, weight, engine type, wheel drive type, body type, and transmission type.

[5]All prices are converted into the 2010 January value using the monthly consumer price index reported by the Statistics Bureau of Japan.

The technology to photograph receipts and odometer for reporting simplifies the process and helps minimize the typing errors (see Online Appendix Figure A.1). In addition, the drivers can indicate if there is any unreported refuelling since the last report to avoid inflating distance traveled for the reported fuel consumption. The additional processes to guard against outliers and unreasonable values are described in Online Appendix A. Our sample is limited to gasoline-powered passenger vehicles and minicars[6] manufactured by domestic automakers.

Table 1 reports the summary statistics of our final sample used for the analysis. In total, the sample includes over 4 million observations of fuel consumption at every refueling from 2005 to 2014 for more than 90,000 driver-vehicle pairs driving more than 3,900 configurations. On average, drivers consume 3.54 liters per day (L/day) (equivalent to 0.93 gallons per day), drive 36.7 kilometers per day (km/day) (22.8 miles), and pay ¥136.6 per liter ($5.21 per gallon). Average frequency of refueling is every 14.1 days. The observations come from every prefecture with some preponderance on large prefectures such as Saitama, Kanagawa, Aichi, Tokyo, Chiba, and Osaka (Online Appendix Table A.2).

It would be ideal to have randomly selected representative drivers record on-road fuel consumptions at every trip. In the absence of such data, our data rely on information submitted by drivers who voluntarily engage with the application. We can compare VKT, fuel consumption, and average fuel economy in our sample to a representative sample of Japanese drivers and vehicles from the Annual Statistical Report on Motor Vehicle Transport.[7] Our sample drives more, consumes more gasoline, but has greater fuel economy. The survey reports an average VKT for vehicles, conditional on driving during a given day, that is quite close to our average; the survey's average is 35.5 km/day, compared to our average of 36.7 km/day. However, once you account for the fact that vehicles in the national survey are only driven 67.0% of the days, the unconditional mean in the survey is lower (23.8 km/day). The gasoline consumption per day in the national survey is 3.62 L as opposed to 3.54 L/day in our sample, which translates into actual fuel efficiency of 10.01 km/L in the survey, and this

[6]Minicars (called *"kei-cars"*) constitute one of the primary classifications of vehicles in Japan. They are tiny vehicles whose displacement is 660 cubic centimeter or lower and are popular because roads are typically narrow, and automobile-related taxes are substantially lower than those imposed on passenger vehicles.

[7]This is one of the fundamental statistics managed by the Ministry of Land, Infrastructure, Transport and Tourism (MLIT). The survey is conducted every month for randomly selected owners of all registered vehicles with the sample size of 33,000 vehicles in February, June, and October, and 10,000 vehicles in the remaining months. The subjects are mandated to answer the survey. The reports (both monthly and annual) can be downloaded directly from the MLIT website. We use the report in 2009 because the data after 2010 report vehicles for business use only. We also use the values based on the passenger transport instead of the freight transport. These values are reported separately for passenger cars and minicars. We use the share of passenger cars in our data to compute the weighted average. Unfortunately, there is no information on national average official fuel economy of vehicles on the road to investigate the similarity of vehicle composition of our sample in this respect.

is lower than our average fuel efficiency of 10.85 km/L.

Given how drivers select into the sample—the app's goal is to provide information on how drivers can improve their fuel efficiency—one may expect our estimated fuel economy elasticity to be larger than the population's. However, it is not clear whether they will have a larger elasticity than the population. It may be the case that they turned to the app as a way to respond to gasoline prices because they have less discretion over their VKT. Below, we explore heterogeneities in the estimated elasticities across various dimensions to offer some insights on how the elasticities would look like for the general population relative to what we find in our sample.

Appendix Figure A.2 plots the weekly observations of the national average retail gasoline prices per liter over our study period. Clearly, the prices have been very volatile during this time; the prices have gone up and peaked at ¥185.0 on August 4, 2008 but declined sharply to the bottom value of ¥110.3 on January 13, 2019, and have been rising more steadily ever since. Note that the price trend is very similar to that of the U.S. during this period, although the fuel prices in Japan are substantially higher than those in the U.S. The short-term fluctuations in fuel prices as illustrated provide an important source of variation for our identification of demand elasticities.

III. The Price Elasticity of Demand for Gasoline

We begin with a simple log-log model of gasoline demand, given by:

$$\ln Y_{ivt} = \alpha + \beta \times \ln Price_{ivt} + \mu_t + \nu_{iv} + \varepsilon_{ivt}, \tag{1}$$

where $\ln Y_{ivt}$ denotes the log of gasoline consumption per day (L/day) for driver i, driving the vehicle v, at time t, and $Price_{ivt}$ is the fuel price per liter paid by driver for that amount of gasoline consumption. We include a variant of the time fixed effects, μ_t, to control for any correlations between gasoline consumption and gasoline price. This is crucial because there are strong seasonality effects in both demand for gasoline and fuel prices, whereas the macroeconomic conditions can also lead to a spurious correlation. In our preferred model, we include the year-by-month fixed effects to account for the transitory shocks specific to each month of the year.

One advantage of our data is that we can include the driver-by-vehicle fixed effects, ν_{iv}, which allows us to estimate the relationship within the driver-vehicle levels.[8] Thus, any

[8] In our sample, 79.0% of all drivers are matched with a single vehicle, whereas 16.8% report two vehicles. It would be pointless given the purpose of the program for multiple drivers to report for a single vehicle.

heterogeneity across drivers that is likely to correlate gasoline consumption and fuel prices paid will not be a threat to identification. We compare our results with those that would be estimated in comparable studies using the vehicle model fixed effects to understand the potential bias that may arise.

An important identification issue is reverse causality. For instance, drivers can search for cheaper gasolines when they consume more, in which case the estimated elasticities are overstated. Alternatively, when drivers drive a long distance on highways (which are all toll roads in Japan) or in rural areas, drivers are more likely to pay high gasoline prices due to little competition among gasoline stations, as drivers are required to utilize gasoline stations at the service areas or those out of few options in rural areas, causing a positive correlation between fuel consumption and prices paid.

To address this issue, we use the instrumental variable (IV) approach to estimate the model. The first stage of the IV model is:

$$\ln Price_{ivt} = \gamma + \delta \times \ln Price_t + \mu_t + \nu_{iv} + \epsilon_{ivt}, \tag{2}$$

where actual prices paid by drivers are instrumented by $Price_t$, the average gasoline price in the same prefecture on the date of the purchase.[9]

The coefficient of interest, β, estimated in the second stage of the IV model measures the price elasticity of demand for gasoline consumption. The identification assumption is that after controlling for time effects, the day-to-day fluctuations in gasoline price in the market are orthogonal to unobserved factors that affect the driving decisions by individual drivers other than going through the fuel prices paid. This is a common assumption and likely to hold as the market price of gasoline is determined largely by the world supply and demand of crude oil (Knittel and Sandler 2018). All standard errors are clustered at the driver-vehicle level.

Figure 1 plots the elasticities estimated from various models (individual coefficients are presented in Table 2) and the distribution of prices paid by individual drivers in our sample. The coefficient estimated from the OLS model is positive (shown in Column (1) in Table 2), suggesting that the endogeneity of price results in substantial upward bias in the estimated elasticity.[10] Conversely, all estimates illustrated in the figure based on either IV or the reduced

[9]The national average daily prices are obtained from the same company that we obtained the fuel consumption data. The information is available only after 2010. For data before 2009, we use the weekly gasoline retail prices at the prefecture level reported by the Institute of Energy Economics, Japan. We computed the daily fuel prices for non-reported days by taking the arithmetic averages of the two most recently reported values. All fuel prices are converted into the January 2010 yen using the consumer price index.

[10]This evidence effectively suggests a limited role of searching behaviors by drivers in biasing the estimates. Dorsey et al. (2019) also show little search by drivers in choosing where to stop for gasoline by tracing all trips made and refueling patterns by 108 drivers driving the test vehicles for forty days.

form models show consistently negative elasticities. The model with only the basic year and month fixed effects suggests less elastic demand. In contrast, all estimated elasticities with more granular time fixed effects present relatively more elastic demand with the order of -0.213 to -0.371. The preferred IV model with the year-by-month fixed effects produces an estimated elasticity of -0.371, which represents an order of magnitude more elastic than those inferred from aggregate gasoline expenditure data. To put this into the context, our estimated elasticities suggest that a one standard deviation increase in fuel prices leads to about a 4.14%, or 0.146 L, fewer gasoline consumption a day.

