

On Factors of Consumer Heterogeneity in (Mis)-valuation of Future Energy Costs: Evidence for the German Automobile Market

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Abstract

The present paper uses a novel identification strategy to recover individual valuation of future fuel costs at the time of a car purchase. Consumer heterogeneity in expected driving intensity and car ownership length, observed in survey data on household purchases of new passenger cars in Germany over seven years, allows us to construct individual values of the present-discounted fuel costs. The variation in these values is then compared to prices paid by buyers of identical car specifications. Individual tastes for car attributes are recovered nonparametrically within a “preference inversion” procedure. The study contributes to the literature by explicitly exploring how various factors explain the recovered consumer undervaluation of fuel savings (on average, consumers’ willingness-to-pay for a €1 reduction in fuel costs is below €0.50). The financial ability, education, and choice-inertia of consumers are found to be the most important determinants of their investment efficiency while disentangling their effects from those of insufficient information, time preferences, and uncertainty regarding car usage. These effects are studied for both diesel and gasoline vehicles of various car classes, controlling for unobservable product attributes, correlations in consumer tastes over car features, and a potential to deduct a part of annual fuel costs from taxes.

Keywords: fuel efficiency; hedonic price; nonparametrics; revealed preferences; vehicle purchase decision; willingness-to-pay

1 Introduction

The literature on consumer valuation of energy-using durable goods has long discussed the trade-off between the higher upfront capital costs for a more efficient product and potentially lower future operating costs linked to its usage over the ownership period (e.g., [Hausman, 1979](#); [Dubin and Mcfadden, 1984](#)). Economic theory suggests that a “rational” consumer should be willing to invest upfront in a better energy efficiency as much as it allows to save in the expected operating costs given expectations of energy prices and intensity of product usage. If, however, a consumer is willing to pay less (more) than these savings, then an undervaluation (overvaluation) of energy efficiency is present.

Empirical studies provide mixed evidence regarding the consumer valuation of future energy costs and energy efficiency of a product. One stream of research concluded that future energy costs do play an important role in the choice-making process and that consumers correctly account for a trade-off between capital costs and operating costs (e.g., [Busse et al., 2013](#); [Sallee et al., 2016](#)). Other studies have found that consumers pay little attention to energy costs when purchasing energy-using durable good and do not make calculations for future energy savings from a more efficient product (e.g., [Turrentine and Kurani, 2007](#); [Larrick and Soll, 2008](#)).

The present study contributes to this discussion by explicitly exploring the roles of various consumer and purchase transaction characteristics in the extent of consumers’ (mis)valuation of ongoing energy costs. The investigation is based on revealed preferences using household-level survey data on new automobile purchases in Germany over a period of seven years. Being a highly involved decision-making process with extensive financial consequences, an automobile purchase should encourage consumers to compare the upfront costs and potential savings in operational costs over a car’s period of usage. However, even in this case, results of previous studies have been inconclusive regarding the extent to which consumers’ car purchase decisions are in line with optimal (cost-minimizing) behavior. [Greene \(2010\)](#) and [Helfand and Wolverton \(2011\)](#) provide a good overview of the relevant studies and their findings on how consumers respond to and value fuel efficiency. We summarize the selected studies on consumer valuation of car fuel efficiency based on revealed preferences in Table

[A1](#), along with positioning of our research.

The richness and structure of the data used in this study provide several conceptual and methodological advantages for an empirical investigation. First and foremost, the values stated by the respondents with respect to their expected annual driving and approximate car ownership length from previous experience allows us to construct individual values for the expected fuel costs. The variation in these values, in turn, is compared to the prices paid by buyers of identical cars described by observed attributes, including fuel economy, and various extra features, such as sunroof and leather seats, among others. This comparison constitutes the identification strategy of our study that differs from previous approaches. Under the “rational” cost-minimizing behavior principle, the prices paid for cars should move one-to-one with changes in future fuel costs for a given car quality. As we rely on the panel data to identify the fuel efficiency value while controlling for time-invariant unobservable attributes, our study is closely related to [Allcott and Wozny \(2014\)](#), [Sallee et al. \(2016\)](#), and [Busse et al. \(2013\)](#) that found either moderate or full valuation of fuel efficiency by consumers. However, these studies do not account for consumer heterogeneity in the expected driving intensity and car ownership length. We, in contrast, incorporate substantial heterogeneity across consumers in their car utilization along with heterogeneity in their tastes for car attributes while computing the future fuel savings from a more fuel-efficient vehicle. The importance of accounting for the consumer heterogeneity in annual vehicle usage is emphasized, for example, by [Allcott et al. \(2015\)](#), who addressed the relative effectiveness and targeting characteristics of the energy efficiency policies. [Bento et al. \(2012\)](#) used a data simulation to show that ignoring consumer heterogeneity in their tastes and product usage in empirical analyses can significantly affect the estimated willingness-to-pay values and be a source of the undervaluation of energy costs stated in the previous literature.

Second, the presence of various consumer characteristics linked to choices in the dataset enables the current study to use a flexible and computationally tractable method proposed by [Benkard and Bajari \(2005\)](#). This method combines the merits and addresses the weaknesses of the discrete choice (DCM) and hedonic demand models - two commonly used estimation approaches in applications to revealed preference data. The methodological advantages of the estimation procedure developed by [Benkard and Bajari \(2005\)](#) as compared to the discrete

choice models arise from recovering the taste distribution for product attributes directly from the data without a need to impose any distributional assumptions (usually from a parametric family). Thus, it overcomes the interpretation problem for a ratio between attribute and price coefficients and ambiguities in whether to specify utility function in preferences or willingness-to-pay space that are present in the discrete choice models (e.g. [Sonnier et al., 2007](#)).

Moreover, the procedure suffices in using only observations on the chosen products without a need to construct choice sets faced by a consumer, which might become extremely difficult for a highly differentiated product category (as is the case for the automobile market). The undesirable properties of the discrete choice models due to “symmetric unobserved product differentiation” (see e.g. [Akerberg and Rysman, 2005](#)) are also removed as the logit error term is omitted from the utility function.

Compared to the classical Rosen hedonic demand two-step model ([Rosen, 1974](#)), the exploited estimation method extends it by allowing consumers to be heterogeneous in their willingness-to-pay values for product attributes. This can be referred to as a “preference inversion”: it recovers heterogeneous tastes from the (static) utility maximization problem based on the estimation of individual implicit prices from the hedonic price function that serves as a budget constraint to the consumers. The “preference inversion” procedure solves an endogeneity problem emerging at the second stage of the classical hedonic demand model, when implicit values for product attributes (resulting from the price regression at the first stage) are regressed on the demand and supply determinants.

Econometrically, at the first stage, individual tastes for car attributes, including present-discounted value of fuel costs, are derived by estimating the hedonic price function nonparametrically. At the second stage, heterogeneity in the recovered individual willingness-to-pay values for a reduction in fuel costs is then explored via a regression analysis with the consumer- and transaction-related characteristics being explanatory variables. To recover a joint distribution of consumer tastes and heterogeneity determinants, the present study uses the quantile regression method that allows us to investigate a disparity in the covariates’ effects among different levels of the estimated fuel costs’ valuations.

The analysis in this paper focuses on passenger cars with gasoline and diesel engines

from six car classes defined by the German Federal Motor Transport Authority (i.e., minis, superminis, compact class, middle class, upper middle class, and upper class). The dataset allows us to sample only those consumers who had bought a car privately (in contrast to corporate car purchases). Thus, it focuses on decision-makers who should be concerned with the operating costs of a car as they are the ones who must bear these costs in the future.

During the construction of individual values for the expected fuel expenses, the current study accounts for the possibility that “intensive” drivers may subtract a part of the fuel costs from their annual income tax in case a car is used for business purposes. Therefore, for the estimation, only net fuel expenses (after the approximate tax-deducted portion was removed) are considered. This reduces variability in the individual fuel costs and thus lead to a better description of the co-movements between individually paid prices and fuel expenses.

Our estimation results indicate that there is a high extent of undervaluation of potential fuel savings – for a €1 reduction in the future fuel costs, the sampled consumers are estimated to be willing to pay not more than €0.50, on average. The estimated willingness-to-pay varies among engine types and car classes, with higher valuations on average for higher car classes and diesel vehicles.

Our result of the high level of consumer myopia are in contrast to the recent study by [Grigolon et al. \(2017\)](#) on the European data. In their analysis, the authors could not reject the hypotheses of consumers’ full valuation of fuel costs. The discrepancy in the results could lie in both the methodology applied and characteristics of the dataset used. The estimation in [Grigolon et al. \(2017\)](#) is performed over several European countries and with recent years of observations that might lead to a higher valuation parameter. Furthermore, the authors include consumer heterogeneity in driving into their estimation by drawing from the distribution of the aggregate mileage in the UK. We, in contrast, use the stated by the consumers themselves their expected annual kilometers for the chosen car. Thus, for the analyzed sample in our study, we can directly relate the heterogeneity in mileage to willingness-to-pay for fuel savings. Methodologically, our study also differs from [Grigolon et al. \(2017\)](#) in that we do not impose any distributional assumptions on consumer tastes over car attributes and allow for their correlation.

By exploring effects of consumer- and purchase-related factors on the variation in the

valuation of fuel costs, we find that better financial status of consumers, higher level of education, and brand loyalty facilitate a better understanding of the benefits from investments in fuel-efficient vehicles. In this regard, we also contribute to the literature on various factors that might deter private households from purchasing an economically optimal energy-efficient product, such as insufficient information, limited attention, choice-inertia, capital constraints, time preferences, and uncertainty (see e.g., [Gerarden et al., 2015](#) for a review). [Grigolon et al. \(2017\)](#), for example, also highlight the importance of understanding the reasons for consumer heterogeneity in valuation of usage costs. This understanding may help firms to better address various consumer groups in their car purchase decisions and to assist policymakers in assessing instruments that address externalities related to car use.

In the remainder of this paper we proceed as follows. In section [2](#) we present the conceptual framework and the methodology applied. Section [3](#) describes the data and gives first insights for the following estimation, the results of which are presented in section [4](#). In section [5](#) we compare our findings on the determinants of consumers' valuation of future fuel costs to those in previous literature and discuss the resulting policy implications. Section [6](#) concludes, highlights the conceptual contributions and limitations of the study, and proposes future research directions.

2 The Model

We use the hedonic discrete choice model ([Bajari and Benkard, 2005](#)) to recover individual valuation of the future fuel costs and to investigate the effects of consumer- and transaction-related characteristics on the variation in this valuation. In the hedonic discrete choice model, a consumer (n) is assumed to purchase a product (j) that provides the highest utility for a bundle of its attributes subject to a consumer's budget. The budget is presented by the household income Y_n that is distributed among the purchase of a product and the consumption of all other goods ("outside option", C). Following the literature on discrete-choice models and addressing an identification concern in case of a single choice observation per consumer (see [Bajari and Kahn, 2005](#); [Benkard and Bajari, 2005](#)), the utility function is

assumed to have a known parametric functional form as in Equation 1.

$$U_{nj} = \beta_{n,PVFC}PVFC_{nj} + \sum_k \beta_{n,k}X_{kj} + \beta_{n,\xi}\xi_j + (Y_n - P_{nj}) \quad (1)$$

The utility depends on the present value of fuel costs (PVFC), observed (X_{kj}) and unobserved by the analyst (ξ_j) car characteristics, and consumer income (Y_n) net from the paid price (P_{nj}). The coefficients $\beta_{n,PVFC}$, $\beta_{n,k}$, $\beta_{n,\xi}$ represent individual consumer tastes over the respective car characteristics, and $(Y_n - P_{nj})$ represents consumer's spending on the "outside option". The price of the outside option is normalized to unity for identification purposes. The vehicle price is modeled by the hedonic price function, i.e. $P_{nj} = \mathbf{p}(X_{kj}, \xi_j)$. It defines how the price of a product varies with its underlying attributes and reflects a combination of implicit values for each attribute of a durable good (Rosen, 1974, p. 34). The relationship between prices and product attributes is assumed to be exogenous to the consumer choice. From the first-order condition (FOC), the marginal rate of substitution between a product attribute k and the composite commodity C equals to the partial derivative of the hedonic price function with regard to this attribute for the chosen product j^* (see Equation 2). It reflects the willingness-to-pay value for marginal improvements in the attribute.

$$\frac{U_{nj}}{\partial X_{kj}} / \frac{\partial U_{nj}}{\partial C} = \frac{\partial \mathbf{p}(X_{kj^*}, \xi_{j^*})}{\partial X_{kj}} \quad (2)$$

Our main focus lies on the consumer valuation of the present-discounted value of expected fuel costs. Formally, the value of PVFC depends on fuel prices (FP, €/liter), fuel consumption of a vehicle (FC, liter/100 km), annual kilometers driven (KM), length of a car possession (T, years), and discount rate for future savings versus present costs (r). We follow previous literature and assume consumers' expectations for future fuel prices to follow a random walk for real fuel prices, measured at the time of a car purchase (see e.g., Anderson et al., 2013). The discount rate is taken as exogenous and fixed at the level that corresponds to the average market interest rate (similar to Allcott and Wozny, 2014). We differ from previous studies in that we use information in our data on the stated expected driving intensity and car ownership length to construct individual PVFC values (Equation 3). The values that consumers place on the expected fuel expenses are then identified by

comparing a variation in the individual PVFC values with that in the prices paid by buyers of identical car specifications. A highly-detailed definition of a car specification allows us to mitigate the possible effect of omitted car attributes on the estimation (more details in Section 3).

$$PVFC_{nj} = \sum_{t=0}^{T_n} \frac{1}{(1+r)^t} \times (FP \times KM_n \times FC_j) \quad (3)$$

Since the utility specification in this setting is given in “willingness-to-pay” space (see e.g., [Train and Weeks, 2005](#)), the individual willingness-to-pay for marginal savings in PVFC is directly reflected in $\beta_{n,PVFC}$ after controlling for tastes over other product attributes, i.e. $\frac{\partial U_{nj}}{\partial PVFC_{nj}} / \frac{\partial U_{nj}}{\partial C} = \beta_{n,PVFC}$. For a rational (cost-minimizing) consumer, $\beta_{n,PVFC}$ should equal -1. If $|\beta_{n,PVFC}|$ is less (more) than 1, then consumers undervalue (overvalue) potential fuel savings. The parameter $\beta_{n,PVFC}$ is referred to as “attention weight”, “future valuation”, or ‘valuation weight’ in the literature (e.g., [Allcott and Greenstone, 2012](#); [Allcott and Wozny, 2014](#)). Note also that the recovered valuation parameter is isomorphic to both the implicit discount rate at which consumers discount the future and the consumers’ required payback period. By knowing one of these values, one can retrieve any other of these measures.

