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

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Abstract

In this paper, we first recover the individual valuation of expected future fuel costs at the time of a car purchase and then explore how various factors relate to the recovered consumer undervaluation of fuel savings (on average, consumers' willingness-to-pay for a €1 reduction in fuel costs is below €0.20). For this purpose, we use survey data on the individual purchases of new passenger cars in Germany over seven years and use the expected driving intensity and the expected length of car ownership as stated by consumers to construct individual values of the present-discounted fuel costs. We then compare the variation in these values to that in the prices paid by buyers of cars with identical specifications. Individual tastes for car attributes are recovered nonparametrically within a "preference inversion" procedure for diesel and gasoline vehicles of various car classes, controlling for unobservable product attributes, correlations in tastes for car features, and the possibility to deduct a portion of annual fuel costs from taxes. Our results indicate that consumers' better financial ability, higher education, and brand loyalty facilitate a better understanding of the benefits of investments in fuel-efficient vehicles.

Keywords: Energy-efficiency paradox; hedonic discrete choice model; vehicle purchase; willingness-to-pay

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1 Introduction

The literature on consumer valuation of energy-using durable goods has long discussed the trade-off between the higher upfront capital costs of a more efficient product and the potentially lower future operating costs linked to the product's 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 better energy efficiency as much as it allows the consumer to save on the expected operating costs given expectations of energy prices and the intensity of product usage. If, however, a consumer is willing to pay less (more) than these savings, undervaluation (overvaluation) of energy efficiency occurs.

Empirical studies provide mixed evidence on the consumer valuation of the future energy costs and energy efficiency of a product. One stream of research concluded that consumers correctly account for a trade-off between capital costs and operating costs (e.g., Busse et al., 2013; Sallee et al., 2016; Grigolon et al., 2017). Other studies have found that consumers either pay little attention to energy costs when purchasing energy-using durable goods and do not make calculations for future energy savings from a more efficient product (Turrentine and Kurani, 2007; Allcott, 2011) or exhibit certain biases and errors in their valuation (e.g., "MPG Illusion"; Larrick and Soll, 2008). Although extensive financial investments in car purchases should encourage consumers to compare upfront costs and potential savings in future fuel costs, the results of previous studies have been inconclusive regarding the extent to which consumers' car purchase decisions are in line with optimal (cost-minimizing) behavior (see Greene, 2010 and Helfand and Wolverton, 2011 for an overview of the studies).

The present study aims at contributing to this discussion. We first quantify the direction and magnitude of consumers' trade-off between the higher upfront capital costs and the lower ongoing usage costs of a more fuel-efficient car. Second, we explore the role of various consumer- and transaction-specific characteristics in consumers' valuation of future fuel costs. Our investigation is based on a detailed dataset from an anonymous survey of consumers who bought a new car within the previous three months in Germany over a period of seven years. The richness and structure of the data provide several conceptual and methodological advantages for an empirical analysis to obtain insights on factors of consumer heterogeneity in the valuation of future fuel costs.

First, we complement previous research on the consumer valuation of future fuel costs by considering various types of observed consumer heterogeneity during the investigation. In addition to the observed heterogeneity in tastes for car attributes, we incorporate differences in consumers' anticipated driving intensity and length of car ownership. Most previous studies have examined the valuation of energy costs only at the aggregate (market) level while failing to account for consumer heterogeneity at all (e.g., Ohta and Griliches, 1986; Dreyfus and Viscusi, 1995; Allcott and Wozny, 2014), incorporating consumer heterogeneity in tastes for product attributes only through random coefficients within a discrete choice framework (e.g., Berry et al., 1995; Train and Winston, 2007), or controlling for socio-demographic characteristics within a hedonic demand framework (Busse et al., 2013; Fan and Rubin, 2010). Several recent studies have also incorporated differences in consumers' vehicle miles traveled. For example, Grigolon et al. (2017) used a specification of the aggregate random coefficient logit demand model (Berry et al., 1995) that accounts for heterogeneous responses to fuel costs due to consumers' differences in annual mileage. Sallee et al. (2016) used variations in the odometer readings for identical used cars to test whether used vehicle prices move one-for-one with the value of remaining future operating costs, thus identifying the value consumers place on fuel economy after controlling for other attributes. Bento et al. (2012) used a simulation to show that ignoring heterogeneity in consumers' tastes and product usage in empirical analyses can significantly affect the estimated willingness-to-pay values and could be a source of the undervaluation of energy costs highlighted in the previous literature. The current paper differs from these studies in the methodology and data used for identification.[1] In our study, we use information on the length of ownership of previous cars and the expected driving intensity for a new car as stated by the consumers themselves to construct individual values for the present-discounted future fuel costs (PVFC). The values that consumers place on the expected fuel expenses for new vehicles are then identified by comparing the variation in the individual PVFC values with that in the prices paid by buyers of cars with identical specifications. Under the "rational" cost-minimizing behavior

[1] Table B2 compares the current study with previous empirical work on consumer valuation of fuel efficiency based on revealed preferences.

principle, the prices paid for cars should move one-to-one with changes in future fuel costs for a given car quality.