To see how gasoline consumption is determined, we decompose the effect between the vehicle distance traveled and the actual on-road fuel economy of the vehicle. These results are reported in Columns (6) and (7) of Table 2. We find that about 81% of reductions in fuel consumption come from reduced vehicle distance traveled, whereas the remaining 19% come from improvement in fuel conserving driving behaviors. The estimated elasticities are -0.302 for vehicle distance traveled and 0.070 for actual fuel efficiency, and both are statistically significant at the 1% level, suggesting that a one standard deviation increase in gasoline prices leads to a 3.37% (1.237 km) fewer vehicle distance traveled a day and a 0.776% (0.084 km/L) increase in actual fuel economy.[11] These findings highlight the importance to account for driving behaviors in fully understanding how gasoline prices affect fuel consumption.

We conduct several robustness checks to these results. First, we include observations of extremely long vehicle distance traveled[12] and repeat the same analysis. The results are consistent with our findings above (Online Appendix Table B.4). Notably, the point estimate with the OLS model enlarges, whereas all estimates based on the IV model are smaller in magnitude. This is consistent with our story that positive bias arises due to higher gasoline prices paid by longer distance drivers (driving on toll roads or rural places). In contrast, these extremely long distance drivers are less elastic to prices possibly because these trips cannot be simply reduced.

Second, we explore alternative functional forms, in particular linear and semi-log models. The double-log specifications, as we model in the main analysis, is the most conventional in the literature. Yet, some have proposed for other specifications (Hsing 1990). We find that the findings are robust to both linear and semi-log functional forms (Online Appendix Table B.5).

[11]It is worth noting that since drivers have control over and simultaneously determine all three variables: gasoline consumption, distance traveled, and actual fuel economy, their relationship should not be interpreted as causal but only indicate a correlational relationship among the three variables.

[12]The main analysis removes observations beyond 100 km/day of daily distance traveled since they are unlikely to reflect normal driving distances in Japan. Nonetheless, this robustness check includes observations of up to 250 km/day, a 6% increase in the number of observations.

Finally, we also define fuel prices based on the average fuel price of all days since the last refuel until this time as the main independent variable, in Table B.6. Our results are robust to this alternative definition.

The comparison of our results to those estimated only with the vehicle configuration fixed effects (presented in Online Appendix Table B.7) reveals that the elasticities estimated with driver-vehicle fixed effects are consistently more elastic, suggesting that estimates based on repeated cross-sectional data (e.g., the National Household Travel Survey in the U.S.) may be understated. This provides strong support to account for important heterogeneities across drivers to better estimate the demand elasticities.

IV. Learning Effect

The evidence thus far suggests that drivers alter their driving style (or vehicle maintenance) in response to price changes. The second question we investigate is how persistent such effects remain over time. To test this, we explore whether the fuel prices paid in the distant past affect behavior in similar ways than more recent prices, where we can measure driving style via real-world fuel economy. Implicitly, this is a test as to whether there is a utility cost of driving less aggressively. If consumers value aggressive driving either because it provides utility directly or through their value of time, then the effect of gasoline prices on real-world fuel economy will be temporary. If, instead, high gasoline prices prompt consumers to learn about the virtues of less aggressive driving, we will see long-run effects from price changes.

One way to flexibly estimate the effects from past events is to separately include all prices paid in the past at every refuel level by estimating a distributed lag model of the form:

$$\ln Y_{ivt} = \alpha + \sum_{j=0}^{k} \beta_j \ln P_{t-j} + \mu_t + \nu_{iv} + \epsilon_{ivt}, \tag{3}$$

where P_{t-j} is the price paid at the j-th previous refuel.

However, such a flexible estimation faces two challenges. First, prices paid this time and the recent past are highly serially correlated. For instance, the correlation coefficient between the price paid for this cycle and the previous one is 0.959.[13] Second, we do not observe a consistent set of past prices across, and even within, drivers, since refills do not occur at fixed intervals. With these issues being noted, below we present the results when we include the six most recent prices paid by a given driver.

We formalize an approach based on the household finance models within the seminal works of Ulrike et al. (2011), Greenwood and Shleifer (2014), and Malmendier and Nagel

[13]Online Appendix Table C.1 shows the correlation coefficient matrix for the most recent six prices paid.

(2016).[14] In particular, we summarize all prices paid in the past as a weighted average of those prices, while allowing the weight to increase, be constant, or decline over time. If the weight is constant, then all past prices affect behavior equally, if the weight is increasing over time, then more recent prices matter more, while if the weight is decreasing over time, consumers are adopting behavioral changes that are not costly once adopted. Most importantly, we allow the data to identify the weighting function. In particular, for each price paid at the k-th refuel, we construct the following weighted average of past prices:

$$\Omega_{ivk}(\lambda) = \sum_{j=0}^{k} w_j \ln P_{t-j}, \tag{4}$$

and

$$w_j = \frac{\lambda^j}{\sum_{m=0}^{k} \lambda^m}, \tag{5}$$

where the sum of all past weights is equal to one.

The parameter λ determines how quickly fuel-consuming driving manners die out in actual driving behaviors. To illustrate how the parameter λ determines the shape of the weighting function, Figure 2 Panel A plots the weights for a 100th refuel for two values of λ. If $\lambda > 1$ (e.g., for $\lambda = 1.1$), the weight is decreasing over time, assigning greater weights toward past prices, and thereby being indicative that current driving behavior is influenced more by the distant past events. Alternatively, for $\lambda < 1$ (e.g., $\lambda = 0.9$), the influences of past events fade away, while the recent events carry greater weights on the current driving behaviors. With $\lambda = 1$, each event in the past is equally weighted.

The cost of this approach, compared to a distributed lag model, is that the weighting function is more parametric and constrained to be monotonic.

In our estimation, we include all prices paid from the first observation in our data and simultaneously estimate the price elasticity of demand and the weighting parameter by the specification:

$$\ln Y_{ivt} = \alpha + \beta \times \Omega_{ivk}(\lambda) + \mu_t + \nu_{iv} + e_{ivt}, \tag{6}$$

where the outcome variable of interest is the log of actual fuel economy.[15] Because $\Omega_{ivk}(\lambda)$ is a nonlinear function with respect to the weighting parameter, λ, we adopt a nonlinear least

[14] Ulrike et al. (2011) studies the effect of life-time experiences in stock market returns on current risk attitudes and financial market participation; Greenwood and Shleifer (2014) studies investor's expectation of future stock market returns as a function of a series of past returns; and Malmendier and Nagel (2016) show how the lifetime experiences of inflation form the future inflation expectation.

[15] To reduce the computational burden, we adopt the reduced form analysis with year and month fixed effects and include up to 100th refuel, which accounts for 87% of all sample. The evidence on the actual fuel economy suggests that including up to 200th refuel, accounting for 98% of all observations, remains similar.

squares method that minimizes the sum of squared residuals. As starting values, we first estimate the model without the weighted average of past prices to obtain the parameters for other variables and set them as well as $\lambda = 1$.

Figure 2 Panel B plots the estimated λ for KPL (individual coefficients and β values are reported in Online Appendix Table C.2 for all three dependent variables: KPL, VKT, and gasoline consumption).[16] For all variables, the estimated λ's are statistically significantly lower than one, suggesting that more recent prices have greater impacts on the current driving behaviors than the distant past prices. This suggests that although changes in driving style can increase fuel economy, there is a utility cost to these changes. Therefore real-world fuel economy will depend only on the current price of gasoline and not past prices.

The results based on Equation (3) also provide consistent evidence that the driving behaviors respond to the most recent prices more strongly than the second or third most recent prices paid (Online Appendix Table C.4). The point estimates suggest that the effects of recent prices quickly lessen; even the fifth most recent prices have no longer any influence on the current behavior. The finding that there is little path dependence in driving behaviors contrasts with recent evidence by Severen and van Benthem (2019) showing that consumers who experienced the 1979/80 oil crisis around age 16 substantially lowered vehicle usage later years at both extensive and intensive margins.

V. Asymmetric Price Elasticities of Demand

The final part of our analysis explores the heterogeneity of elasticities across a number of dimensions. We start with comparing elasticities across price increases and decreases, where the price change is based on the price at the previous fill up. The neoclassical economic theory predicts that consumers respond similarly to the given price changes regardless of the direction. To simplify the analysis, we focus on the reduced-form analysis where the outcome variable is regressed upon the daily average gasoline price in the market on the day of the purchase.[17] In particular, the regression models are:

[16] We focus our discussions on λ because the estimated β has little economic interpretation. The coefficient β measures how much the outcome changes with respect to a unit change in $\Omega_{ivk}(\lambda)$, holding everything else constant. Thus, multiplying β by $\Omega_{ivk}(\lambda)$ with the estimated weight $w_j(\lambda, j)$ measures the effect of price paid at j-th time ago on the current outcome.