In our analysis, we first recover individual implicit values for PVFC along with other car attributes by estimating the hedonic price function nonparametrically. The nonparametric estimation uses the fraction of data around the chosen bundles of product attributes, individual PVFC values, and the purchase prices. We assume that (locally) the hedonic price function takes the semi-logarithmic functional form of dependency (Equation 4).

$$\ln P_{nj} = \alpha_{n,PVFC} PVFC_{nj} + \sum_k \alpha_{n,k} X_{kj} + \xi_{nj} \quad (4)$$

The semi-logarithmic specification fits the data at best and is in line with the majority of previous studies on hedonic price regression (e.g. [Triplett, 1969](#); [Matas and Raymond, 2009](#)). By estimating Equation 4, we test whether the individually paid prices for vehicles move one-for-one with changes in the individual values for PVFC after controlling for other product attributes. The residuals of the hedonic price regression reflect the unobserved product attribute, ξ_j , which is assumed to be one-dimensional and mean-independent of the

observed product attributes. The resulting hedonic price gradients ($\widehat{\alpha}_{n,PVFC}$) are used to compute individual willingness-to-pay values for savings in future fuel costs. Based on the utility function and hedonic price specification, it is computed as in Equation 5.

$$\widehat{\beta}_{n,PVFC} = \frac{\partial \widehat{\mathbf{p}}(\cdot)}{\partial PVFC} = \widehat{\alpha}_{PVFC,n} \times Price_{nj} \quad (5)$$

As the next step, we explore the joint distribution of the estimated individual valuation of fuel costs and heterogeneity determinants. The modeled relationship is presented in Equation 6, where Z_n contains heterogeneity characteristics of interest and η_n is an idiosyncratic household level preference shock that is assumed to be exogenous and independent of other consumer-specific covariates, $E(\eta_n|Z_n) = 0$.

$$\widehat{\beta}_{n,PVFC} = h(Z_n) + \eta_n \quad (6)$$

3 Data and descriptive evidence

3.1 Data sources and sample

The main data source for the analysis in this paper is presented by a dataset with monthly cross-sectional information on new vehicles purchased in Germany over a period of seven years from 2000 to 2006 (henceforth, transaction data). The data are provided by a market research company for (non-commercial) scientific goals and are collected through an anonymous survey. The dataset contains information on the purchased car models by a sample of consumers along with a description of (basic) car attributes, prices paid for the chosen cars, and various consumer- and purchase-related characteristics. Furthermore, the dataset provides values for the anticipated annual car use stated by the consumers themselves and for a length of ownership for a previously owned car that is taken as a proxy for a new car.

The transaction data describe the purchased vehicles by car model name (e.g., VW Golf), engine type (e.g., diesel), transmission (e.g. manual), horse power (e.g., 125 HP), and displacement (e.g., 1997 cm³) for each month-of-year observation. Values for fuel consumption, weight, and car class of the purchased vehicles are additionally retrieved from a

web database of the largest automobile club in Germany, ADAC (<http://www.adac.de/infotestrat/autodatenbank>). The ADAC dataset provides information at a very detailed level for all unique car specifications available in Germany since the mid-1990th. Among three measures of fuel consumption in ADAC – city, highway, and weighted average of both these values – the latter measure is considered in this paper. Two datasets are merged by a set of car attributes stated in the transaction data for each observation. Month-of-year of the transactions serves as an additional condition for identifying a precise match-car based on the dates of its production start and end given in ADAC. The latter condition reads: a date of the transaction (car purchase) should lie between dates of the production start and end for the purchased car model.

Information on fuel prices at the monthly level for 2000-2006 also comes from the ADAC web-database. The interest rate to discount the future fuel costs is taken as 3%, which is an average of the ECB interest rates for the main refinancing operations over 2000-2006 provided by the German Federal Bank at <http://www.bundesbank.de/>. Table 1 gives an overview of the fuel prices and interest rates over time.

Table 1: Fuel prices and benchmark interest rate over time

Year	Gasoline (2010 €cent/l)	Diesel (2010 €cent/l)	Interest Rate, %
2000	118.33	93.33	4.04
2001	116.75	93.58	4.25
2002	118.06	94.37	3.21
2003	121.91	98.73	2.25
2004	124.52	103.02	2.00
2005	131.57	114.68	2.02
2006	136.35	118.08	2.79
Average	123.93	102.26	2.94

NOTE: The table gives an overview of average annual fuel prices and interest rate over 2000-2006. The interest rate reflects the ECB rate for the main refinancing operations provided by the German Federal Bank at <http://www.bundesbank.de/>.

For the analysis, non-passenger cars (pick-ups and large vans) and vehicles with engine and fuel types other than diesel and gasoline (electric, CNG, LPG, hydrogen, methanol) are excluded because of their minimal representation in the car purchases during the considered period. To prevent the analysis’ reliance on outlier values, extreme values for some socio-demographic variables (selected are households with age between 17 and 81 years; total

number of household members ≤ 6) and values lower than 1st and higher than 99th percentiles of the distribution for transaction prices and PVFC values within each car class and engine type are removed. The final dataset with matched transactions to ADAC data contains 121313 observations in total within a period of 2000-2006 and only for those consumers who purchased a car privately. There are 38761 (31.95%) and 82552 (68.05%) observations for diesel and gasoline vehicles, respectively. Table A4 presents detailed descriptive statistics for the car attributes by car class and engine type used in the analysis, with examples of vehicles belonging to each car class.

Additional information in the transaction data on supplementary car features that the consumers individually selected at the time of a car purchase enables the analysis to use a very detailed definition of a product. It distinguishes the purchased vehicles by car class; engine type; model name; model year; transmission; horse power; displacement; and a set of extra car features that includes sunroof, air conditioning, cruise control, leather seats, GPS navigation system, and park distance sensor. Accounting for these additional attributes is especially important for higher car classes, where the presence of these features is increasing (see Table 2).

Table 2: Mean shares of additional car features

	Minis	Superminis	Compact class	Middle class	Upper Middle class	Upper class
Sunroof (“yes”=1)	0.17	0.09	0.10	0.15	0.32	0.64
Automatic air conditioning (“yes”=1)	0.04	0.17	0.30	0.38	0.41	0.44
Manual air conditioning (“yes”=1)	0.26	0.35	0.21	0.07	0.06	0.03
Cruise control (“yes”=1)	0.02	0.08	0.25	0.44	0.75	0.80
Leather seats (“yes”=1)	0.03	0.03	0.07	0.17	0.42	0.58
GPS navigation system (“yes”=1)	0.01	0.02	0.06	0.14	0.38	0.69
Park distance sensor (“yes”=1)	0.02	0.07	0.17	0.30	0.47	0.55
Sum of extra features	0.55	0.82	1.15	1.65	2.80	3.73
N observations	4158	23958	48116	35160	9252	669

NOTE: The table presents average choice shares for and total amount of supplementary features for each car class over engine types.

3.2 Description of consumer heterogeneity

Consumers differences can be described by social-demographic and purchase-specific characteristics, individual expectations on car utilization, and heterogeneous tastes for car attributes. In this study we aim at understanding how a variation in the consumer valuation of the expected future fuel costs relates to the observed consumer- and transaction-specific characteristics.

First, we look at a variation in both the individual prices paid by different consumers and the present values of fuel costs for the same car specifications. A product specification is defined by car model, engine type, transmission, horse power, displacement, and a set of supplementary features (e.g., sunroof, leather seats, etc.). In our analysis, the present value of fuel costs varies at the individual level due to the observed consumer heterogeneity in anticipated vehicle usage and length of car possession. We use the length of previous car possession to approximate the car ownership length for the new vehicle. As a robustness check, we also used fixed values for the time horizon as in previous studies (for example, 10 and 15 years) and did not find any significant differences (see Table A8 for the robustness check estimates) Table 3 provides average values for the summary statistics (mean and standard deviation) of the purchase prices, PVFC, and its consumer-specific components within the same products. By first computing the values for mean and standard deviation of the variables for each car specification, the averages over these values are then taken. For example, values of the standard deviation for the purchase price show how consumers on average differ in the prices they paid for the same car qualities. A one standard deviation change in the transaction price varies from one to six thousand euros over both engine types, indicating a vast heterogeneity in consumers' willingness-to-pay values. A dispersion in the purchase prices becomes larger for more expensive cars. The difference between the transaction price and manufacturer's suggested retailer price (MSRP) for the same products also increases with car class. In most cases, the price paid for a product is higher than that assigned by the manufacturer. Both patterns can indicate either the presence of unobserved extra attributes that are still not accounted for or a high heterogeneity in the traits, preferences, and bargaining power with car dealers of the buyers of luxurious cars.

Table 3: Heterogeneity in purchase prices, PVFC, and its consumer-specific components within the same products (average values)

		Minis	Superminis	Compact class	Middle class	Upper Middle class	Upper class
Diesel vehicles							
Purchase price (2010€)	Mean	16,338.69	19,154.53	26,197.62	33,749.17	45,528.92	66,851.66
	SD	1,216.76	1,433.24	1,969.30	2,489.53	3,415.14	5,280.34
Purchase price - MSRP (2010€)	Mean	1,127.97	1,150.22	1,272.75	1,330.76	2,431.33	4,452.52
	SD	1,231.31	1,454.14	1,958.98	2,484.39	3,441.07	5,505.06
PVFC (2010€)	Mean	3,422.64	3,883.72	4,718.48	5,602.40	6,737.98	8,148.74
	SD	1,915.30	2,073.53	2,210.69	2,556.37	3,143.57	3,946.22
Net PVFC (2010€)	Mean	2,668.13	3,005.18	3,713.32	4,373.93	5,345.53	5,901.87
	SD	1,353.01	1,672.65	1,883.14	2,090.10	2,601.47	3,158.42
Expected annual KM	Mean	15,235.41	17,841.35	18,136.32	18,745.54	19,060.83	19,641.95
	SD	5,037.52	5,386.54	5,509.92	5,656.25	6,341.62	8,470.17
Holding length, years	Mean	5.12	4.95	5.09	5.07	5.06	4.65
	SD	2.60	2.41	2.29	2.22	2.28	2.33
Number of products		42	792	2939	4108	1909	132
Number of consumers		234	4134	14884	14328	4869	312
Gasoline vehicles							
Purchase price (2010€)	Mean	13,460.99	17,104.27	23,424.80	31,396.87	45,186.61	79,084.14
	SD	1,214.18	1,337.11	1,779.75	2,152.96	3,137.35	6,177.42
Purchase price - MSRP (2010€)	Mean	465.17	921.39	1,009.78	1,202.38	2,482.26	3,111.55
	SD	1,197.74	1,354.68	1,770.32	2,141.91	3,107.80	6,250.31
PVFC (2010€)	Mean	3,500.58	4,330.55	5,617.86	6,737.22	8,340.06	10,100.88
	SD	1,840.89	2,108.61	2,492.23	2,944.20	3,615.84	4,047.65
Net PVFC (2010€)	Mean	2,613.73	3,141.84	4,416.06	5,147.67	6,795.43	8,610.68
	SD	1,399.16	1,514.85	1,891.16	2,136.18	2,702.30	3,067.04
Expected annual KM	Mean	9,841.12	10,458.76	12,179.19	13,318.79	14,741.26	15,911.40
	SD	3,538.79	3,490.46	4,033.36	4,321.14	5,145.92	5,567.75
Holding length, years	Mean	5.73	6.02	5.78	5.47	5.35	5.06
	SD	2.80	2.54	2.36	2.29	2.20	1.95
Number of products		309	2204	4881	5459	1791	168
Number of consumers		3924	19824	33232	20832	4383	357

NOTE: The table reports average values of the summary statistics for the same product specifications. A product specification is defined by car model, engine type, transmission, horse power, displacement, and a set of supplementary features (e.g., sunroof, leather seats, etc.). Net PVFC is computed as a present-discounted value of annual fuel costs that are left to bear after subtracting tax-deductible expenses for a potential amount of kilometers driven for business purposes. Number of consumers is the total number of observations (not product-specific) within engine type and car class.

In line with expectations, buyers of diesel vehicles expect to drive annually more than those of gasoline vehicles. While there are no significant differences in the mean expected kilometers over car classes for diesel car buyers, the driving intensity for gasoline car buyers is higher for larger car classes. The length of a car ownership is higher for gasoline car owners, without significant variations across car classes. The values are comparable to 6 years from the official statistics for Germany (see www.statista.com). Due to lower values for both diesel (fuel) prices and fuel consumption, the discounted value of fuel costs (PVFC) for diesel vehicles is significantly lower compared to gasoline vehicles (despite a higher average driving intensity) for all but the mini car classes. Dispersion of these values for both engine types is

significant over all car classes. It indicates that some consumers expect to incur €2000-€4000 more or less in their fuel expenses compared to the mean values in the car class.

For our further analysis, we additionally adjust the values of expected annual fuel expenses by accounting for a potential that a person can use a vehicle for vocational trips. Individuals may deduct the value of fuel costs for a work-related car usage from their annual income tax values. The German government sets a fixed deduction rate per (one-way) kilometer driven for business purposes at €0.30 (according to 9 of the Income Tax Act (Einkommensteuergesetz)). This value is assumed to reflect all fuel expenses and maintenance costs related to a car’s use per kilometer. In the current analysis, the limit for a distance after which the incurred fuel costs can be tax-deducted is set at a level equal to the median of expected annual driving within the car class for each engine type. For diesel car owners, this level varies between 18,000 and 20,000 km, whereas for gasoline car buyers, it varies between 10,000 and 15,000 km. The amount of additionally driven kilometers above the set limits is multiplied by €0.15 (a half of €0.30 to account for two-way trips in most cases) and is subtracted from the annual fuel expenses. The resulting net values for PVFC (net PVFC) are used in the following estimation. This variable is considered to better reflect a relationship between the individual fuel costs and the individual willingness to invest upfront in a more fuel-efficient car.

Next, we present the descriptive statistics for consumer- and transaction-specific characteristics from the dataset. These characteristics are used in the later analysis to determine their roles in the degree of consumers’ valuation of future fuel costs. For ease of the following discussion, all determinants are grouped into three types – characteristics related to demographics, car usage, and capital constraints. Table 4 presents summary statistics for the taste determinants under consideration. See Table A5 for more details on the categorical variables. Overall, we observe a high heterogeneity in the observed characteristics over both engine types. Many of these characteristics have been to a various extent discussed in previous studies as important sources of differences in the vehicle choice and usage along with willingness-to-pay for car attributes. Among the investigated factors that have not been investigated previously in the similar context are the purposes of a car use and consideration of a used car for the purchase. We discuss the effects of the investigated determinants on

the individual valuations of fuel costs when presenting the empirical results in Section 4.

Table 4: Consumer- and purchase-related characteristics

Characteristics	Units	Diesel vehicles (N = 38761)		Gasoline vehicles (N = 82552)		
		Mean	SD	Mean	SD	
Demographics						
Gender (“male” = 1)	0/1	0.83	0.38	0.72	0.45	
Age	years old	48.22	13.56	52.15	14.57	
Family size	number	2.64	1.10	2.39	0.98	
Children under 18	number	0.52	0.87	0.35	0.71	
University degree (“yes” = 1)	0/1	0.28	0.45	0.20	0.40	
Town size	group	3.89	1.92	4.21	2.02	
Region (“east” = 1, “west” = 0)	0/1	0.13	0.33	0.24	0.43	
Capital Constraints						
Monthly net income	group	8.43	2.76	7.39	2.88	
Financing (“savings” =1)	0/1	0.60	0.49	0.64	0.48	
Financing (“loan” =1)	0/1	0.35	0.48	0.32	0.47	
Considered used car (“yes”=1)	0/1	0.33	0.47	0.28	0.45	
Car Usage						
Holiday driving (“frequent usage”=1)	0/1	0.93	0.25	0.86	0.34	
Weekend driving (“frequent usage”=1)	0/1	0.71	0.45	0.67	0.47	
Cars in use	number	1.65	0.72	1.48	0.65	
Two cars and more (“yes” = 1)	0/1	0.53	0.50	0.40	0.49	
Same make as previous (“yes”=1)	0/1	0.53	0.50	0.58	0.49	

NOTE: Averages for group variables (hometown size and income) are computed without a “not answered” option. Hometown size has 8 categories ranging from “< 2,000” to “≥ 500,000”, with the median over both engine types being the group 4 (20,000-49,999). Income has 15 categories ranging from “<€1,000” to “≥€15,000”, with the median over both engine types being the group 8 (€2,500-€2,999). See Table A5 for more details.

4 Empirical Results

4.1 Hedonic price regression

We perform the entire investigation of the relationship between purchase prices and future fuel costs for buyers of identical passenger cars separately for six different car classes of two engine types (diesel and gasoline). The main motivation for the separate estimation is that the equilibrium conditions in each of these twelve markets (6 car classes × 2 engine types) can differ. First, technological differences between diesel and gasoline engines may result in different interdependencies between car prices and car characteristics. Second, consumers’ preferences for car attributes and their attention to ongoing usage costs may structurally

differ among engine types and car classes. [Sallee \(2014\)](#), for example, argued that consumers may correctly value fuel cost differences between vehicles of different classes but be unable or unwilling to understand this difference within a class. Thus, to correctly investigate the extent of valuation of future fuel expenses, we find it important to estimate by car class. We additionally estimated the hedonic price regression by pooling over car classes while controlling for car class fixed effects. We did not find significant differences on average, but the valuation coefficient from the pooled regression under- or over-estimated those for car classes in a separate regression (see [Table A8](#) for the robustness check estimates).

With the help of a nonparametrically estimated hedonic price regression, the individual implicit prices for PVFC and car attributes are separately recovered for each of the twelve markets. A specific formulation of the hedonic price function in [Equation 7](#) includes the following observed vehicle attributes (X) along with PVFC: horse power related to car weight (HPW), car weight (W), displacement ($Disp$), transmission (automatic versus manual), and supplementary car attributes ($Extras$).

$$\begin{aligned} \ln(\text{Price})_{njt} = & \alpha_{PVFC,n}PVFC_{nj} + \alpha_{HPW,n}HPW_j + \alpha_{W,n}W_j + \alpha_{Disp,n}Disp_j \\ & + \alpha_{A,n}Automatic_j + \sum_s \alpha_{s,n}Extras_{sj} + \mu_j + \tau_t + q_t + r_n + \xi_{njt} \end{aligned} \quad (7)$$

The coefficient of our primary interest is that of the PVFC measure, $\alpha_{PVFC,n}$. The identifying variation for the relationship between transaction car prices and PVFC comes from differences in these values among consumers and over time (net from any seasonal variations controlled by year- and quarter-fixed effects) after controlling for preferences over other car attributes. Horse power related to weight (HPW) controls for the car performance (e.g., [Berry et al., 1995](#); [Andersson, 2005](#)), and car weight characterizes the size of a car (e.g., [Arguea et al., 1994](#); [Bajic, 1993](#)). Displacement enters the hedonic price function as a dichotomous variable with five categories ("≤1399"; "1400-1999"; "2000-2499"; "2500-2999"; and "≥3000" cm³). It is taken as a categorical variable for two main reasons: first, its distribution is highly discrete in the data, and the choices are concentrated over few distinct values along the continuum; second, to eliminate the "curse of dimensionality" –

in a nonparametric regression, the speed of estimation depends on a number of continuous variables. *Extras* contains dummy variables that indicate whether the purchased car has any extra car attributes out of those presented in Table 2.

An extensive set of fixed effects is also added. To account for temporal changes in product qualities and seasonality of the purchases, fixed effects for year, τ_t , and quarter-of-year, q_t , for the purchase occasion were included. An indicator of whether the purchase is done in a west or an east German state, r_n , was added to control for regional differences in prices (with prices in the east region usually being lower) and other unobserved household and dealer characteristics that may vary by region. Additionally, fixed effects for make-models (e.g. Audi A3, BMW 1 Series, VW Golf, etc.), μ_j , controlled for unobservable car qualities, such as reliability, premium status, and other model-specific features that are constant over time. During the estimation, the reference category is presented by the first quarter of the year, year 2000, west region, model of VW (VW Lupo for minis, VW Polo for superminis, VW Golf for compact class, VW Passat for middle class, VW Toureg for upper middle class, and VW Phaeton for upper class), displacement of "2000-2499" cm^3 , and manual transmission.

In a nonparametric regression, the choice of kernel and bandwidth (smoothing parameters) is very important. Because there are too many observations for most car classes to directly use a commonly applied cross-validation method to select smoothing parameters, an approach outlined in Racine (1993) was applied here (computational time necessary for the cross-validation methods is proportional to the square number of observations). The method is based on the fact that a window width for a variable k (h_k) is proportional to the variation in that variable (σ_k), the sample size (n), and the number of regressors (r), with a constant of proportionality c_k ("the scale factor") that is independent of the sample size, i.e. $h_k \sim c_k \sigma_k n^{-1/(2p+r)}$. Thus, one can conduct the bandwidth selection on a large number of subsets drawn randomly from the full dataset. Taking the median value over the scale factors from these subsets, one proceeds with estimation for the entire sample (for more details, see Hayfield and Racine, 2008). According to the rules discussed by Racine (1993), we estimate the local-linear hedonic price regression by using 50 resamples, each with 230 observations to select smoothing parameters. The results are robust to the amount of resamples and number of observations higher than 230. We use the cross-validation bandwidth selection method

based on the Akaike information criterion (AICCV) with a Gaussian kernel for continuous variables and a Li-Racine kernel for discrete variables and apply the Li-Racine generalized product of kernel functions (Li and Racine, 2003; Hayfield and Racine, 2008). It efficiently uses information on both continuous and discrete variables without splitting the sample as in the frequentist approach in the case of dichotomous variables.

Table 5 provides fit statistics for the estimated hedonic price regression. The within-sample goodness-of-fit was assessed with a similar to a parametric R^2 measure that is computed as in Equation 8 using the observed ($Price$), fitted (\widehat{Price}), and average (\overline{Price}) values of the dependent variable for all observations.

$$R^2 = \left[\sum_{n=1}^N (Price_{nj} - \overline{Price})(\widehat{Price}_{nj} - \overline{Price}) \right]^2 / \sum_{n=1}^N (Price_{nj} - \overline{Price})^2 \sum_{n=1}^N (\widehat{Price}_{nj} - \overline{Price})^2 \quad (8)$$

Overall, the results indicate a moderate to good fit of the regression based on the selected car attributes. Due to a small number of observations, the fit is lowest for diesel vehicles belonging to the smallest car class (minis). Summary statistics for the parameter estimates from nonparametric hedonic price regression for all car attributes are presented in Table A6.

Table 5: Fit statistics for nonparametric hedonic price regression

	Diesel vehicles						Gasoline vehicles					
	N	MSE	MAPE	SE	CORR	R2	N	MSE	MAPE	SE	CORR	R2
Minis	234	0.0066	0.0066	0.0053	0.7908	0.6248	3924	0.0107	0.0087	0.0017	0.8413	0.7078
Superminis	4134	0.0076	0.0069	0.0014	0.8159	0.6648	19824	0.0103	0.0081	0.0007	0.8312	0.6896
Compact Class	14884	0.0067	0.0063	0.0007	0.8657	0.7492	33232	0.0072	0.0066	0.0005	0.8803	0.7749
Middle Class	14328	0.0057	0.0057	0.0006	0.9048	0.8184	20832	0.0054	0.0055	0.0005	0.9349	0.8738
Upper Middle Class	4869	0.0055	0.0054	0.0011	0.9373	0.8784	4383	0.0051	0.0051	0.0011	0.9633	0.9279
Upper Class	312	0.0077	0.0061	0.0050	0.9563	0.9146	357	0.0088	0.0063	0.0050	0.9309	0.8666

NOTE: Based on the local-linear hedonic price regression with cross-validation bandwidth selection method based on the Akaike information criterion (AICCV), Gaussian kernel for continuous variables, and Li-Racine kernel for discrete variables. MSE is mean square error; MAPE is mean absolute percentage error; SE refers to standard errors; CORR is an absolute value of Pearson’s correlation coefficient between fitted and observed values; R^2 is computed based on Equation 8.

4.2 Recovered consumer valuation of fuel costs

Individual valuation of fuel costs ($\widehat{\beta}_{n,PVFC}$) is given by the estimate of a price gradient with respect to PVFC that is evaluated at the prices paid by consumers for the purchased vehicles. The cost-minimizing trade-off between PVFC and purchase price by a “rational” consumer behavior requires that the willingness-to-pay for a €1 reduction in PVFC should be equal

to €1. Table 6 provides summary statistics for the estimates of this value. Here, the mean values along with standard deviation, median, 10th-, and 90th-percentiles give an overview of the distribution of individual estimates. We compute the summary statistics only for those observations that have a negative price gradient of PVFC into account (82% of observations in total). N(%) is the number and percentage of observations (compared to the full sample) with the negative price gradients of PVFC. The price gradient values are all significant (not shown) and, as expected, are mainly negative (between 70% and 90% of the observations). Only for diesel cars belonging to minis is there approximately a half-half split in the number of positive and negative gradient estimates. This pattern is due to a very small number of observations (N=234) and product specifications (N=42) for minis with diesel engines, but a high variability in car characteristics and consumer-specific PVFC.

Overall, a high degree of undervaluation is evident. There are only 0.26% of observations with an overvaluation of fuel savings. On average, consumers' willingness-to-pay for a €1 reduction in the discounted future fuel costs is below €0.50. Buyers of diesel cars are characterized on average as having a lower degree of myopia than those of gasoline vehicles. Differences between the estimated willingness-to-pay for diesel and gasoline cars are statistically significant over all car classes, with the smallest discrepancy for compact class. The extent of PVFC valuation increases with car classes and achieves a full valuation for some owners of upper class cars (in 90th and 95th-percentiles of the distribution).

Based on the valuation parameter we recover in our analysis, the individual implicit discount rates or payback period can also be determined. Our results suggest implicit discount rates of 109% and 144% over car classes on average, for diesel and gasoline car owners respectively. The payback period for investments into fuel efficiency is less than one year.

Relatively high values for the standard deviation in all cases reflect a high heterogeneity among consumers. The next section aims to investigate factors that can help explain this heterogeneous degree of fuel cost undervaluation.