[17] The reduced-form approach helps avoid the case of multiple endogenous variables with multiple instrumental variables, which makes the interpretation of their coefficients difficult. Nonetheless, we also conducted the instrumental variable approach and present the results in Online Appendix Table D.1. In general, the estimated elasticities from the IV regressions are greater than those from the reduced-form regressions.

$$\ln Y_{ivt} = \alpha + \beta^{+} \times \ln Price^{+}_{vt} + \beta^{-} \times \ln Price^{-}_{vt} + \rho \times 1(P_{vt} \geq P_{vt-1}) + \mu_t + \nu_{iv} + \varepsilon_{ivt}, \quad (7)$$

where

$$\begin{aligned} Price^{+}_{vt} &= P \times 1(P_{vt} \geq P_{vt-1}) \\ Price^{-}_{vt} &= P \times 1(P_{vt} < P_{vt-1}), \end{aligned} \quad (8)$$

and $1(\cdot)$ is an indicator function.

Figure 3 shows the estimated elasticities with 95% confidence intervals (individual coefficients are presented in Online Appendix Table D.1). For each elasticity, we compute and list changes in the amount of gasoline consumption per day with respect to a one standard deviation increase in fuel prices and its associated 95% confidence interval. What is striking is that the elasticity is substantially higher when prices go up than when they go down with elasticities of -0.415 and -0.224 respectively, suggesting that drivers are relatively more sensitive to increased prices than decreased prices.[18] The evidence that for a given amount of price change, consumers perceive a price increase more strongly than a price decrease is consistent with the behavioral model of loss aversion (Kahneman and Tversky 1979).

In addition, we explore if elasticities differ when prices are above or below the mean value of what individual drivers paid during the study period.[19] The coefficients are estimated from the single regression when Equation (8) is replaced by:

$$\begin{aligned} Price^{+}_{vt} &= P \times 1(P_{vt} \geq \bar{P}) \\ Price^{-}_{vt} &= P \times 1(P_{vt} < \bar{P}), \end{aligned} \quad (9)$$

where $\bar{P} = \frac{1}{N}\sum_{t=0}^{N} P_{ivt}$, and N represents the total number of observations for each driver-vehicle pair in our data. We find that the elasticity is higher when prices are low relative to when they are high. Combining this result with the results with respect to price increases and decreases is consistent with consumers being more responsive to price increases in the very short period but soon adapt to persistently high prices. However, we can not rule out the case where elasticities vary over time and prices are mean reverting and those periods with price increases are also periods where prices are low.

[18]Note that the weighted average elasticity of these two cases, which is essentially the β coefficient in Equation (1) when $1(P_{vt} \geq P_{vt-1})$ is additionally controlled for, is -0.321 with the standard error of 0.025.

[19]We take advantage of our observations of the history of prices individual drivers paid with the expectation that prices each driver paid are more salient than the market prices. Nonetheless, we also repeated the analysis using the market average price during the same period, and the results are similar.

Next we explore heterogeneity across drivers in our sample and the vehicles they drive. We split the sample by the vintage of the vehicle, the fuel economy, vehicle type, when the driver signed up with the app, and the average distance the driver drives per day. We find that drivers with more recently manufactured vehicles than the average time in our sample are more elastic than those driving older vehicles, and those who are driving more fuel efficient vehicles than the average in our sample are more elastic than the counterparts. We also find that drivers of minicars are more elastic than those of passenger vehicles, indicating that those who prefer smaller and thus cheaper cars are more elastic. Online Appendix D show that drivers of cheaper cars consistently have greater elasticities among both passenger cars and minicars owners. Together, consumers who are more sensitive about vehicle prices are also responsive to fuel prices.

Next, we find that users who started using application before and after the mean starting time have similar elasticities. This suggests that those consumers that selected into the app earlier are not different from those that selected into the sample later. While ideally we could compare elasticities of our sample with the population, this provides some, albeit weak, evidence that sample selection may not be a big concern. Lastly, we compare drivers whose average distance traveled per day is greater and less than the sample average vehicle distance traveled. The point estimates suggest that drivers who drive more are more price elastic than those who drive less, yet their difference is not statistically significantly different each other.

VI. Conclusions

This study offers three important findings. First, the short-run price elasticities of fuel consumption are in the order of magnitude larger than what is previously estimated using more aggregated data. In addition, fuel consumption responds to price changes not only by adjusting vehicle distance traveled but also by altering driving manners. Second, a price increase is more salient to consumers than a price fall, a finding that is consistent with the behavioral model of loss aversion. Third, drivers adjust their driving manners in response to prices they actually paid for that trip, suggesting little driving habit formation over time. Although increases in gasoline taxes may be more salient than daily fluctuations in gasoline prices we exploit, as evidenced in Li et al. (2014), our findings suggest only a transitory impact of such price increase, and consumers adapt to that level of prices. These findings suggest limited efficacy of gasoline taxes alone on reducing gasoline consumption and may provide support to other instruments including fuel economy standards and other incentives programs such as feebate policies.

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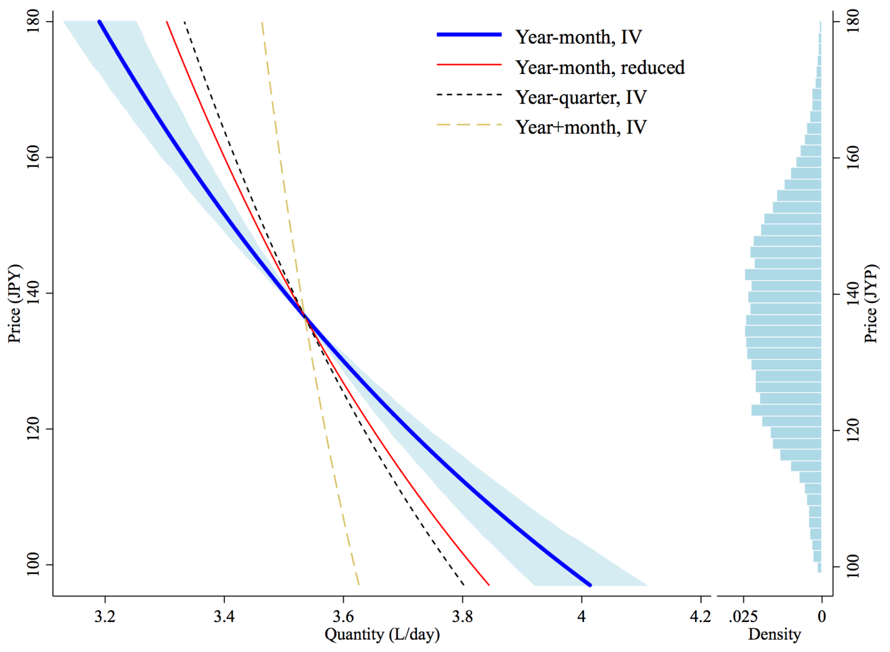
Figures

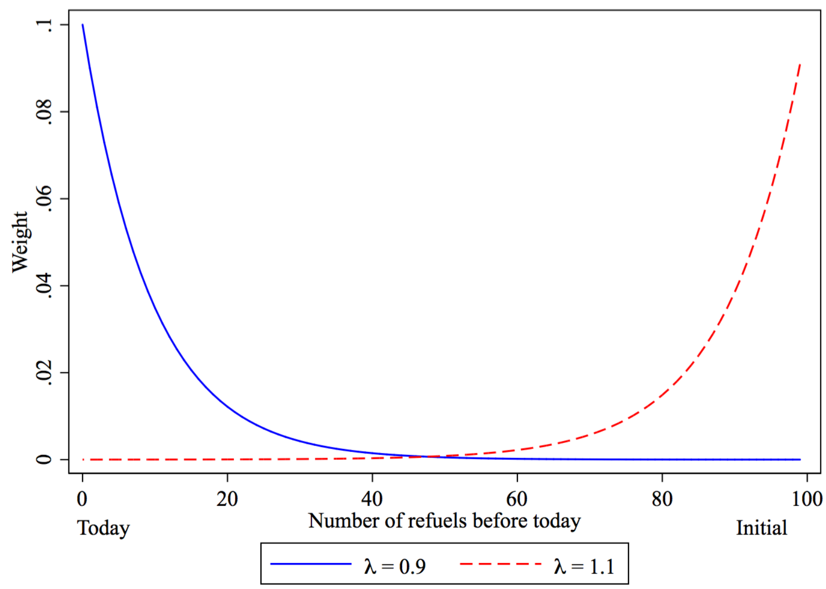
Figure 1: Price Elasticity of Demand for Gasoline