4.3 Determinants of fuel costs' undervaluation

At this stage, the derived individual willingness-to-pay values for a reduction in the discounted future fuel costs are regressed on the heterogeneity characteristics of interest to

Table 6: Number and percentage of observations with negative price gradients of PVFC and summary statistics for the PVFC valuation parameter

	Diesel vehicles						Gasoline vehicles						Mean
	N (%)	Mean	SD	P10	Median	P90	N (%)	Mean	SD	P10	Median	P90	differences
Minis	114 (49.15)	0.17	0.17	0.06	0.11	0.32	3468 (88.56)	0.12	0.08	0.04	0.11	0.22	0.05 (p=0.003)
Superminis	3733 (90.37)	0.13	0.09	0.04	0.11	0.23	17247 (87.11)	0.09	0.08	0.02	0.08	0.16	0.04 (p<0.001)
Compact Class	12207 (82.10)	0.14	0.11	0.03	0.12	0.25	27504 (82.88)	0.12	0.11	0.03	0.10	0.24	0.01 (p<0.001)
Middle Class	11376 (79.55)	0.20	0.16	0.04	0.17	0.37	16384 (78.75)	0.16	0.16	0.03	0.12	0.33	0.04 (p<0.001)
Upper Middle Class	3825 (78.64)	0.23	0.19	0.05	0.19	0.47	3191 (72.90)	0.20	0.17	0.04	0.17	0.39	0.03 (p<0.001)
Upper Class	226 (72.44)	0.45	0.55	0.03	0.31	1.05	297 (83.47)	0.41	0.35	0.11	0.32	0.90	0.04 (p=0.041)

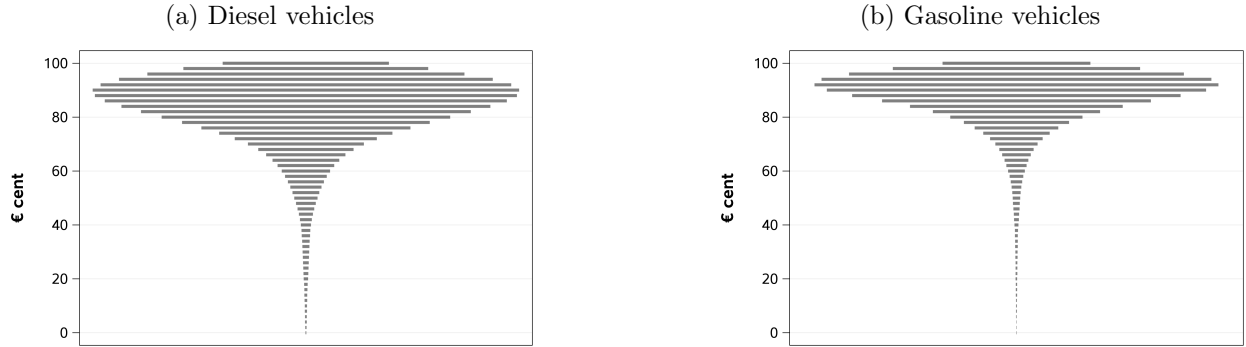
NOTE: The table displays summary statistics for the valuation parameter $\beta_{n,PVFC}$ for a subset of observations with the negative estimates for the price gradients of PVFC (82% of observations in total). The valuation parameter is evaluated by Equation 5 at the prices paid by the consumers. N(%) is the number and percentage of observations (compared to the full sample) with the negative price gradient of PVFC. Mean differences are differences in the average valuation parameter for diesel versus gasoline vehicles. The price gradient is estimated by a local-linear hedonic price regression with cross-validation bandwidth selection method based on the Akaike information criterion (AICCV), Gaussian kernel for continuous variables, and Li-Racine kernel for discrete variables. All price gradient values are statistically significant (not shown).

understand their role in the consumers' valuations of energy-saving technology. The subsequent analysis is performed for the sub-sample with the negative price gradient estimates with respect to PVFC (82% of observations).

For ease of interpretation, we construct a variable that indicates the extent of undervaluation of the fuel savings to use it as our dependent variable. It is defined as 1 (€) less the derived individual valuation parameter ($\beta_{n,PVFC}$). As evident from Figure 1, the distribution of the constructed dependent variable for both diesel and gasoline vehicles indicates a high heterogeneity in the willingness-to-pay values for fuel savings and is negatively skewed. Hence, conventional least squares regression methods that estimate the conditional mean of the dependent variable given values of covariates will not be able to capture the size and nature of the effects for heterogeneity determinants on the lower and upper tails of the undervaluation distribution. To obtain a comprehensive understanding of the effects for the selected determinants at different levels of undervaluation, we use a quantile regression. Quantile regression estimates the whole family of conditional quantile functions (not only the mean function) of the response variable and is insensitive to extreme values in its conditional distribution (Koenker and Hallock, 2001).

Equation 9 shows a specification for the quantile regression that is estimated for each

Figure 1: Distribution of consumers' undervaluation of €1 reduction in future fuel costs



NOTE: Presented violin plots of the undervaluation distribution show both the interquartile range and the probability density of the data. Undervaluation is computed as 1 - (individual) willingness-to-pay for €1 reduction in the discounted future fuel costs. The values are given in € cents.

quantile τ in $(0,1)$ of the conditional undervaluation distribution given all covariates, with $\gamma_0(\tau)$ and $\gamma_d(\tau)$ presenting the intercept and the corresponding estimate for each covariate Z_d , respectively. The error term $\eta_n(\tau)$ is interpreted as a household-specific taste shock.

$$\text{Undervaluation}_n = \gamma_0(\tau) + \sum_d \gamma_d(\tau)Z_{dn} + \eta_n(\tau) \quad (9)$$

Heterogeneity determinants (Z_d) include gender, age, number of children under 18, an indicator for university degree, hometown size, net monthly income, an indicator for consideration of a used car for the purchase, financing method (savings versus loan), an indicator for holiday driving (frequent versus infrequent usage), an indicator for weekend driving (frequent versus infrequent usage), number of cars in use, and an indicator for make-inertia. For coefficient estimates, the Frisch-Newton interior point method with standard errors obtained via Markov chain marginal bootstrap (MCMB) is used, which is robust and computationally tractable for large data sizes (Portnoy and Koenker, 1997). Given the robustness of quantile regression to distributional assumptions regarding error terms, the error term η_n is not required to be normally distributed. In the preliminary analysis, no statistically significant differences in the parameter estimates for covariates over various car classes are found. Therefore, the quantile regression is estimated for diesel and gasoline vehicles separately but pooled over car classes. Fixed effects for car classes are added to control for a location shift in the undervaluation distribution over classes.

For brevity, we include a table with the estimated effects for all covariates into Appendix (Table A7). It displays values for the covariate effects on the conditional undervaluation distribution along with the least-squares estimates (OLS) for both diesel and gasoline vehicles. The resulting regression coefficients at each quantile are interpreted similarly to the conventional least squares regression: a one-unit increase in a covariate Z_d results in a $\gamma_d(\tau)$ unit (here, € cents) change in the conditional quantile of the response variable, ceteris paribus. Because we analyze the undervaluation distribution, negative $\gamma_d(\tau)$ values mean lower myopia regarding the expected future fuel costs. The intercept ($\gamma_0(\tau)$) shows the estimated conditional quantile function of the undervaluation distribution for the reference group. It is presented by a female owner of an upper class car, without a university degree, with a monthly net income of \geq €500,000, who uses a loan to finance a car purchase, does not consider a used car for the purchase, possesses only one car in the household, buys a make other than that of the previous car, and does not use a car for weekend or holiday trips. In the data, many categorical explanatory variables have multiple missing values. We add "NA" instead of a missing value and treat it as a separate category during the estimation to keep all observations.

Overall, the estimated effects are found to be more pronounced at lower and average quantiles of the undervaluation distribution. At high levels of undervaluation (from approximately 90th percentile), the observed characteristics of consumers and purchase transactions are not able to explain the variation in the response values. For all covariates, the conditional mean (OLS) estimates tend to under- or over-estimate the covariate effects.

We find that both components of the present-discounted values of fuel costs – expected annual driving and fuel prices – have significant negative effects on the degree of undervaluation. If a consumer expects to drive a lot or expects higher fuel prices, then the extent of myopia in the purchase decision becomes lower. The impact of other consumer- and transaction-related characteristics are discussed next.

Demographic characteristics. The effects of social-demographic characteristics indicate that male drivers, older drivers, those with more minors in the household, and more educated drivers can better assess the potential savings in future fuel costs. It can be linked

to a reduced uncertainty of own driving preferences due to more car experience, a better assessment of car information by those consumers, and importance of any marginal changes in the expenditures for consumers with larger families. For example, [De Borger et al. \(2016\)](#) found that an increase in the number of children raises the demand for driving. Due to also lower disposable "wealth" for these consumers, the importance of making a "right" car choice increases as we also find in our investigation.

The effect of hometown size is significant and negative for both engine types. It shows that buyers from larger cities recognize the value of a better fuel economy to a higher degree than those from smaller towns. This pattern can potentially be explained by a relatively greater necessity of a car use in smaller towns (that can also be seen as rural areas). This can be, for example, because of a need to drive regularly to nearby cities and/or due to a less developed public transportation system.

Capital constraints. Previous studies have demonstrated that low income households consistently place lower values on future fuel cost, which could result either from lower expectations regarding expected vehicle use or from the existence of borrowing constraints (e.g., [Berkovec and Rust, 1985](#)). In our study we confirm this pattern. Overall, higher income drivers, individuals who do not use their own savings to purchase a car, and individuals who do not consider buying used cars also display less bias in their valuation of future fuel costs. Although the valuation of fuel savings increases with the personal income, the results also show that consumers with the highest income are no longer sensitive to fuel expenses. Additionally, a significant positive effect for the interaction between education and income for gasoline car buyers suggests that a difference in the undervaluation between consumers with and without university degree decreases with income. We link a smaller myopia for households with higher income level to their better ability to invest into an improved car quality.

To our knowledge, no previous studies have provided any evidence on the link between consumers' consideration of a second-hand car for the purchase and valuation of future cost savings. We find a significant downward effect on the valuation weight parameter. It can be motivated from an economic perspective. If a consumer has restricted financial resources for

purchasing a new vehicle, the second-hand market becomes a valid alternative to search for a product (e.g., [Guiot and Roux, 2010](#)). In our sample, consumers with the lowest income tend to consider the second-hand vehicles more often (on average 1.5 times more often ($p=0.01$)). Thus, both variables – income and consideration of used cars – being indicative of consumer financial ability, have an impact on the degree of fuel savings’ valuation in the same direction. A method to finance the vehicle purchase is also linked to the financial ability of households. We find that individuals who used their savings for the purchase are more prone to undervaluation of fuel costs than those who used a loan, after controlling for other indicators of capital constraints. It can be explained by a higher loan rate for borrowers relative to a lower return that could be realized on savings. Additional analysis find no significant interaction effects of income with either financing method or the indicator for used car consideration. The estimated positive effects of these covariates are also robust to exclusion of the income variable.

Car usage. We also address a commonly raised concern from previous studies that consumers who own multiple vehicles should have different patterns in their willingness to pay for car attributes compared to one-vehicle households (e.g., [Wadud et al., 2010](#)). We find no significant effect of this variable on the valuation extent after controlling for other indicators of capital constrains. This finding can be due to its correlation with income. Exclusion of the income variable results in a significant negative effect for the variable indicating multiple car ownership. An interaction term between these two variables is, however, not significant.

While some previous studies have mentioned the importance of a purpose of car use to consumers’ purchase decisions (e.g., [Steg, 2005](#); [Baltas and Saridakis, 2013](#)), no studies have explicitly explored the role of this factor in consumers’ valuation of fuel costs. Our results demonstrate its significant effect in the expected direction – a higher frequency of the car use for recreational purposes (holiday and weekend driving) improves consumer recognition of the fuel economy value resulting in a less bias.

A variable that indicates whether the same brand has been purchased as the previously owned car has a negative effect on the undervaluation distribution for both engine types. It highlights the importance of building strong brand preferences for a repetitive car purchase.

Here, a smaller bias for brand loyal consumers may be explained by the costs of processing and search for additional information. By sticking to a previously purchased car make, consumers may reduce the choice complexity by evaluating car characteristics, including fuel costs, only for the selected brand. Thus, this finding provides some support for the theory of choice overload (e.g., [Iyengar and Lepper, 2000](#)). However, at a lower degree of myopia, the results suggest that consumers with strong brand preferences are less sensitive to the fuel efficiency of the car.

5 Policy implications

In this section, we discuss managerial and policy implications that can be taken from our results on consumer valuation of future fuel costs and its determinants.

By relating various characteristics of consumer heterogeneity to the valuation of fuel costs, our study relates to those that investigate the role of consumer heterogeneity in the discounting of operating costs for energy-using durable goods. These studies are typically based on stated preference from choice experiments (e.g., [Newell and Siikamäki, 2015](#); [Layton and Brown, 2000](#); [Allcott and Taubinsky, 2015](#)). The valuation parameter (“attention weight”) we recover in our study on revealed preferences can also be used to assess the implicit discount rates that capture consumer investment decisions. Our results suggest the implicit discount rates of 109% and 144% over car classes on average, for diesel and gasoline car owners respectively. Thus, the consumers value savings in the upfront costs much heavily than savings in the ongoing fuel expenses.

In the case when valuation of discounted energy cost savings is less than that of upfront costs, consumers do not choose the cost-effective, energy-efficient technology despite its lower fuel costs at current energy prices. This pattern is defined in the literature as “energy-efficiency paradox” ([Jaffe and Stavins, 1994](#)). Many studies discuss potential explanations for this phenomena (e.g., [Allcott, 2011](#); [Gillingham and Palmer, 2014](#); [Gerarden et al., 2015](#); [Metcalf and Hassett, 1999](#); [Tietenberg, 2009](#) to mention only a few of them). All factors are related either to market failures (insufficient information provision, capital constraints) or behavioral anomalies (inconsistent time preferences, cognitive limitations,

choice-inertia, usage uncertainty). The recommendations for policy implementations depends on the prevailed explanations. A Pigouvian tax on energy that is optimal to deal with energy use externalities under a full valuation of energy costs would not provide the first-best outcome if agents are imperfectly informed or exhibit other behavioral anomalies (e.g., [Allcott and Greenstone, 2012](#)).

Overall, we find that socio-economic conditions explain many differences among consumers in their degree of the fuel cost valuation. Factors that relate to the financial ability of car buyers, importance of capital constraints, and a degree of car ownership necessity have a significant contribution to the reduction in consumers' myopia. Consumers with a lower level of financial stability potentially cannot afford cars with better fuel economy and therefore end up with suboptimal choices. Because investment inefficiencies of the consumers may discourage manufacturers from investing into better fuel economy of cars, it is also crucial to provide economical incentives for the supply side. Proper functioning of the capital market and the provision of subsidies to consumers or manufacturers are thus important to lower the financial burden in the diffusion and adoption of fuel-efficient vehicles.

The recovered consumers' undervaluation of fuel savings from cars with better fuel economy might be caused by either a limited attention of consumers to fuel expenses or insufficient information to identify economically optimal choices. Insufficient information presents a type of market failures, while limited attention refers to the behavioral failure and can be used to describe nonstandard decision-making directly or nonstandard beliefs through cognitive limitations of households ([Gillingham and Palmer, 2014](#); [DellaVigna, 2009](#)). It is difficult to disentangle these causes. However, some insights can be taken from the present research. For our data, it can be true that information on car fuel efficiency during the sample period (2000-2006) could have been costly for the consumers to obtain. The national German regulation regarding energy efficiency labeling for new passenger cars did not come into force before November 2004. Although, a re-estimation of the hedonic price regression for a period 2005-2006 does not yield significantly different valuation parameters (see [Table A8](#) for the robustness check estimates), data on recent years may indeed lead to a higher valuation parameter as information provision has been improved over time.

In addition to costs of acquiring information, limited attention to energy cost savings can

also be a result of cognitive limitations and difficulty to process all information in a correct way. One of the errors that consumers can have in their perceptions of total energy costs is presented by “MPG Illusion” (Larrick and Soll, 2008; Allcott, 2011). It suggests a systematic misperception of improvements in fuel efficiency when it is expressed in miles per gallon . Although this perceptual error does not indicate undervaluation of fuel cost savings per se, it highlights computational difficulties that consumers may encounter. Because in Germany the fuel economy of cars is presented in liters per kilometer, a measure linearly linked to fuel costs, it should be easier for consumers to access the potential fuel savings from a more fuel-efficient vehicles. Therefore, the recovered undervaluation of energy cost savings in our study is rather justified by other market and behavioral failures.

As we observe only one point of investment decisions of the consumers, we cannot interpret the high implicit discount rate (or high degree of myopia) as being a result of time-inconsistent preferences. For this, one needs to observe discount rates of the same households over time. However, a lack of self-control (e.g., Thaler and Shefrin, 1981) that is also related to the time-inconsistency of preferences could still be a potential explanation for our findings. A less fuel-efficient vehicle with a lower purchase price might appear “tempting” for consumers, in spite of its relatively high operating costs. Thus, energy efficiency standards could serve as a commitment device to address investment inefficiencies in consumer choice that stem from temptation (Tsvetanov and Segerson, 2013).

Because both decisions – to save money and to invest in a better car quality – undergo the same psychological mechanism of intertemporal preferences (trade-off of costs and benefits over time), consumers who have savings in an amount enough to purchase a vehicle should be those who weight benefits in the future more. Thus, they should also value the potential fuel savings from better fuel economy higher. However, after controlling for other indicators of capital constraints, we find the opposite effect – these consumers are more myopic in their valuation. This result highlights that there are still other factors than consumers’ shortsightedness that lead to consumer undervaluation of future fuel cost savings. A higher loan rate for borrowers relative to a lower return that could be realized on savings may serve as an additional explanation.

The role of uncertainty in consumers’ expectations regarding car usage should have a

smaller impact on the results in our investigation than in previous studies because the sample of consumers used in the current analysis consists of those who had possessed a car in the past. Experience with a car should assist consumers in understanding their own driving preferences. Additionally, we control for the purpose of a car use also control for differences in driving preferences. The results indicate that if consumers expect to use a car relatively frequently for weekend or holiday trips, their willingness to pay for a €1 reduction in fuel cost increases.

The recovered consumer heterogeneity in the degree of investment inefficiency may serve as a signal for the importance of designing targeted policies to move consumers' choices toward cars with better fuel economy (as also proposed in, e.g., [Allcott et al., 2015](#) and [Allcott et al., 2014](#)). As [Allcott and Greenstone \(2012\)](#) pointed out, “welfare gains will be larger from a policy that preferentially affects the decisions of consumers subject to investment inefficiencies”. The results suggest that capital constraints and potential complexity of car choice tasks are the most important determinants of the recovered undervaluation of car fuel efficiency. Hence, a set of complementary policies can help to reduce the energy-efficiency gap. While information provision policies may contribute to the adoption of better fuel economy due to consumers being better informed, financial incentive schemes could efficiently support those consumers with tighter capital constraints. A Pigouvian tax on energy consumption would be more effective for the consumers with higher car utilization (e.g., [Grigolon et al., 2017](#)), whereas a policy that combines fuel economy standards with taxes can lead to a first-best outcome for consumers with lower mileage and/or higher temptation to focus on low purchase prices ([Tsvetanov and Segerson, 2013](#)). In addition to financial tools, a development in social preferences could also help to shift consumer attention to fuel efficiency as being a signal of pro-environmental behavior to peers ([Gsottbauer and van den Bergh, 2011](#)). Hence, policy tools should aim at developing intrinsic (inner motivation) as well as extrinsic (external financial and non-financial) incentives for consumers to adopt better fuel efficiency.

6 Conclusion

Using observed car choices from a sample of consumers in Germany within the period 2000-2006, the present study, first, quantifies the direction and magnitude of the consumers' trade-off between the higher upfront capital costs and the lower ongoing usage costs of a more fuel-efficient car at the time of a car purchase. Second, it explains the recovered heterogeneity in consumers' valuation with the help of observed consumer- and purchase-related characteristics.

The current study contributes to the literature on consumer valuation of fuel efficiency in several ways. First, in our analysis we control for various dimensions of consumer heterogeneity. Along with heterogeneity in tastes over car attributes, we account for consumer differences in the stated expected car usage intensity and car ownership length. These additional sources of consumer heterogeneity allows us to contrast a variation in the individual values for present-discounted fuel expenses with that in the prices individually paid by the buyers of identical cars. This constitutes our identification strategy to recover consumer valuation of potential fuel savings from better fuel economy. A detailed definition of a car specification enables the analysis to control for many car attributes (including supplementary features such as leather seats or sunroof). It reduces the potential effect of the omitted variable bias.

Second, individual values for the present-discounted fuel costs are recovered in a non-restrictive way by estimating a nonparametric price regression within the hedonic discrete choice model. The applied framework does not require distributional assumptions on the consumer tastes for car attributes. It uses a variation in the observed choices among bundles of car attributes and individual PVFC and relates this variation to that in prices. The nonparametric estimation also allows consumer tastes for car attributes to be correlated without a need to model the variance-covariance matrix.

In our study we find that consumers do not fully recognize the value of cost-effective, energy-efficient technology at the time of a car purchase. The rate at which consumers undervalue future energy costs varies significantly across buyers of various engine technologies and car classes. The recovered undervaluation of future fuel savings from a more fuel-efficient

car is an example of the energy-efficiency gap in the automobile market (Jaffe and Stavins, 1994). The third contribution of the current study lies in exploring the effects of various determinants on the extent of consumers' valuation of future fuel savings from a more fuel-efficient car. Along with demographic characteristics (gender, age, education, number of minors, hometown size), the analysis in this paper also considers different indicators for consumers' financial ability, purposes of car use, multiple car ownership, and make-inertia. Some of these factors have not yet been discussed in the literature regarding consumer valuation of energy costs (e.g., consideration of the used cars; purposes of car use). With the help of quantile regression, we recover the covariate effects for various quantiles of the conditional distribution for the valuation variable.

There are some possible concerns and extensions for the presented analysis. First, the current paper does not account for potential rebound effects - either direct (influence of fuel prices on car usage) or indirect (influence of fuel prices on consumption of other than cars energy-consuming goods). We maintain the assumption that annual kilometers driven remain constant over the entire car ownership and are equal to the stated expected driving intensity by the consumers for the chosen fuel economy. We find this assumption justifiable for the present research because consumers stated their expected driving at the time of the car purchase, and the estimation aims to recover the value of fuel costs at this same time. Additionally, we maintain the standard assumption for the hedonic price estimation that the unobserved product attribute is independent of the observed product characteristics. Although it might be a strong assumption, it is imposed here because appropriate instrumental variables are difficult to find.

Depending on the available data, future research could explore other determinants of consumer heterogeneity in the valuation of future energy costs. The framework used in this study could be applied to other energy-used durable goods. Additionally, information on characteristics of other cars within multi-vehicle households could enable researchers to test whether differences in the valuation of fuel savings depend on a constitution of the household car portfolio. Additionally, with data over longer and more recent time periods, the effects of current environmental policies on consumer preferences could provide new insights.

References

- Akerberg, D. A. and Rysman, M. (2005). Unobserved Product Differentiation in Discrete Choice Models: Estimating Price Elasticities and Welfare Effects. *The RAND Journal of Economics*, 36(4):1–19.
- Allcott, H. (2011). Consumers’ perceptions and misperceptions of energy costs. *American Economic Review*, 101(3):98–104.
- Allcott, H. and Greenstone, M. (2012). Is There an Energy Efficiency Gap? *Journal of Economic Perspectives*, 26(4):3–28.
- Allcott, H., Knittel, C., and Taubinsky, D. (2015). Tagging and Targeting of Energy Efficiency Subsidies. *American Economic Review: Papers & Proceedings*, 105(5):187–191.
- Allcott, H., Mullainathan, S., and Taubinsky, D. (2014). Energy policy with externalities and internalities. *Journal of Public Economics*, 112:72–88.
- Allcott, H. and Taubinsky, D. (2015). Evaluating behaviorally motivated policy: Experimental evidence from the lightbulb market. *American Economic Review*, 105(8):2501–2538.
- Allcott, H. and Wozny, N. (2014). Gasoline Prices, Fuel Economy, and The Energy Paradox. *The Review of Economics and Statistics*, 96(5):779–795.
- Anderson, S. T., Kellogg, R., and Sallee, J. M. (2013). What Do Consumers Believe About Future Gasoline Prices? *Journal of Environmental Economics and Management*, 66(3):383–403.
- Andersson, H. (2005). The Value of Safety as Revealed in the Swedish Car Market: An Application of the Hedonic Pricing Approach. *Journal of Risk and Uncertainty*, 30(3):211–239.
- Arguea, N. M., Hsiao, C., and Taylor, G. A. (1994). Estimating Consumer Preferences Using Market Data - An Application to Us Automobile Demand. *Journal of Applied Econometrics*, 9(1):1–18.

- Bajari, P. and Benkard, C. L. (2005). Demand Estimation with Heterogeneous Consumers and Unobserved Product Characteristics: A Hedonic Approach. *Journal of Political Economy*, 113(6):1239–1276.
- Bajari, P. and Kahn, M. E. (2005). Estimating Housing Demand With an Application to Explaining Racial Segregation in Cities. *Journal of Business & Economic Statistics*, 23(1):20–33.
- Bajic, V. (1993). Automobiles and Implicit Markets: An Estimate of a Structural Demand Model for Automobile Characteristics. *Applied Economics*, 25(4):541–551.
- Baltas, G. and Saridakis, C. (2013). An empirical investigation of the impact of behavioural and psychographic consumer characteristics on car preferences: An integrated model of car type choice. *Transportation Research Part A: Policy and Practice*, 54:92–110.
- Benkard, C. L. and Bajari, P. (2005). Hedonic Price Indexes With Unobserved Product Characteristics, and Application to Personal Computers. *Journal of Business & Economic Statistics*, 23(1):61–75.
- Bento, A. M., Li, S., and Roth, K. (2012). Is there an energy paradox in fuel economy? A note on the role of consumer heterogeneity and sorting bias. *Economics Letters*, 115(1):44–48.
- Berkovec, J. and Rust, J. (1985). A nested logit model of automobile holdings for one vehicle households. *Transportation Research Part B: Methodological*, 19(4):275–285.
- Berry, S., Levinsohn, J., and Pakes, A. (1995). Automobile Prices in Market Equilibrium. *Econometrica*, 63(4):841–890.
- Busse, M. R., Knittel, C. R., and Zettelmeyer, F. (2013). Are Consumers Myopic? Evidence from New and Used Car Purchases. *American Economic Review*, 103(1):220–256.
- De Borger, B., Mulalic, I., and Rouwendal, J. (2016). Measuring the rebound effect with micro data: A first difference approach. *Journal of Environmental Economics and Management*, 79:1–17.

- DellaVigna, S. (2009). Psychology and economics: Evidence from the field. *Journal of Economic Literature*, 47(2):315–372.
- Dreyfus, M. K. and Viscusi, W. K. (1995). Rates of Time Preferences and Consumer Valuations of Automobile Safety and Fuel Efficiency. *Journal of Law and Economics*, 38(1):79–105.
- Dubin, J. A. and Mcfadden, D. L. (1984). An Econometric Analysis of Residential Electric Appliance Holdings and Consumption. *Econometrica*, 52(2):345–362.
- Espey, M. and Nair, S. (2005). Automobile Fuel Economy: What is it Worth? *Contemporary Economic Policy*, 23(3):317–323.
- Fan, Q. and Rubin, J. (2010). Two-Stage Hedonic Price Model for Light-Duty Vehicles. *Transportation Research Record: Journal of the Transportation Research Board*, 2157(2157):119–128.
- Gerarden, T., Newell, R. G., and Stavins, R. N. (2015). Deconstructing the Energy-Efficiency Gap: Conceptual Frameworks and Evidence. *American Economic Review*, 105(5):183–186.
- Gillingham, K. and Palmer, K. (2014). Bridging the Energy Efficiency Gap: Policy Insights from Economic Theory and Empirical Evidence. *Review of Environmental Economics and Policy*, 8(1):18–38.
- Goldberg, P. K. (1995). Product Differentiation and Oligopoly in International Markets: The Case of the U.S. Automobile Industry. *Econometrica*, 63(4):891–951.
- Goldberg, P. K. (1998). The Effects of the Corporate Average Fuel Efficiency Standards in the US. *The Journal of Industrial Economics*, XLVI(1).
- Greene, D. L. (2010). How Consumers Value Fuel Economy: A Literature Review. *U.S. Environmental Protection Agency report EPA-420-R-10-008*.
- Grigolon, L., Reynaert, M., and Verboven, F. (2017). Consumer valuation of fuel costs and the effectiveness of tax policy: Evidence from the European car market. *American Economic Journal: Economic Policy (Forthcoming)*.