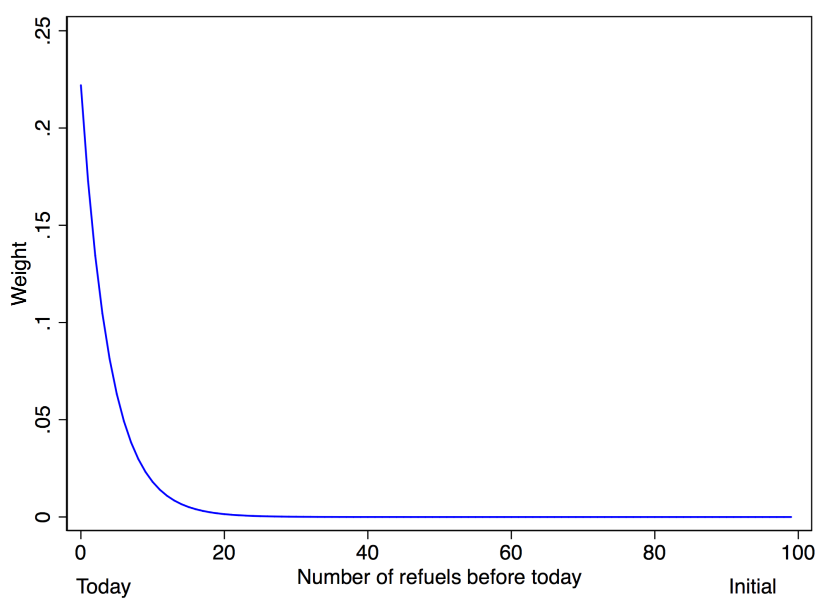
Notes: The left figure plots the estimated elasticities from various time effects and methods (IV or reduced) as specified in the labels. The intercepts are adjusted to allow all demand curves to pass the mean price and quantity values. The blue shaded area represents the 95% confidence interval of the elasticity estimated from the model with the year-by-month fixed effects. The right figure plots the distribution of prices paid by individual drivers in our sample. The units are Japanese yen for price and liter per day for quantity. Average exchange rate during this period is US\$ = ¥99.2.

Figure 2: Learning Effect

Panel A: Simulated weight

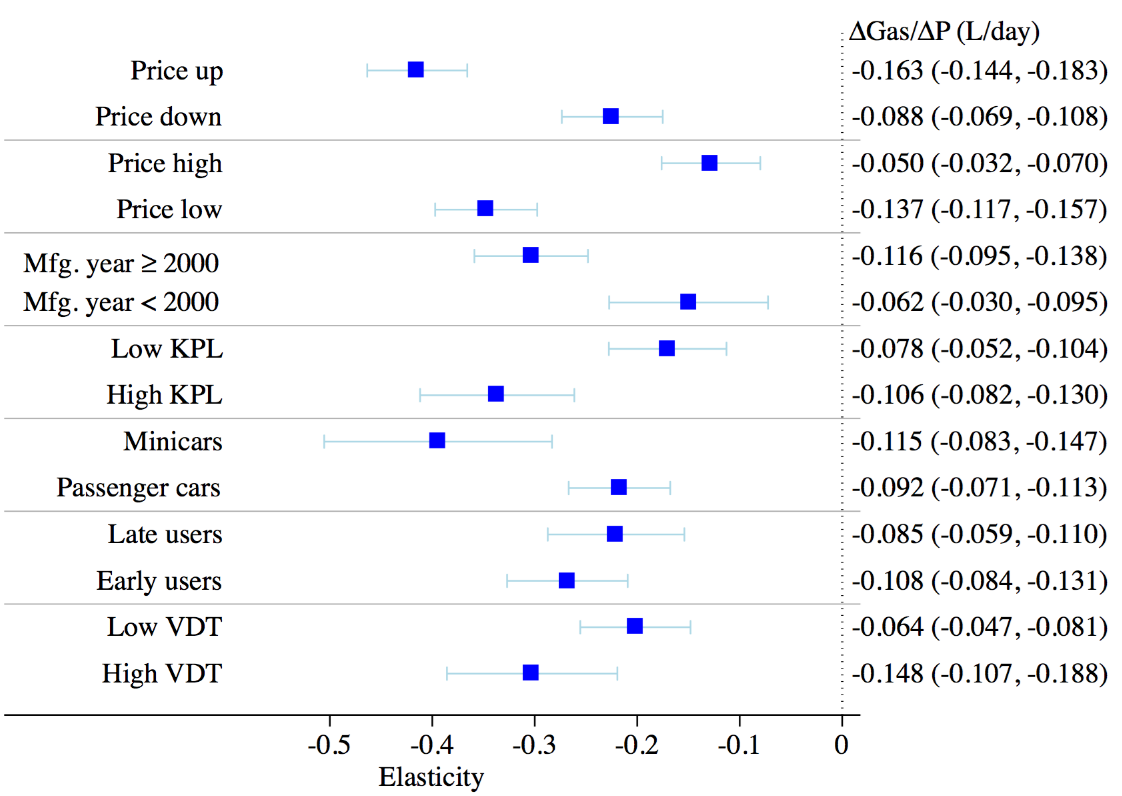


Panel B: Estimated weight



Notes: Panel A plots the weighting function for the two values of λ in Equation (6). Panel B plots the estimated weighting function for KPL ($\lambda = 0.778$) using up to 100th refuel.

Figure 3: Asymmetric Price Elasticities of Demand for Gasoline



Notes: This figure presents the estimated price elasticities of demand for gasoline consumption per day. The square dots represent the coefficients, and the lines indicate the associated 95% confidence interval. The asymmetric effects for fuel prices going up/down and fuel prices high/below are estimated from the single regressions, whereas other specifications are estimated from separate regressions. KPL represents the actual fuel economy in km/L, and VDT represents the vehicle distance traveled per day in km. The effect size is the changes and the associated 95% confidence interval of gasoline consumption per day in liter in response to a one standard deviation increase in gasoline price (¥15.24).

Table 1: Summary Statistics

	Mean	Std.	N	U.S. standard
Panel A: Individual report level				
Gasoline consumption per day (L/day)	3.535	2.034	4,088,789	0.93 gallon/day
Vehicle distance traveled per day (km/day)	36.70	20.66	4,088,789	22.81 mile/day
Actual fuel economy (km/L)	10.85	3.538	4,088,789	25.51 MPG
Gasoline price paid (¥/L)	136.55	15.24	4,088,789	$5.21/Gallon
# of days b/w refueling	14.12	25.54	4,088,789	
Odometer (km)	66,359.8	48,788.9	4,088,789	41,234.2 mile
Panel B: Driver-vehicle level				
# of reports	48.59	49.43	90,411	
Initial year	2008.7	2.906	90,411	
Panel C: Driver level				
Male	0.889	0.314	33,804	
Age	35.514	8.277	33,428	
Panel D: Vehicle level				
Manufacturing year	1,999.7	7.130	3,932	
Vehicle price (¥10,000)	191.0	101.5	3,663	$19,249
Dummy for regular gasoline (vs. highoctane)	0.760	0.427	3,932	
Dummy for passenger vehicle (vs. minicars)	0.695	0.461	3,932	
Seating capacity	4.838	1.130	3,830	
Dummy for automatic transmission	0.710	0.454	3,932	
Vehicle weight (kg)	1192.9	336.9	3,783	2,630 lb
Displacement (cc)	1631.4	851.2	3,931	
Official fuel economy (km/L)	14.71	4.966	3,707	34.6 MPG

Notes: This table reports the summary statistics for the variables of primary interests. Additional information is provided in Online Appendix A.2. Each panel indicates the units of observations. The values of the relevant variables are converted into the U.S. standards for the reference purpose. In Panel C, the total number of drivers is 71,263, only part of which report these driver characteristics.