- Gsottbauer, E. and van den Bergh, J. C. J. M. (2011). Environmental Policy Theory Given Bounded Rationality and Other-regarding Preferences. *Environmental and Resource Economics*, 49(2):263–304.
- Guiot, D. and Roux, D. (2010). A second-hand shoppers’ motivation scale: Antecedents, consequences, and implications for retailers. *Journal of Retailing*, 86(4):383–399.
- Hausman, J. a. (1979). Individual Discount Rates and the Purchase and Utilization of Energy-Using Durables. *The Bell Journal of Economics*, 10(1):33–54.
- Hayfield, T. and Racine, J. S. (2008). Nonparametric econometrics: The np package. *Journal of Statistical Software*, 27(5):1–32.
- Helfand, G. and Wolverton, A. (2011). Evaluating the Consumer Response to Fuel Economy: A Review of the Literature. *International Review of Environmental and Resource Economics*, 5(2):103–146.
- Iyengar, S. S. and Lepper, M. R. (2000). When choice is demotivating: Can one desire too much of a good thing? *Journal of Personality and Social Psychology*, 79(6):995–1006.
- Jaffe, A. B. and Stavins, R. N. (1994). The energy-efficiency gap What does it mean? *Energy Policy*, 22(10):804–810.
- Kahn, J. A. (1986). Gasoline Prices and the Used Automobile Market: A Rational Expectations Asset Price Approach. *The Quarterly Journal of Economics*, 101(2):323–340.
- Koenker, R. and Hallock, K. F. (2001). Quantile Regression. *Journal of Economic Perspectives*, 15(4):143–156.
- Larrick, R. P. and Soll, J. B. (2008). The MPG Illusion. *Science*, 320(5883):1593–1594.
- Layton, D. F. and Brown, G. (2000). Heterogeneous Preferences Regarding Global Climate Change. *The Review of Economics and Statistics*., 82(4):616–624.
- Li, Q. and Racine, J. (2003). Nonparametric estimation of distributions with categorical and continuous data. *Journal of Multivariate Analysis*, 86(2):266–292.

- Matas, A. and Raymond, J.-L. (2009). Hedonic prices for cars: an application to the Spanish car market, 1981-2005. *Applied Economics*, 41:2887–2904.
- Metcalf, G. E. and Hassett, K. a. (1999). Measuring the Energy Savings from Home Improvement Investments: Evidence from Monthly Billing Data. *The Review of Economics and Statistics*, 81(3):516–528.
- Newell, R. and Siikamäki, J. V. (2015). Individual Time Preferences and Energy Efficiency. *American Economic Review: Papers & Proceedings*, 105(5):196–200.
- Ohta, M. and Griliches, Z. (1986). Automobile Prices and Quality: Did the Gasoline Price Increases Change Consumer Tastes in the U.S.? *Journal of Business & Economic Statistics*, 4(2):187–198.
- Portnoy, S. and Koenker, R. (1997). The Gaussian hare and the Laplacian tortoise: computability of squared-error versus absolute-error estimators. *Statistical Science*, 12(4):279–300.
- Racine, J. (1993). An efficient cross-validation algorithm for window width selection for non-parametric kernel regression. *Communications in Statistics - Simulation and Computation*, 22:1107–1114.
- Rosen, S. (1974). Hedonic Prices and Implicit Markets: Product Differentiation in Pure Competition. *Journal of Political Economy*, 82(1):34–55.
- Sallee, J. M. (2014). Rational Inattention and Energy Efficiency. *The Journal of Law and Economics*, 57(3):781–820.
- Sallee, J. M., West, S. E., and Fan, W. (2016). Do consumers recognize the value of fuel economy? Evidence from used car prices and gasoline price fluctuations. *Journal of Public Economics*, 135:61–73.
- Sonnier, G., Ainslie, A., and Otter, T. (2007). Heterogeneity distributions of willingness-to-pay in choice models. *Quantitative Marketing and Economics*, 5(3):313–331.

- Steg, L. (2005). Car Use: Lust and Must. Instrumental, Symbolic and Affective Motives for Car Use. *Transportation Research Part A: Policy and Practice*, 39(2-3):147–162.
- Thaler, R. H. and Shefrin, H. M. (1981). An Economic Theory of Self-Control. *Journal of Political Economy*, 89(2):392–406.
- Tietenberg, T. (2009). Reflections—Energy Efficiency Policy: Pipe Dream or Pipeline to the Future? *Review of Environmental Economics and Policy*, 3(2):304–320.
- Train, K. and Weeks, M. (2005). Discrete Choice Models in Preference Space and Willingness-to Pay Space. In Alberini, A. and Scarpa, R., editors, *Applications of simulation methods in environmental and resource economics*. Dordrecht: Springer.
- Train, K. E. and Winston, C. (2007). Vehicle choice behavior and the declining market share of U.S. automakers. *International Economic Review*, 48(4):1469–1496.
- Triplett, J. E. (1969). Automobiles and Hedonic Quality Measurement. *Journal of Political Economy*, 77(3):408–417.
- Tsvetanov, T. and Segerson, K. (2013). Re-evaluating the role of energy efficiency standards: A behavioral economics approach. *Journal of Environmental Economics and Management*, 66(2):347–363.
- Turrentine, T. S. and Kurani, K. S. (2007). Car buyers and fuel economy? *Energy Policy*, 35(2):1213–1223.
- Wadud, Z., Noland, R. B., and Graham, D. J. (2010). A Semiparametric Model of Household Gasoline Demand. *Energy Economics*, 32(1):93–101.

SUPPLEMENTARY MATERIAL

Transaction data set: The data set used in the study is provided by a market research company for (non-commercial) scientific research. Due to privacy issues, all information that can help tracking a concrete car make or a household has been de-identified. According to the data use agreement, the data set is not allowed to be transferred to anyone besides the editors and reviewers for the purposes of evaluating the manuscript. Unauthorized uses, disclosures, or sharing of the data set is prohibited (file: carsurvey.csv)

Code for the analysis: The code is mainly written in SAS (file: carsurvey.sas). For the nonparametric hedonic price regression, “NP” package of R is used (file: NPHP.R)

Additional tables:

Table [A1](#) “Overview of the selected studies on consumer valuation of car fuel efficiency based on revealed preference data”

Table [A2](#) “Description of variables in the transaction data set ‘carsurvey’ ”

Table [A3](#) “Description of the data sample for investigation”

Table [A5](#) “Consumer- and purchase-related characteristics (group variables)”

Table [A6](#) “Descriptive statistics for the nonparametric hedonic price regression estimates”

Table [A7](#) “Quantile regression for undervaluation of fuel savings on a set of consumer-related characteristics”

Table [A8](#) “Valuation parameters from alternative assumptions”

Table A1: Overview of the selected studies on consumer valuation of car fuel efficiency based on revealed preference data

Study	Framework	Dependent Variable	Market	Data level	Time period	Fuel efficiency measure	Transaction prices	Taste heterogeneity	KM heterogeneity	Holding heterogeneity	Results on valuation
Ohta and Griliches (1986)	Hedonic demand	vehicle prices	used	aggregate	1966-1980	1/MPG	no	no	no	no	just
Kahn (1986)	Price regression	vehicle prices	used	aggregate	1971-1981	PVFC	no	no	no	no	under
Arguea et al. (1994)	Hedonic demand	vehicle prices	new	aggregate	1969-1986	MPG	no	no	no	no	under
Dreyfus and Viscusi (1995)	Price regression	vehicle prices	new & used	individual	1988	PVFC	no	no	no	no	just
Goldberg (1995)	Discrete choice	vehicle choices	new	individual	1983-1987	FP/MPG	no	yes	no	no	just
Berry et al. (1995)	Discrete choice	sales shares	new	aggregate	1971-1990	MPG/FP	no	yes	no	no	under
Goldberg (1998)	Discrete choice	vehicle choices	new	individual	1984-1990	FP/MPG	no	yes	no	no	just
Espey and Nair (2005)	Price regression	vehicle prices	new	aggregate	2001	1/MPG	no	no	no	no	just
Train and Winston (2007)	Discrete choice	vehicle choices	new	aggregate	2000	1/MPG	no	yes	no	no	under
Fan and Rubin (2010)	Hedonic demand	vehicle prices	new	aggregate	2007	log(MPG)	no	yes	no	no	under
Busse et al. (2013)	Sales & price regression	sales shares & vehicle prices	new & used	aggregate	1999-2008	MPG quantiles	yes	yes	no	no	just
Allcott and Wozny (2014)	Price regression	vehicle prices	new & used	aggregate	1999-2008	PVFC	yes	no	no	no	under
Sallee et al. (2016)	Price regression	vehicle prices	used	individual	1990-2009	PVFC	yes	yes	yes	no	just
Grigolon et al. (2017)	Discrete choice	sales shares	used	aggregate	1998-2011	PVFC	no	yes	yes	no	just
Current study	Hedonic discrete choice	vehicle prices	new	individual	2000-2006	PVFC	yes	yes	yes	yes	under

Table A2: Description of variables in the transaction data set “carsurvey”

Name	Type	Label
date	Date	Purchase date
year	Numeric	Year of the purchase
YYQQ	Date	Year-Quarter of the purchase
quarter	Numeric	Quarter of the purchase
month	Numeric	Month of the purchase
CPI_X2010	Numeric	Consumer price index (relative to 2010)
SuperBenzin_E10	Numeric	Gasoline price (€ cent/litre)
Diesel	Numeric	Diesel price (€ cent/litre)
SuperBenzin_2010	Numeric	Gasoline price (2010€ cent/litre)
Diesel_2010	Numeric	Diesel price (2010€ cent/litre)
Pfuel_2010	Numeric	Fuel price (2010€)
Car description		
VehicleID	Numeric	Vehicle ID (distinguishes cars by engine type; car class; model year; model name; engine size; HP; transmission)
segmentADAC	Numeric	Car class (1=“Minis”; 2=“Superminis”; 3=“Compact class”; 4=“Middle class”; 5=“Upper middle class”; 6=“Upper class”)
New_EngineType	Character	Engine type
New_Transmission	Character	Transmission type
GEARBOXA	Numeric	Automatic transmission (“yes”)
MAKEMODEL_ID	Character	ID for Make-Models
engsz_new	Numeric	Displacement (cm ³)
HUBGRU	Numeric	Displacement group (1=“<1400”; 2=“1400-1999”; 3=“2000-2499”; 4=“2500-2999”; 5=“≥3000”cm ³)
PS	Numeric	Horsepower (HP)
Gesamtgewicht	Numeric	Total admissible vehicle weight (kg)
HP_W	Numeric	Horsepower per Weight
VerbrauchI	Numeric	City fuel consumption (litre/100 km)
VerbrauchA	Numeric	Highway fuel consumption (litre/100 km)
VerbrauchG	Numeric	Fuel consumption, litre/100 km
FEc	Numeric	Fuel economy (km/litre)
Supplementary car attributes		
SUN1	Numeric	Sunroof (“yes”=1)
CCON_AUT1	Numeric	Automatic air conditioning (“yes”=1)
CCON_MAN1	Numeric	Manual air conditioning (“yes”=1)
aircond	Character	Air conditioning (manual, automatic, none)
CRUISE1	Numeric	Cruise control (“yes”=1)
LEATHER_SEAT1	Numeric	Leather seats (“yes”=1)
NAV1	Numeric	GPS navigation system (“yes”=1)
PARK_DIST1	Numeric	Park distance sensor (“yes”=1)
sum.extras	Numeric	Sum of extra features
Consumer-specific characteristics		
PID	Numeric	Consumer ID
ownership	Numeric	Car ownership (private versus corporate)
P_PRICE	Numeric	Purchase price (€)
PPrice_2010	Numeric	Purchase price (2010€)
Grundpreis	Numeric	MSRP (€)
MSRP_2010	Numeric	MSRP (2010€)
Diff_Price_MSRP	Numeric	Purchase price minus MSRP (2010€)
EKM	Numeric	Expected annual kilometres (KM)
holding_years	Numeric	Holding years of previous car
EKM_ths	Numeric	Expected annual kilometres (’000 KM)
FuelCost_ob	Numeric	Fuel costs (2010€)
DiscountFactor	Numeric	Discount factor
PVFuelC_sum	Numeric	Present discounted value of fuel costs (2010€)
EKM_Median	Numeric	Median EKM by car class and engine type

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Table A2: Description of variables in the transaction data set “carsurvey” (cont’d)

Name	Type	Label
KMdeduct	Numeric	Kilometres for business purposes
Taxdeduct	Numeric	Tax-deductible amount of fuel costs for kilometres for business purposes (€)
FuelCostafterTax	Numeric	Net fuel costs (2010€)
PVFCafterTax	Numeric	Net present discounted value of fuel costs (2010€)
Heterogeneity determinants		
INF_SEX	Numeric	Gender (1=“Male”; 2=“Female”)
Male	Numeric	Male (“yes”=1)
INF_AGE	Numeric	Age of driver
INF_NUMINHOUSE	Numeric	Family size
INF_CHUN18	Numeric	Children under 18
kidsgroup	Numeric	Kids group (1=“No kids under 18”; 2=“1 kid under 18”; 3=“2+ kids under 18”)
INF_SZTOWN	Numeric	Hometown size
region	Character	Region
east	Numeric	East German state (“yes”)
UNI	Numeric	University degree (0=“Not answered”; 1=“Yes”; 2=“No”)
UNI_0	Numeric	University degree (“Not answered”=1)
UNI_1	Numeric	University degree (“Yes”=1)
UNI_2	Numeric	University degree (“No”=1)
INF_HOUSEINC	Numeric	Net monthly household income (€)
financing	Numeric	Financing method (0=“Not answered”; 1=“Savings”; 2=“Loan”; 3=“Lease”)
FINANCING_0	Numeric	Financing method (“Not answered”=1)
FINANCING_1	Numeric	Financing method (“Savings”=1)
FINANCING_2	Numeric	Financing method (“Loan”=1)
PUR_CONSUSED	Numeric	Considered used car (0=“Not answered”; 1=“Yes”; 2=“No”)
CONSUSED	Numeric	Considered used car (1=“Yes”; 0=“No”)
CONSUSED_0	Numeric	Considered used car (“Not answered”=1)
CONSUSED_1	Numeric	Considered used car (“Yes”=1)
CONSUSED_2	Numeric	Considered used car (“No”=1)
CARS_INUSE	Numeric	Number of cars in regular use
Twocars	Numeric	Two cars and more in regular use (1=“Yes”; 2=“No”)
TWOCARS_1	Numeric	Two cars and more in regular use (“Yes”=1)
TWOCARS_2	Numeric	Two cars and more in regular use (“No”=1)
VC.WEEKEND	Numeric	Weekend trips (1=“Almost every day”; 2=“At least once a week”; 3=“At least once a month”; 4=“At least once a year”; 5=“Never/not applicable”)
FREQUSAGE_weekend	Numeric	Weekend trips (0=“Not answered”; 1=“Frequent usage”; 2=“Infrequent usage”)
FREQUSAGE2_weekend	Numeric	Weekend trips (1=“Frequent usage”; 0=“Infrequent usage”)
VC.HOLIDAY	Numeric	Holidays trips (1=“Almost every day”; 2=“At least once a week”; 3=“At least once a month”; 4=“At least once a year”; 5=“Never/not applicable”)
FREQUSAGE_Holiday	Numeric	Holidays trips (0=“Not answered”; 1=“Frequent usage”; 2=“Infrequent usage”)
FREQUSAGE2_Holiday	Numeric	Holidays trips (1=“Frequent usage”; 0=“Infrequent usage”)
same_make	Numeric	Bought the same car make as previous one (1=“Yes”; 2=“No”)
SAME_MAKE_1	Numeric	Bought the same car make as previous one (“Yes”=1)
SAME_MAKE_2	Numeric	Bought the same car make as previous one (“No”=1)

Continues on the next page

Table A2: Description of variables in the transaction data set “carsurvey” (cont’d)

Name	Type	Label
Hedonic price regression estimates		
grad_PVFC	Numeric	Hedonic price regression estimate PVFC
grad_HP	Numeric	Hedonic price regression estimate HP/W
grad_Weight	Numeric	Hedonic price regression estimate Weight
grad_ES	Numeric	Hedonic price regression estimate Displacement
grad_SUN1	Numeric	Hedonic price regression estimate Sunroof
grad_aircond	Numeric	Hedonic price regression estimate Airconditioning
grad_CRUISE1	Numeric	Hedonic price regression estimate Cruise control
grad_LEATHER_SEAT1	Numeric	Hedonic price regression estimate Leather seats
grad_NAV1	Numeric	Hedonic price regression estimate GPS navigation system
grad_PARK_DIST1	Numeric	Hedonic price regression estimate Park distance sensor
grad_Transmission	Numeric	Hedonic price regression estimate Transmission
grad_Year	Numeric	Hedonic price regression estimate Year
grad_Quarter	Numeric	Hedonic price regression estimate Quarter
grad_Model	Numeric	Hedonic price regression estimate Model
grad_Region	Numeric	Hedonic price regression estimate Region
graderr_PVFC	Numeric	Hedonic price regression standard error estimate PVFC
graderr_HP	Numeric	Hedonic price regression standard error estimate HP/W
graderr_Weight	Numeric	Hedonic price regression standard error estimate Weight
graderr_ES	Numeric	Hedonic price regression standard error estimate Displacement
graderr_SUN1	Numeric	Hedonic price regression standard error estimate Sunroof
graderr_aircond	Numeric	Hedonic price regression standard error estimate Air-conditioning
graderr_CRUISE1	Numeric	Hedonic price regression standard error estimate Cruise control
graderr_LEATHER_SEAT1	Numeric	Hedonic price regression standard error estimate Leather seats
graderr_NAV1	Numeric	Hedonic price regression standard error estimate GPS navigation system
graderr_PARK_DIST1	Numeric	Hedonic price regression standard error estimate Park distance sensor
graderr_Transmission	Numeric	Hedonic price regression standard error estimate Transmission
graderr_Year	Numeric	Hedonic price regression standard error estimate Year
graderr_Quarter	Numeric	Hedonic price regression standard error estimate Quarter
graderr_Model	Numeric	Hedonic price regression standard error estimate Model
graderr_Region	Numeric	Hedonic price regression standard error estimate Region
NP_residuals	Numeric	Residuals from nonparametric hedonic price regression
LCLM_grad_PVFC	Numeric	Lower bound of the confidence interval for hedonic price regression estimate PVFC
UCLM_grad_PVFC	Numeric	Upper bound of the confidence interval for hedonic price regression estimate PVFC
SIGN_grad_PVFC	Numeric	Significance of hedonic price regression estimate PVFC (“Yes”=1)
N_used	Numeric	Number of observations used in nonparametric hedonic price regression
MSE	Numeric	Mean square error of nonparametric hedonic price regression
MAPE	Numeric	Mean absolute percentage error of nonparametric hedonic price regression
SdErr	Numeric	Standard errors of nonparametric hedonic price regression
Corr	Numeric	Absolute value of Pearson’s correlation coefficient between fitted and observed values of nonparametric hedonic price regression
R2	Numeric	Pseudo-R ² of nonparametric hedonic price regression

Table A3: Description of the data sample for investigation

	Conditions
Time period	monthly level, 2000-2006
Engine type	Gasoline; Diesel
Car classes	Minis; Superminis; Compact; Middle; Upper Middle; Upper
Purchase price	∈ [1; 99] percentiles for each car class
PVFC	∈ [1; 99] percentiles for each car class
Car ownership	Private

Table A4: Descriptive statistics for vehicle attributes

			Minis	Superminis	Compact class	Middle class	Upper Middle class	Upper class
Diesel vehicles (N=38761)								
Purchase price	2010€	Mean	15,877.34	18,256.44	25,033.25	32,242.05	45,261.52	63,792.14
		SD	2,079.97	2,708.01	4,030.41	5,681.84	9,367.14	18,389.00
MSRP	2010€	Mean	15,278.01	17,509.15	24,407.64	31,685.16	42,845.23	60,104.92
		SD	1,324.04	1,868.50	2,909.88	4,044.79	6,707.22	15,000.97
Fuel consumption	l/100km	Mean	4.60	4.68	5.57	6.49	8.20	10.26
		SD	0.57	0.37	0.52	0.89	1.48	1.28
Fuel economy	km/l	Mean	22.17	21.50	18.11	15.67	12.60	9.91
		SD	3.45	1.90	1.62	1.91	2.29	1.36
Horse power	HP	Mean	70.55	85.50	111.99	130.03	163.34	192.22
		SD	3.69	16.39	19.72	20.97	29.29	34.92
Displacement	cm ³	Mean	1,323.79	1,563.28	1,881.24	2,060.10	2,539.62	3,147.84
		SD	92.65	240.12	153.33	227.37	355.49	463.61
Weight	kg	Mean	1,465.93	1,608.44	1,872.49	2,134.40	2,416.53	2,905.79
		SD	94.53	108.53	137.48	212.59	304.27	272.88
Power per weight	HP/ton	Mean	48.28	53.02	59.77	61.39	68.41	67.22
		SD	3.30	8.63	9.31	10.86	13.60	16.32
Automatic transmission	0/1	Mean	0.01	0.03	0.09	0.15	0.57	0.71
		SD	0.11	0.18	0.28	0.36	0.49	0.46
Number of consumers		N	234	4134	14884	14328	4869	312
Gasoline vehicles (N=82552)								
Purchase price	2010€	Mean	12,134.06	15,791.04	21,577.83	28,639.61	43,741.01	82,665.92
		SD	2,371.53	2,905.93	3,842.69	6,235.92	11,615.09	20,442.22
MSRP	2010€	Mean	12,073.09	15,250.87	21,143.29	28,171.04	41,608.49	78,355.04
		SD	1,737.53	2,136.72	3,062.41	4,843.61	9,208.16	16,148.83
Fuel consumption	l/100km	Mean	5.95	6.36	7.40	8.61	10.23	12.19
		SD	0.54	0.57	0.72	1.10	1.44	1.39
Fuel economy	km/l	Mean	16.96	15.84	13.64	11.79	9.95	8.30
		SD	1.68	1.36	1.26	1.39	1.31	0.85
Horse Power	HP	Mean	63.19	79.24	108.71	138.59	184.01	280.46
		SD	10.71	17.52	19.82	27.31	42.66	52.28
Displacement	cm ³	Mean	1,161.51	1,337.98	1,645.41	2,008.60	2,656.14	3,987.93
		SD	156.12	178.85	208.71	333.63	590.35	762.01
Weight	kg	Mean	1,307.88	1,509.16	1,734.13	1,948.85	2,134.23	2,491.23
		SD	95.42	100.44	121.67	157.21	178.68	235.18
Power per weight	HP/ton	Mean	48.38	52.36	62.61	71.13	85.86	112.89
		SD	7.53	10.32	10.10	12.64	16.70	19.93
Automatic transmission	0/1	Mean	0.05	0.10	0.12	0.21	0.59	0.96
		SD	0.22	0.30	0.33	0.41	0.49	0.21
Number of consumers		N	3924	19824	33232	20832	4383	357
Examples of vehicles			Citroen C1	Audi A2/S2	Audi A3/S3	Audi A4/RS4/S4	Audi A6/S6	Audi A8
			Ford Ka	Citroen C2	BMW 1 Series	BMW 3 Series	BMW 5 Series	BMW 7 Series
			Opel Agila	Ford Fiesta	Citroen C4	Citroen C5	Mercedes E	Mercedes S
			Toyota Aygo	Opel Corsa	Ford Focus	Ford Mondeo	Opel Signum	VW Phaeton
			VW Lupo	Toyota Yaris	Mercedes A, B	Mercedes C	Toyota Camry	
				VW Polo	Opel Astra	Opel Vectra	VW Touareg	
					Toyota Corolla	Toyota Avensis		
					VW Golf	VW Passat		

NOTE: MSRP, fuel consumption, weight, and car class are retrieved and matched to transaction data from ADAC web-database (<http://www.adac.de/infote strat/autodatenbank>). All € values are real values transferred into 2010€ based on the consumer price index for 2000-2010, retrieved from <https://www.destatis.de>.

Table A5: Consumer- and purchase-related characteristics (group variables)

Hometown Size				Monthly Net Income, €					
		N	Percent			N	Percent		
0	Not answered	547	0.45	0	Not answered	15764	12.99		
1	< 2,000	10142	8.36	1	< 1000	1284	1.06		
2	2,000 - 4,999	13117	10.81	2	1000 - 1249	3012	2.48		
3	5,000 - 19,999	32436	26.74	3	1250 - 1499	5321	4.39		
4	20,000 - 49,999	22881	18.86	4	1500 - 1749	7166	5.91		
5	50,000 - 99,999	11341	9.35	5	1750 - 1999	8806	7.26		
6	100,000 - 299,999	13987	11.53	6	2000 - 2249	10152	8.37		
7	300,000 - 499,999	4286	3.53	7	2250 - 2499	10358	8.54		
8	≥500,000	12576	10.37	8	2500 - 2999	12618	10.40		
	Overall	121313	100	9	3000 - 3499	14654	12.08		
				10	3500 - 3999	14107	11.63		
				11	4000 - 4999	10091	7.90		
				12	5000 - 7499	6478	5.07		
				13	7500 - 9999	1411	1.16		
				14	10000 - 14999	662	0.55		
				15	≥15000	557	0.46		
					Overall	121313	100		
Children under 18				Number of cars in use					
		N	Percent			N	Percent		
1	None	90211	74.36	1	One	67569	55.70		
2	One	16228	13.38	2	Two	44310	36.53		
3	≥Two	14874	12.26	3	Three	7679	6.33		
	Overall	121313	100	4	≥Four	1755	1.45		
					Overall	121313	100		
Financing				Holiday driving					
		N	Percent			N	Percent		
0	Not answered	5628	4.64	0	Not answered	NA	8315	6.85	
1	Savings	75652	62.36	3	At Least Once A Month	Frequent	5969	4.92	
2	Loan	39869	32.86	4	At Least Once A Year	Frequent	94079	77.55	
3	Lease	164	0.14	5	Never/Not Applicable	Infrequent	12950	10.67	
	Overall	121313	100			Overall	121313	100	
Weekend driving				Holiday driving					
		N	Percent			N	Percent		
0	Not answered	NA	13843	11.41	0	Not answered	NA	8315	6.85
1	Almost Every Day	Frequent	15245	12.57	3	At Least Once A Month	Frequent	5969	4.92
2	At Least Once A Week	Frequent	58544	48.26	4	At Least Once A Year	Frequent	94079	77.55
3	At Least Once A Month	Infrequent	26313	21.69	5	Never/Not Applicable	Infrequent	12950	10.67
4	At Least Once A Year	Infrequent	7368	6.07			Overall	121313	100
5	Never/Not Applicable	Infrequent	372	0.31					
	Overall	121313	100						

Table A6: Descriptive statistics for the nonparametric hedonic price regression estimates (cont'd)

		Diesel Vehicles					Gasoline Vehicles				
		Mean	SE	P10	Median	P90	Mean	SE	P10	Median	P90
Leather seats	Minis	3.31E-04	3.44E-04	-1.31E-05	3.31E-04	6.75E-04	3.07E-02	1.83E-03	7.12E-03	2.90E-02	5.63E-02
	Superminis	8.39E-02	4.93E-03	9.49E-03	8.45E-02	1.48E-01	5.97E-02	2.52E-03	-1.09E-02	6.90E-02	1.28E-01
	Compact Class	8.15E-02	1.85E-03	8.15E-03	7.73E-02	1.62E-01	4.14E-02	1.28E-03	-1.38E-02	3.50E-02	1.08E-01
	Middle Class	4.62E-02	9.90E-04	-1.68E-02	4.79E-02	1.07E-01	2.97E-02	1.00E-03	-3.93E-02	3.08E-02	9.43E-02
	Upper Middle Class	1.57E-02	3.84E-04	-3.61E-03	1.39E-02	4.00E-02	6.72E-03	4.81E-04	-1.44E-02	4.67E-03	3.01E-02
	Upper Class	6.10E-03	6.43E-04	-2.82E-03	4.01E-03	1.58E-02	-1.40E-03	1.34E-03	-1.83E-02	-6.22E-03	1.98E-02
GPS navigation	Minis	8.64E-02	5.50E-02	3.26E-03	6.54E-02	1.90E-01	1.40E-02	4.15E-03	-8.54E-03	1.28E-02	4.24E-02
	Superminis	1.56E-02	1.91E-03	-4.03E-03	1.14E-02	3.75E-02	2.23E-02	2.19E-03	-2.09E-02	1.44E-02	8.18E-02
	Compact Class	4.85E-02	1.41E-03	-7.82E-03	4.60E-02	1.15E-01	5.21E-02	1.72E-03	-1.92E-02	5.20E-02	1.36E-01
	Middle Class	2.94E-02	6.22E-04	-5.32E-03	2.88E-02	6.61E-02	4.62E-02	1.08E-03	-1.74E-02	4.66E-02	1.11E-01
	Upper Middle Class	2.48E-02	3.97E-04	4.35E-03	2.44E-02	4.63E-02	2.62E-02	6.79E-04	-4.51E-03	2.89E-02	5.67E-02
	Upper Class	1.46E-02	1.49E-03	-3.46E-03	1.02E-02	4.04E-02	3.57E-03	3.55E-04	-1.50E-03	1.51E-03	1.10E-02
Park distance sensor	Minis	-1.03E-04	3.77E-05	-3.67E-04	-9.71E-05	3.32E-05	3.16E-03	3.13E-03	-2.01E-02	-1.77E-03	2.70E-02
	Superminis	1.28E-02	1.37E-03	-1.51E-02	1.45E-02	4.21E-02	6.41E-02	2.19E-03	-1.71E-02	5.98E-02	1.57E-01
	Compact Class	1.68E-02	4.38E-04	-8.79E-03	1.47E-02	5.00E-02	1.92E-02	4.39E-04	-1.06E-02	1.54E-02	5.82E-02
	Middle Class	1.24E-02	3.22E-04	-1.48E-02	1.24E-02	3.97E-02	1.70E-02	3.81E-04	-1.41E-02	1.60E-02	5.04E-02
	Upper Middle Class	7.29E-03	3.14E-04	-1.02E-02	6.38E-03	2.59E-02	5.93E-03	4.02E-04	-1.42E-02	5.35E-03	2.73E-02
	Upper Class	5.31E-04	1.22E-04	-8.17E-04	9.33E-05	2.77E-03	5.44E-04	1.44E-04	-1.95E-03	1.73E-04	3.77E-03