Table 2: The Price Elasticities of Driving Behaviors

Dep. Var.	ln(Gasoline)					ln(VKT)	ln(KPL)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ln(Price)	0.139***	-0.0743***	-0.213***	-0.371***	-0.245***	-0.302***	0.0695***
	(0.00599)	(0.00782)	(0.0128)	(0.0348)	(0.0230)	(0.0367)	(0.00735)
Model	OLS	IV	IV	IV	Reduced	IV	IV
Driver-vehicle FE	Y	Y	Y	Y	Y	Y	Y
Time FE	Year + month	Year + month	Year × quarter	Year × month	Year × month	Year × month	Year × month

Notes: The outcome variables are the logs of gasoline consumption (in liter) per day (i.e. 24 hours) in Columns (1)–(5), vehicle-kilometer traveled (VKT) per day in Column (6), and the real-world fuel economy (in km/liter) (KPL) obtained by dividing gasoline consumption by vehicle-kilometer traveled in Column (7). All models except Column (1) and (5) are estimated by the instrumental variable approach, whose first stage results are presented in Online Appendix Table B.3. All specifications include the driver-vehicle fixed effects and variant time fixed effects as specified in each column. The number of observations is 4,088,789. Standard errors clustered at the driver-vehicle level are reported in the parentheses.
***$p < 0.01$

Driving Behavior and the Price of Gasoline: Evidence from Fueling-Level Micro Data

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Supplementary Materials

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Contents

A. Additional Information on Data

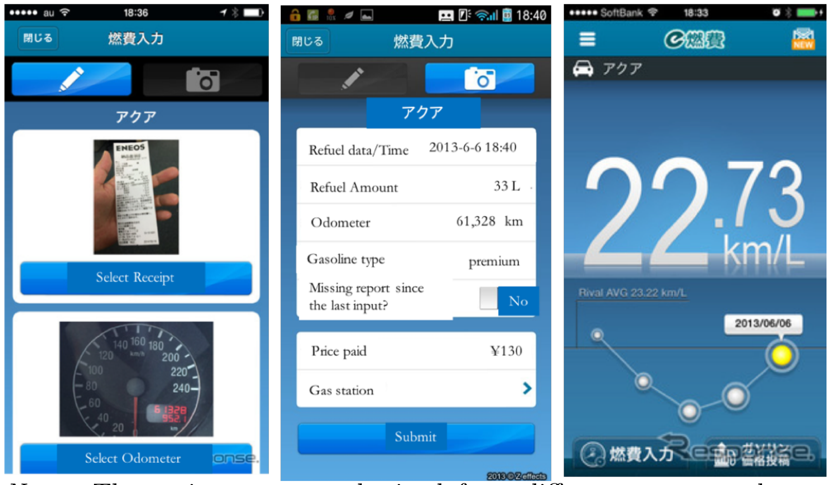
The primary data we use for the analysis were obtained and can be purchased from the IID, Inc. Group, the private company that operates the mobile phone application, called *e-nenpi* (*nenpi* means fuel economy). The application is free to download and use for users. Figure A.1 illustrates the sample screenshots of the application. Using this application, users report the amount of gasoline purchased, odometer values, and gasoline prices paid at every time they refuel. The information can be uploaded by simply taking the photographs of the receipt and the odometer to minimize the typing errors. Using the date and time of the gasoline purchase, we computed the daily (e.g., 24 hours) gasoline consumed and distance traveled between the two consecutive refuels. Further, the actual fuel-economy figures were computed by dividing the distance traveled by the gasoline consumption.

The original data we obtained included 5,884,179 observations at the refueling level. The data used for the analysis are limited to gasoline-powered passenger vehicles and minicars by domestic automakers. Minicars (called *"kei-cars"*) constitute one of the primary classifications of vehicles in Japan. They are tiny vehicles whose displacement is 660 cubic centimeter (cc) or lower and are popular because roads are typically narrow, and automobile-related taxes are substantially lower than passenger vehicles. Passenger cars include light duty vehicles whose displacement is under 2000 cc for gasoline-powered vehicles and regular vehicles but excludes motorcycles, buses, and trucks. According to the report by the Japan Automobile Dealers Association, passenger cars and minicars together account for close to 84% of all new vehicles sold (slightly more than 5 million vehicles) within the domestic economy, 30 percentage points of which are minicars. This process effectively removes trucks (0.42% of the original sample), hybrid cars (3.13%), foreign automakers (8.12%), and other fuel types (1.84% of diesel) as shown in Table A.1.

As a guard against extreme values and potential typing errors, we removed outliers in terms of the bottom and top one percentile of vehicle distance traveled and the actual fuel-economy. Because daily vehicle distance traveled was highly skewed to the right tail, the main analysis is limited to observations where travel is less than 100 kilometers (km) per day to focus on a range of daily lives. As a robustness check, we expand observations with up to 250 km a day (adding about 7% more observations). Lastly, because our model includes the driver-vehicle fixed effects, we removed single observations at this level. Ultimately, the sample for the analysis came down to 4,088,789 observations.

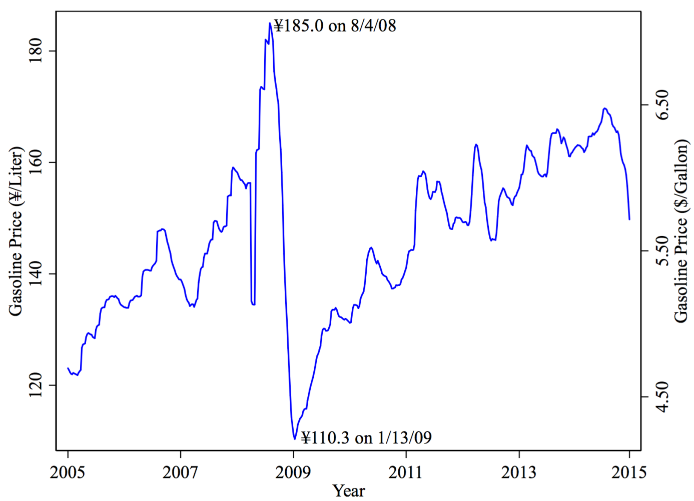
The national daily average gasoline prices are also collected by and obtained from the IID, Inc. Group. Their data start from 2010, and thus for years before 2009, we use the weekly gasoline retail price at the prefecture level reported by the Institute of Energy Economics, Japan. We computed the daily fuel prices for non-reported days by taking the arithmetic averages of the two most recently reported values. All fuel prices are converted into the January 2010 yen using the consumer price index.

Figure A.1: Sample Screenshots of the Application



Notes: These pictures were obtained from different sources only to illustrate how the application can be operated and do not necessarily reflect actual reports. The author translated the language originally in Japanese to English.

Figure A.2: Gasoline Price Trend



Notes: This figure plots the weekly average price of the regular and high octane gasoline between 2005 and 2014. The units are Japanese yen per liter in January 2010 value. Average exchange rate during this period is US\$ = ¥99.2.

Table A.1: Share of the original sample

Category	Percentage
Truck	0.42
Hybrid	3.13
Foreign maker	8.12
Fuel type	
Regular	66.84
High octane	31.31
Electricity	0.00
LP Gas	0.00
Diesel	1.84

Notes: The original sample includes 5,884,179 observations at the driver-vehicle level.

Table A.2: Summary Statistics

	Mean	Std.	N	US standard
Panel A: Individual report level				
Gasoline consumption per day (L/day)	3.535	2.034	4,088,789	0.93 gallon/day
Vehicle distance traveled per day (km/day)	36.70	20.66	4,088,789	22.81 mile/day
Actual fuel economy (km/L)	10.85	3.538	4,088,789	25.51 MPG
Gasoline price paid (¥/L)	136.55	15.24	4,088,789	$5.21Gallon
# of days b/w refueling	14.12	25.54	4,088,789	
Odometer (km)	66,359.8	48,788.9	4,088,789	41,234.2 mile
Prefecture (%)				
Saitama	5.30		4,088,789	
Kanagawa	5.23		4,088,789	
Aichi	4.81		4,088,789	
Tokyo	4.35		4,088,789	
Chiba	4.04		4,088,789	
Osaka	3.15		4,088,789	
Report year (%)				
2005	8.69		4,088,789	
2006	10.13		4,088,789	
2007	10.27		4,088,789	
2008	11.12		4,088,789	
2009	11.00		4,088,789	
2010	11.87		4,088,789	
2011	10.51		4,088,789	
2012	9.59		4,088,789	
2013	8.27		4,088,789	
2014	8.54		4,088,789	
Panel B: Driver-vehicle level				
# of reports	48.59	49.43	90,411	
Initial year	2008.7	2.906	90,411	
Panel C: Driver level				
Total number of drivers			71,263	
Male	0.889	0.314	33,804	
Age	35.514	8.277	33,428	

Summary Statistics cont.

	Mean	Std.	N	US standard
Panel D: Vehicle level				
Manufacturing year	1,999.7	7.130	3,932	
Vehicle price (¥10,000)	191.0	101.5	3,663	$19,249
Dummy for regular gasoline (vs. highoctane)	0.760	0.427	3,932	
Dummy for passenger vehicle (vs. minicars)	0.695	0.461	3,932	
Seating capacity	4.838	1.130	3,830	
Dummy for automatic transmission	0.710	0.454	3,932	
Vehicle weight (kg)	1192.9	336.9	3,783	2,630 lb
Displacement (cc)	1631.4	851.2	3,931	
Official fuel economy (km/L)	14.71	4.966	3,707	34.6 MPG
Automaker (%)				
Toyota	21.44		3,932	
Nissan	16.91		3,932	
Suzuki	11.72		3,932	
Honda	11.06		3,932	
Mitsubishi	10.40		3,932	
Subaru	9.16		3,932	
Daihatsu	9.21		3,932	
Mazda	9.00		3,932	
Isuzu	0.56		3,932	
Lexus	0.53		3,932	

Notes: Prefectures are shown only for the six largest shares, and prefecture is unknown for about 30.9% of the sample.

B. Additional Information on Price Elasticities of Demand for Gasoline

Table B.1: The Price Elasticity of Vehicle Distance Traveled

Dep. Var.	ln(VKT)				
	(1)	(2)	(3)	(4)	(5)
ln(Price)	0.179***	-0.0408***	-0.0551***	-0.302***	-0.199***
	(0.00643)	(0.00839)	(0.0136)	(0.0367)	(0.0242)
Model	OLS	IV	IV	IV	Reduced
Driver-vehicle FE	Y	Y	Y	Y	Y
Time FE	Year + month	Year + month	Year $\times$ quarter	Year $\times$ month	Year $\times$ month

Notes: The outcome variables are the log of vehicle-kilometer traveled (VKT) per day. All models except Column (1) and (5) are estimated by the instrumental variable approach, whose first stage results are presented below. All specifications include the driver-vehicle fixed effects and variant time fixed effects specified in each column. The number of observations is 4,088,789. Standard errors clustered at the driver-vehicle level are reported in the parentheses.
$^{***}p < 0.01$

Table B.2: The Price Elasticity of Actual Fuel Economy

Dep. Var.	ln(KPL)				
	(1)	(2)	(3)	(4)	(5)
ln(Price)	0.0399***	0.0336***	0.158***	0.0695***	0.0459***
	(0.00164)	(0.00209)	(0.00295)	(0.00735)	(0.00485)
Model	OLS	IV	IV	IV	Reduced
Driver-vehicle FE	Y	Y	Y	Y	Y
Time FE	Year	Year	Year	Year	Year
	+ month	+ month	× quarter	× month	× month

Notes: The outcome variables are the log of real-world fuel economy (in km/liter) (KPL) obtained by dividing gasoline consumption by vehicle distance traveled. All models except Column (1) and (5) are estimated by the instrumental variable approach, whose first stage results are presented below. All specifications include the driver-vehicle fixed effects and variant time fixed effects specified in each column. The number of observations is 4,088,789. Standard errors clustered at the driver-vehicle level are reported in the parentheses.
$^{***}p < 0.01$

Table B.3: The First Stage Results of the IV Estimates

Dep. Var.	ln(Price paid)		
	(1)	(2)	(3)
ln(Price)	0.965***	0.888***	0.660***
	(0.00109)	(0.00149)	(0.00237)
Driver-vehicle FE	Y	Y	Y
Time FE	Year	Year	Year
	+ month	× quarter	× month
F-stat	779,684	353,091	77,504

Notes: This table presents the first stage results from the IV estimates with variant time fixed effects as specified in each column. The F-statistics of the excluded instrument are also reported. The number of observations is 4,088,789.
$^{***}p < 0.01$

Table B.4: Robustness: Including Long Distance traveled

Dep. Var.	ln(Gasoline)					ln(VDT)	ln(KPL)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ln(Price)	0.264***	-0.0482***	-0.123***	-0.225***	-0.148***	-0.142***	0.0832***
	(0.00676)	(0.00846)	(0.0135)	(0.0358)	(0.0235)	(0.0380)	(0.00738)
Model	OLS	IV	IV	IV	Reduced	IV	IV
Driver-vehicle FE	Y	Y	Y	Y	Y	Y	Y
Time FE	Year	Year	Year	Year	Year	Year	Year
	+ month	+ month	× quarter	× month	× month	× month	× month

Notes: This table presents the analogous results to Table 2 in the main text except that the sample includes observations whose vehicle distance traveled is up to 250 km per day. The number of observations is 4,304,452.
***$p < 0.01$

Table B.5: Robustness: Alternative Specifications

Dep. Var.	Gasoline					VKT	KPL
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Level-level							
Price	0.00158***	-0.00289***	-0.00569***	-0.0160***	-0.00698***	-0.106***	0.00769***
	(0.000131)	(0.000177)	(0.000266)	(0.00144)	(0.000630)	(0.0149)	(0.00126)
Panel B: Semi-log							
Price	0.000770***	-0.000560***	-0.00132***	-0.00399***	-0.00174***	-0.00334***	0.000650***
	(0.0000426)	(0.0000515)	(0.0000791)	(0.000430)	(0.000188)	(0.000477)	(0.000129)
Model	OLS	IV	IV	IV	Reduced	IV	IV
Driver-vehicle FE	Y	Y	Y	Y	Y	Y	Y
Time FE	Year	Year	Year	Year	Year	Year	Year
	+ month	+ month	× quarter	× month	× month	× month	× month

Notes: This table presents the results of the robustness check in Table 2 to alternative specifications: the level-level specification in Panel A and the semi-log specification in Panel B. The dependent variables are in levels in Panel A and in logs in Panel B. The number of observations is 4,088,789.
***$p < 0.01$

Table B.6: Robustness: Using Average Daily Prices between Refuels

Dep. Var.	ln(Gasoline)			ln(VKT)	ln(KPL)
	(1)	(2)	(3)	(4)	(5)
ln(Price)	-0.117***	-0.288***	-0.684***	-0.642***	0.0420***
	(0.00704)	(0.0108)	(0.0317)	(0.0337)	(0.00717)
Model	Reduced	Reduced	Reduced	Reduced	Reduced
Driver-vehicle FE	Y	Y	Y	Y	Y
Time FE	Year	Year	Year	Year	Year
	+ month	× quarter	× month	× month	× month

Notes: The outcome variables are the logs of gasoline consumption (in liter) per day (i.e. 24 hours) in Columns (1)–(3), vehicle-kilometer traveled (VKT) per day in Column (4), and the real-world fuel economy (in km/liter) (KPL) obtained by dividing gasoline consumption by vehicle-kilometer traveled in Column (5). The main independent variable reflects the average fuel price of all days since the last refuel until this time. All specifications include the driver-vehicle fixed effects and variant time fixed effects as specified in each column. The number of observations is 4,088,789. Standard errors clustered at the driver-vehicle level are reported in the parentheses.
***$p < 0.01$

Table B.7: The Price Elasticity of Vehicle Distance Traveled Using Configuration FE

Dep. Var.	ln(VKT)				
	(1)	(2)	(3)	(4)	(5)
ln(Price)	0.146***	0.00252	-0.0187	-0.246***	-0.133***
	(0.0135)	(0.0137)	(0.0237)	(0.0644)	(0.0355)
Model	OLS	IV	IV	IV	Reduced
Configuration FE	Y	Y	Y	Y	Y
Time FE	Year	Year	Year	Year	Year
	+ month	+ month	× quarter	× month	× month

Notes: This table presents the analogous results to Table B.1 with including the vehicle configuration fixed effects in place of driver-vehicle fixed effects.
***$p < 0.01$

C. Additional Information on Learning Effect

Table C.1: Correlation Coefficients

	$Price_t$	$Price_{t-1}$	$Price_{t-2}$	$Price_{t-3}$	$Price_{t-4}$	$Price_{t-5}$
$Price_t$	1.000					
$Price_{t-1}$	0.959	1.000				
$Price_{t-2}$	0.899	0.960	1.000			
$Price_{t-3}$	0.832	0.901	0.961	1.000		
$Price_{t-4}$	0.765	0.836	0.903	0.961	1.000	
$Price_{t-5}$	0.699	0.769	0.837	0.902	0.959	1.000

Notes: This table presents the correlation coefficients of the six most recent prices, of which the most recent one at time t is the price paid for the current trip.

Table C.2: Learning Effect of Price on Driving Behavior

Dep. var.	ln(KPL) (1)	ln(VKT) (2)	ln(GPD) (3)
Panel A: Up to 50th obs.			
β	0.0575***	-0.204***	-0.262***
	(0.00310)	(0.0148)	(0.0142)
λ	0.747***	0.814***	0.810***
	(0.0187)	(0.0156)	(0.0115)
Test: $\lambda = 1$	p=0.000	p=0.000	p=0.000
Panel B: Up to 100th obs.			
β	0.0621***	-0.311***	-0.373***
	(0.00293)	(0.0136)	(0.0129)
λ	0.778***	0.833***	0.830***
	(0.0135)	(0.00846)	(0.00659)
Test: $\lambda = 1$	p=0.000	p=0.000	p=0.000

Notes: The table reports the estimated β and λ based on Equation (6) for the dependent variable specified at the column head using up to 50th refuel from the initial one in Panel A and up to 100th one in Panel B. The test statistics for the null hypothesis: $\lambda = 1$ are also reported. The numbers of observations are 2,705,006 (66% of total observations) and 3,565,208 (87%), respectively.
$^{***}p < 0.01$