NOTE: Based on the local-linear hedonic price regression with cross-validation bandwidth selection method based on the Akaike information criterion (AICCV), Gaussian kernel for continuous variables, and Li-Racine kernel for discrete variables. Effects for make, year, quarter-of-year, and region fixed effects are not shown. For continuous variables (PVFC, HPW, Weight), the statistics for both the gradient estimates of the hedonic price function with respect to the attributes (“Estimate”) and their standard errors (SE) are shown.

Table A7: Quantile regression for undervaluation of fuel savings on a set of consumer-related characteristics

Variable	Diesel vehicles (N=31248)						Gasoline vehicles (N=67352)					
	OLS	Q10	Q25	Q50	Q75	Q90	OLS	Q10	Q25	Q50	Q75	Q90
Male	-0.17 (0.20)	-0.45 (0.41)	-0.46** (0.23)	-0.11 (0.16)	-0.10 (0.18)	-0.14 (0.16)	-0.25** (0.10)	-0.62*** (0.19)	-0.50*** (0.11)	-0.13* (0.07)	0.01 (0.07)	-0.01 (0.05)
Age	-0.00 (0.01)	-0.00 (0.02)	-0.00 (0.01)	0.00 (0.01)	0.00 (0.01)	-0.00 (0.01)	-0.02*** (0.00)	-0.03*** (0.01)	-0.02*** (0.00)	-0.01*** (0.00)	-0.01*** (0.00)	-0.01*** (0.00)
Children under 18	-0.05 (0.09)	0.17 (0.18)	-0.21** (0.10)	-0.31*** (0.09)	-0.37*** (0.08)	-0.19** (0.09)	0.08 (0.06)	0.15 (0.12)	0.06 (0.08)	0.04 (0.06)	-0.02 (0.05)	-0.08** (0.04)
Town size	-0.12*** (0.04)	-0.28*** (0.10)	-0.09** (0.05)	-0.06* (0.03)	-0.06* (0.04)	-0.06** (0.03)	-0.09*** (0.02)	-0.10** (0.05)	-0.05** (0.03)	-0.03* (0.02)	-0.02 (0.02)	0.00 (0.01)
University degree (NA)	5.95 (13.04)	15.04 (943.48)	11.40 (115.42)	5.96 (37.48)	-0.05 (82.18)	-3.95 (242.70)	-17.69* (10.73)	1.85 (189.36)	-10.98 (42.20)	-21.20 (21.52)	-28.30 (22.04)	-32.53 (24.69)
University degree (yes)	-1.06 (1.96)	-0.82 (4.51)	-0.79 (2.91)	0.64 (1.79)	0.89 (2.27)	1.46 (2.00)	-6.82*** (1.41)	-9.34** (4.29)	-7.16*** (2.35)	-6.08*** (1.52)	-3.64*** (1.06)	-3.45*** (0.89)
Financing (NA)	0.36 (0.37)	0.86 (0.70)	0.35 (0.45)	-0.12 (0.33)	-0.16 (0.31)	0.06 (0.31)	0.29 (0.20)	0.40 (0.36)	0.40* (0.21)	0.25 (0.16)	0.10 (0.15)	0.05 (0.11)
Financing (Savings)	1.04*** (0.17)	2.00*** (0.33)	1.31*** (0.18)	0.59*** (0.16)	0.25* (0.15)	0.03 (0.13)	0.27*** (0.10)	0.45** (0.20)	0.20* (0.11)	0.25*** (0.07)	0.15** (0.07)	0.14** (0.06)
Cons. used car (NA)	-1.06 (0.68)	-1.34 (1.60)	-0.88 (0.93)	-1.26** (0.60)	-0.39 (0.72)	-0.56 (0.42)	-0.81** (0.38)	-1.76* (0.98)	-0.99* (0.60)	-0.46* (0.28)	-0.30 (0.27)	-0.54** (0.25)
Cons. used car (yes)	0.70*** (0.16)	1.98*** (0.30)	0.73*** (0.17)	0.37** (0.15)	0.06 (0.14)	0.00 (0.12)	0.68*** (0.10)	1.37*** (0.20)	0.73*** (0.11)	0.46*** (0.08)	0.20*** (0.07)	0.07 (0.06)
Income (NA)	2.05 (1.54)	1.14 (3.74)	3.14 (2.36)	3.54** (1.43)	2.71 (1.78)	2.55 (1.78)	-0.45 (0.94)	1.50 (2.85)	-0.43 (1.28)	-1.27* (0.70)	-0.24 (0.68)	-0.13 (0.64)
Income (under 1000)	0.67 (1.79)	-1.11 (4.70)	2.46 (2.49)	2.26 (1.57)	2.37 (2.13)	2.59 (1.94)	0.15 (1.01)	2.49 (2.95)	0.08 (1.29)	-1.28* (0.73)	-0.17 (0.69)	0.05 (0.66)
Income (1000-1249)	2.11 (1.65)	1.11 (5.02)	3.38 (2.60)	3.29** (1.60)	3.07 (1.87)	2.40 (1.99)	-0.06 (0.96)	2.48 (2.89)	-0.05 (1.28)	-1.34* (0.73)	-0.27 (0.69)	-0.26 (0.65)
Income (1250-1499)	2.51 (1.59)	1.33 (4.05)	3.53 (2.50)	4.15*** (1.48)	3.01 (1.92)	2.51 (2.03)	0.10 (0.95)	2.25 (2.82)	0.16 (1.27)	-1.13 (0.72)	-0.14 (0.66)	-0.12 (0.63)
Income (1500-1749)	2.24 (1.57)	1.67 (3.74)	3.29 (2.44)	3.65** (1.46)	2.71 (1.83)	2.51 (1.80)	0.10 (0.95)	2.23 (2.84)	0.04 (1.26)	-1.07 (0.71)	-0.17 (0.67)	-0.06 (0.63)
Income (1750-1999)	2.43 (1.57)	2.36 (3.72)	4.01* (2.35)	3.90*** (1.40)	2.30 (1.78)	2.20 (1.72)	0.21 (0.94)	2.59 (2.84)	0.24 (1.25)	-1.01 (0.70)	-0.08 (0.66)	-0.06 (0.62)
Income (2000-2249)	2.34 (1.55)	1.82 (3.69)	3.69 (2.39)	3.58** (1.41)	2.41 (1.79)	2.33 (1.79)	-0.39 (0.94)	1.68 (2.89)	-0.57 (1.30)	-1.51** (0.71)	-0.32 (0.66)	-0.00 (0.63)
Income (2250-2499)	1.92 (1.55)	0.44 (3.70)	3.24 (2.38)	3.55** (1.41)	2.13 (1.81)	2.11 (1.80)	-0.13 (0.94)	2.06 (2.87)	-0.23 (1.28)	-1.23* (0.71)	-0.26 (0.66)	-0.06 (0.64)
Income (2500-2999)	1.90 (1.54)	1.87 (3.70)	3.24 (2.34)	3.27** (1.43)	2.34 (1.82)	2.40 (1.79)	-0.82 (0.94)	0.83 (2.89)	-0.96 (1.28)	-1.63** (0.72)	-0.54 (0.68)	-0.17 (0.63)
Income (3000-3499)	1.52 (1.54)	0.40 (3.71)	2.71 (2.36)	2.88** (1.42)	2.40 (1.80)	2.32 (1.77)	-0.47 (0.94)	0.88 (2.86)	-0.48 (1.30)	-1.34* (0.70)	-0.36 (0.67)	-0.10 (0.64)
Income (3500-3999)	1.26 (1.54)	-1.01 (3.78)	2.09 (2.38)	3.22** (1.42)	2.13 (1.79)	2.67 (1.78)	-0.61 (0.94)	0.91 (2.91)	-0.55 (1.27)	-1.17 (0.72)	-0.09 (0.68)	-0.02 (0.64)
Income (4000-4999)	0.98 (1.55)	-0.88 (3.73)	1.61 (2.44)	3.13** (1.46)	2.26 (1.81)	2.62 (1.78)	-2.00** (0.95)	-1.79 (2.89)	-1.68 (1.31)	-2.15*** (0.71)	-0.77 (0.72)	-0.26 (0.64)
Income (5000-7499)	0.38 (1.57)	-5.20 (4.17)	1.53 (2.56)	3.05** (1.55)	2.64 (1.83)	2.47 (1.83)	-2.26** (0.97)	-1.55 (3.09)	-2.20 (1.41)	-2.12*** (0.76)	-0.57 (0.71)	-0.19 (0.66)
Income (7500-9999)	-2.22 (1.76)	-7.75 (6.06)	-1.10 (3.10)	1.14 (1.76)	0.91 (2.14)	1.15 (2.66)	-2.47** (1.12)	-3.82 (3.56)	-4.24** (1.68)	-2.65** (1.06)	-0.70 (0.83)	0.22 (0.77)
Income (10000-14999)	0.96 (2.11)	-5.32 (6.87)	4.92 (3.87)	4.31* (2.26)	4.00 (2.84)	3.23 (2.18)	-3.07** (1.32)	-8.17 (6.07)	-2.57 (2.12)	-4.53*** (1.60)	-1.78 (1.40)	-0.40 (1.10)
Income (NA) x Uni (NA)	-5.52 (13.08)	-14.75 (943.22)	-9.93 (115.18)	-4.76 (37.50)	0.38 (82.05)	3.98 (242.59)	17.10 (10.74)	-3.09 (189.39)	10.32 (42.21)	20.89 (21.54)	28.33 (22.06)	32.26 (24.66)
Income (NA) x Uni (yes)	0.58 (2.03)	0.24 (4.70)	0.23 (3.02)	-0.49 (1.81)	-1.20 (2.24)	-1.09 (2.10)	7.11*** (1.45)	9.09** (4.34)	7.27*** (2.40)	6.10*** (1.52)	4.31*** (1.09)	3.83*** (0.91)
Income (under 1000) x Uni (NA)	-3.42 (14.60)	-12.26 (914.38)	-11.70 (115.60)	-5.51 (37.11)	2.01 (87.25)	4.52 (249.07)	11.62 (11.11)	-15.24 (193.09)	3.68 (43.08)	17.19 (22.00)	28.28 (22.21)	31.12 (26.10)
Income (under 1000) x Uni (yes)	4.37 (3.28)	10.36 (9.81)	5.83* (3.47)	0.97 (2.28)	-0.38 (2.95)	-2.75 (3.16)	6.29*** (2.01)	9.46* (5.65)	5.82** (2.62)	5.14** (2.03)	2.38* (1.40)	2.97** (1.43)
Income (1000-1249) x Uni (NA)	1.29 (18.40)	3.79 (2278.59)	0.17 (427.49)	-0.39 (145.69)	-0.45 (329.61)	0.97 (757.79)	12.75 (11.01)	-24.56 (189.27)	4.01 (43.67)	18.21 (22.29)	30.75 (22.44)	35.51 (24.67)
Income (1000-1249) x Uni (yes)	0.70 (2.98)	3.28 (7.65)	-1.47 (4.21)	-2.33 (3.44)	0.65 (2.61)	0.03 (2.40)	6.52*** (1.69)	9.17* (4.91)	6.49** (2.54)	5.51*** (1.60)	3.63*** (1.30)	3.33*** (1.08)

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Table A8: The valuation parameter from alternative assumptions

		Diesel		Gasoline		
		β	SD	β	SD	
Parametric regression						
	By car class	0.09	0.02	0.09	0.02	
Nonparametric regression						
	Over car classes	0.15	0.12	0.11	0.10	
	By car class					
	Base	0.17	0.15	0.13	0.13	
	Interest rate					
	r=10%	0.20	0.17	0.16	0.15	
	r=15%					
	Length of ownership					
	T=10 years	0.11	0.14	0.11	0.14	
	T=15 years	0.08	0.10	0.08	0.10	
Grigolon et al. (2017)	assumptions	T=15; r=6%	0.08	0.09	0.07	0.08
	Time period					
	2005-2006	0.18	0.11	0.13	0.08	

NOTE: The table presents the estimated valuation parameters (β) based on the hedonic price regression in Equation 7 under alternative assumptions. In case of separate estimation by car class, the weighted averages are displayed. “Base” corresponds to the (weighted averages of) valuation parameters from Table 6, where the length of ownership is approximated by that of the previous car in possession and interest rate is 3%. Unless otherwise stated, all specifications include 121313 observations. For the time period of 2005-2006, there are 37001 observations.