Table C.3: Learning Effect of Price on Driving Behavior

	(1) 50th	(2) 100th	(3) 200th
β	0.0575***	0.0621***	0.0679***
	(0.00310)	(0.00293)	(0.00308)
λ	0.747***	0.778***	0.793***
	(0.0187)	(0.0135)	(0.0108)
Test: $\lambda = 1$	p=0.000	p=0.000	p=0.000
N	2,705,006	3,565,208	4,024,897
Share of N	0.66	0.87	0.98

Notes: The table reports the estimated β and λ for the log of actual fuel economy based on Equation (6) in the main text for three subsamples: up to the first 50th observations for each driver in column (1), 100th in column (2), and 200th in column (3). The test statistics for the null hypothesis: λ = 1 are also reported. Each share of the observations to the total observations is reported at the bottom.
$^{***}p < 0.01$

Table C.4: Robustness: Distributed Lag Model

Variable	(1)	(2)	(3)	(4)	(5)	(6)
$ln(Price_t)$	0.0459***	0.0271***	0.0217***	0.0215***	0.0208***	0.0201***
	(0.00485)	(0.00508)	(0.00518)	(0.00524)	(0.00528)	(0.00532)
$ln(Price_{t-1})$		0.0198***	0.0132***	0.00784*	0.00759*	0.00651
		(0.00356)	(0.00417)	(0.00427)	(0.00431)	(0.00435)
$ln(Price_{t-2})$			0.0175***	0.0220***	0.0174***	0.0178***
			(0.00331)	(0.00409)	(0.00419)	(0.00424)
$ln(Price_{t-3})$				0.00141	0.0129***	0.00881**
				(0.00318)	(0.00403)	(0.00413)
$ln(Price_{t-4})$					-0.00791**	-0.000571
					(0.00308)	(0.00402)
$ln(Price_{t-5})$						-0.00415
						(0.00304)
N	4,088,789	3,998,378	3,907,967	3,818,660	3,730,273	3,642,848

Notes: This table reports the coefficients of the six most recent prices paid based on the distributed lag model as specified by Equation (3) in the main text. The regressions are based on the reduced-form, where the fuel price on the day of purchase is used as the instrument. The dependent variable is the log of actual fuel economy. The regressions include the year-by-month fixed effects and the driver-vehicle fixed effects. The standard errors clustered at the driver-vehicle level are reported in the parentheses.
$^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table C.5: Exploring the Potential Mechanisms

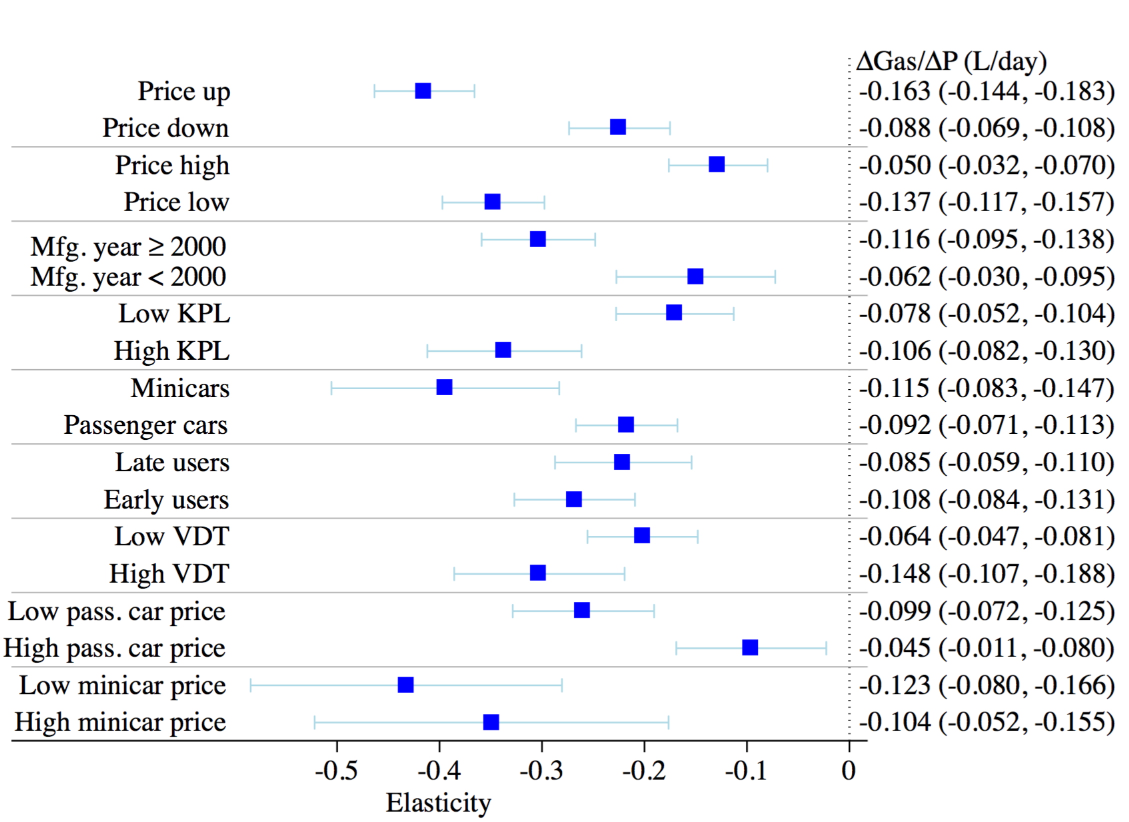
Dep. var	ln(GPD) (1)	ln(VKT) (2)	ln(KPL) (3)
$ln(Price_t)$	-0.165***	-0.128***	0.0373***
	(0.0285)	(0.0290)	(0.00389)
$ln(Price_{t+1})$	-0.184***	-0.164***	0.0197***
	(0.0323)	(0.0344)	(0.00744)

Notes: The dependent variables are the logs of gasoline consumption per day (L/day) in Column (1), vehicle-kilometers traveled per day (km/day) in (2), and the actual fuel economy (km/L) in (3). The independent variables are the logs of prices paid for the current trip ($Price_t$) and for the next trip ($Price_{t+1}$). All specifications include the driver-vehicle fixed effects, and the standard errors clustered at the customer-vehicle level are reported in the parentheses.
$^{***}p < 0.01$

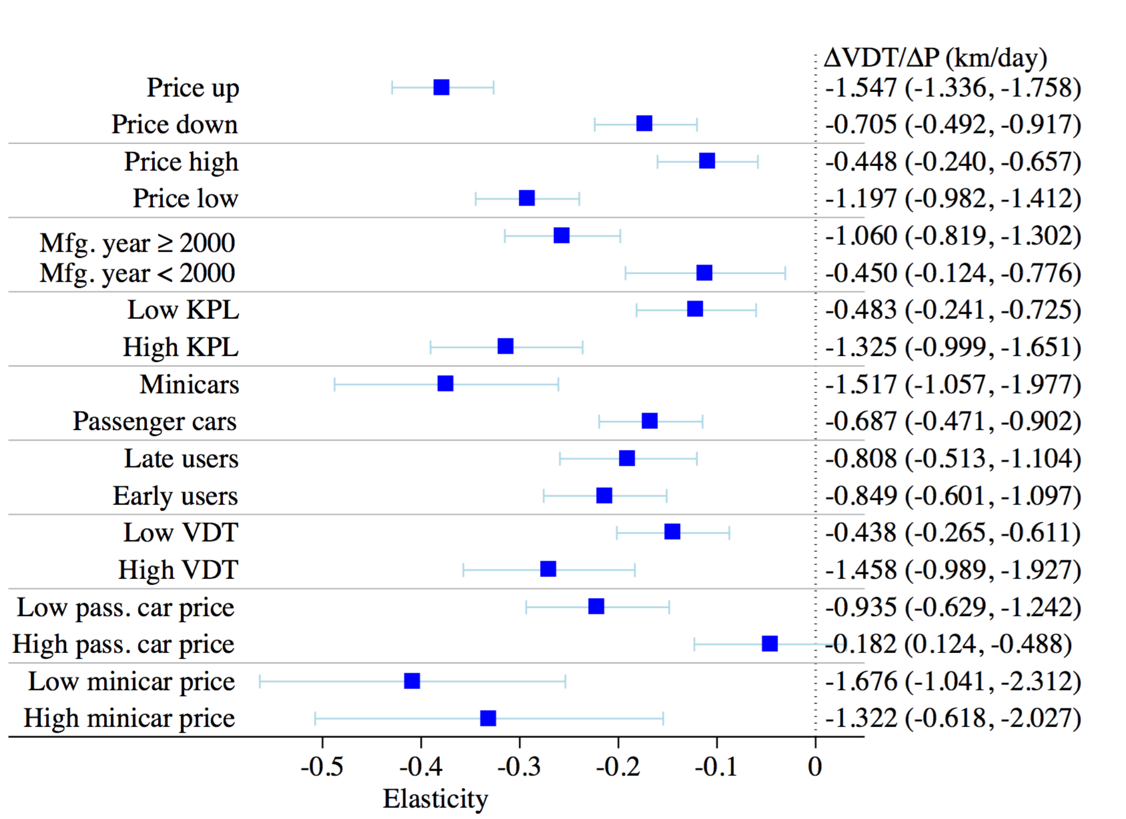
D. Additional Information on Heterogenous Price Elasticities

Figure D.1: Asymmetric Price Elasticities of Demand for Gasoline

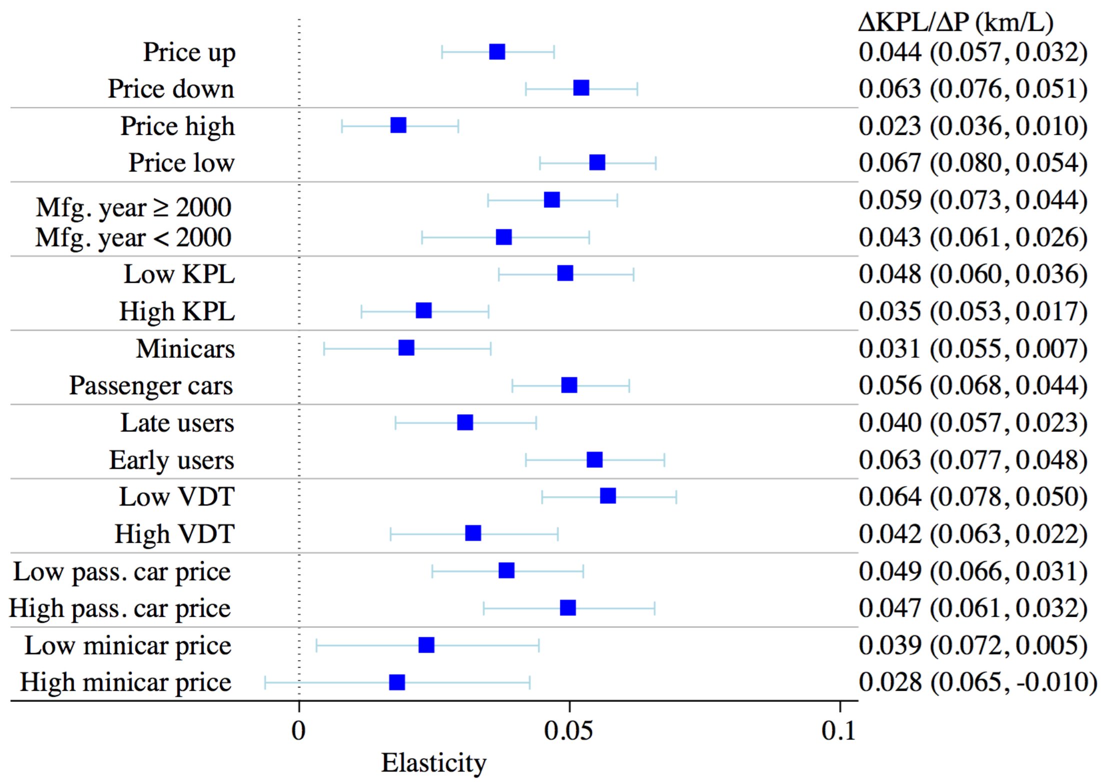
Panel A: Gasoline Consumption



Panel B: Vehicle Kilometers Traveled



Panel C: Actual Fuel Economy



Notes: Each panel presents the estimated price elasticities for the respective dependent variable. The square dots represent the coefficients, and the lines indicate the associated 95% confidence interval. The asymmetric effects for fuel prices going up/down and fuel prices high/low are estimated from the single regressions, whereas other specifications are separately estimated for the relevant subgroup. The effect size indicated on the right side of the figure represents the changes and the associated 95% confidence interval of gasoline consumption per day in liter in response to a one standard deviation increase in gasoline price (¥15.24).

Table D.1: Heterogeneities in Price Elasticities

Dep. var.	ln(Gasoline)		ln(VKT)		ln(KPL)	
Subsample	Reduced	IV	Reduced	IV	Reduced	IV
Price going up	-0.415***	-0.593***	-0.378***	-0.538***	0.0367***	0.0547***
	(0.0249)	(0.0363)	(0.0262)	(0.0382)	(0.00528)	(0.00770)
Price going down	-0.224***	-0.351***	-0.172***	-0.278***	0.0522***	0.0731***
	(0.0251)	(0.0361)	(0.0264)	(0.0380)	(0.00525)	(0.00756)
Price high	-0.128***	-0.00162	-0.109***	-0.00444	0.0186***	-0.00281
	(0.0246)	(0.0323)	(0.0259)	(0.0342)	(0.00547)	(0.00779)
Price low	-0.347***	-0.851***	-0.292***	-0.714***	0.0552***	0.136***
	(0.0254)	(0.0560)	(0.0268)	(0.0590)	(0.00546)	(0.0124)
Mfg. year $\geq$ 2000	-0.304***	-0.454***	-0.257***	-0.384***	0.0469***	0.0702***
	(0.0283)	(0.0422)	(0.0299)	(0.0447)	(0.00610)	(0.00914)
Mfg. year $<$ 2000	-0.150***	-0.227***	-0.112***	-0.170***	0.0381***	0.0579***
	(0.0395)	(0.0599)	(0.0413)	(0.0627)	(0.00790)	(0.0120)
Low KPL	-0.170***	-0.272***	-0.121***	-0.193***	0.0493***	0.0789***
	(0.0293)	(0.0468)	(0.0309)	(0.0494)	(0.00634)	(0.0102)
High KPL	-0.337***	-0.401***	-0.313***	-0.373***	0.0232***	0.0277***
	(0.0253)	(0.0458)	(0.0267)	(0.0469)	(0.00551)	(0.00714)
Minicars	-0.394***	-0.456***	-0.374***	-0.433***	0.0200**	0.0231**
	(0.0567)	(0.0656)	(0.0579)	(0.0669)	(0.00785)	(0.00911)
Passenger vehicles	-0.217***	-0.340***	-0.167***	-0.261***	0.0502***	0.0785***
	(0.0253)	(0.0395)	(0.0267)	(0.0417)	(0.00551)	(0.00863)
Late users	-0.221***	-0.301***	-0.190***	-0.259***	0.0308***	0.0420***
	(0.0340)	(0.0464)	(0.0354)	(0.0483)	(0.00665)	(0.00909)
Early users	-0.268***	-0.429***	-0.213***	-0.342***	0.0547***	0.0875***
	(0.0300)	(0.0480)	(0.0318)	(0.0508)	(0.00651)	(0.0104)
Low VKT	-0.202***	-0.308***	-0.145***	-0.220***	0.0573***	0.0873***
	(0.0275)	(0.0418)	(0.0291)	(0.0443)	(0.00633)	(0.00966)
High VKT	-0.303***	-0.468***	-0.270***	-0.418***	0.0323***	0.0500***
	(0.0424)	(0.0654)	(0.0444)	(0.0684)	(0.00788)	(0.0122)
Low passenger price	-0.260***	-0.366***	-0.221***	-0.311***	0.0386***	0.0543***
	(0.0352)	(0.0496)	(0.0370)	(0.0521)	(0.00712)	(0.0100)
High passenger price	-0.0958**	-0.154**	-0.0459	-0.0737	0.0499***	0.0801***
	(0.0373)	(0.0599)	(0.0394)	(0.0632)	(0.00807)	(0.0130)
Low minicar price	-0.432***	-0.494***	-0.409***	-0.467***	0.0238**	0.0271**
	(0.0775)	(0.0885)	(0.0790)	(0.0902)	(0.0105)	(0.0120)
High minicar price	-0.349***	-0.411***	-0.331***	-0.389***	0.0182	0.0214
	(0.0881)	(0.103)	(0.0900)	(0.106)	(0.0125)	(0.0147)

Notes: This table presents the estimated coefficients and standard errors of price elasticities for gasoline consumption (L/day), vehicle-kilometers traveled (km/day), and actual fuel economy (km/L). For each dependent variable, both the reduced form and IV estimates are presented. In particular, they are elasticities when a price goes up or down, a price is above or below the mean price paid, among vehicles whose manufacturing years are before or after 2000, vehicles with greater or lower than the mean official fuel economy level, minicars vs. passenger vehicles, users who started using the application before or after the average, and vehicle prices above or below the mean prices separately for passenger cars and minicars. The asymmetric effects for fuel prices going up/down and fuel prices high/low are estimated from the single regressions, whereas other specifications are estimated from separate regressions for the respective subsample.
$^{**}p < 0.05$, $^{***}p < 0.01$

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