Second, the presence of various consumer characteristics linked to choices in the dataset enables the current study to use a method proposed by Bajari and Benkard (2005) that addresses weaknesses of the discrete choice and hedonic demand models – two commonly used estimation approaches when using revealed preference data. One of the methodological advantages of the procedure developed by Bajari and Benkard (2005) (hereafter, the hedonic discrete choice model) is its flexibility. In this model – in contrast to the discrete choice model – the distributions of tastes for product attributes are recovered directly from the data without a need to impose any distributional assumptions (usually from a parametric family). Sonnier et al. (2007), for example, discussed the sensitivity of the evaluated willingness-to-pay values to the different parametrization and prior distributional assumptions within the discrete choice model. Moreover, the hedonic discrete choice model uses only observations for the chosen products without needing to construct choice sets faced by a consumer, which might become extremely difficult for a highly differentiated product category (such as automobiles). Thus, one does not have to make assumptions about consumer search and the sets of the considered products. The exploited estimation method extends the classical Rosen hedonic demand two-step model (Rosen, 1974) by allowing for heterogeneity in the values for consumes' willingness-to-pay for product attributes. The method can also be referred to as a "preference inversion" procedure: it recovers heterogeneous tastes from the utility maximization problem based on estimations of individual implicit prices from the hedonic price function, which serves as a budget constraint for consumers. Bajari and Benkard (2005) showed that the proposed methodology can be applied to markets featuring oligopolistic competition for both continuous and discrete product space, controlling for unobservable product attributes. Thus, the methodology relaxes the assumptions in Rosen (1974) on perfect competition, the continuum of products, and the perfect observability of product attributes. The German automobile industry is well suited for the analysis because it is a well-developed market, with the supply characterized by a large number of car versions offered.

Econometrically, in the first stage, individual tastes for car attributes, including the present-discounted value of fuel costs, are derived by estimating the hedonic price function nonparametrically. In 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 using the consumer- and transaction-related characteristics as explanatory variables. For this goal, we use the quantile regression method, which allows us to estimate the differential effects of covariates along the conditional distribution (and not only the conditional mean) of the recovered valuation parameter.

In our analysis, we focus on passenger cars with gasoline and diesel engines from six car classes defined by the German Federal Motor Transport Authority. Our sample includes only consumers who bought a car privately. In contrast to corporate car buyers, private buyers should be concerned about a car's operating costs because they will bear these costs themselves in the future. We also control for the possibility that a portion of fuel costs can be deducted from their annual income taxes if the car is used for work or business purposes. We perform the entire investigation of the relationship between purchase prices and future fuel costs separately for diesel and gasoline car buyers. In this way, we control for the problem of consumers' potential selection into a specific type of car. Previous studies have shown that under certain circumstances this selection issue may lead to biased estimation results and has been addressed by studies that jointly estimate vehicle choice and utilization (e.g., Bento et al., 2009; Feng et al., 2013). In our study, we do not model car utilization. We condition consumers' purchase decisions on their anticipated driving. For example, if a consumer expects to drive intensively, s/he might choose a diesel car because it has lower fuel consumption and because diesel fuel prices are lower. However, diesel vehicles are more expensive than gasoline cars. As a result, the consumer faces a trade-off between the upfront costs and the savings in future fuel costs within the car type. Additionally, if consumers are cost-minimizing, they should value a car of a particular engine type as much as it allows savings in ongoing fuel costs. We do not model consumers' choice of a diesel or a gasoline vehicle conditional on the anticipated driving intensity, and this stage of the consumer's decision should not affect the valuation parameters in our setting.

Our estimation results indicate that there is a high degree of undervaluation of potential fuel savings – for a €1 reduction in future fuel costs, the sampled consumers are estimated to be willing to pay no more than €0.20 on average. The estimated willingness-to-pay varies among engine types and car classes, with higher average valuations for higher car classes and for diesel vehicles. The estimates remain robust to specifications under various assumptions, including the time period under investigation, the interest rate, and the length of car ownership.

Our finding of a high level of consumer myopia contrasts to the recent study by Grigolon et al. (2017), who used European data. In their analysis, the authors could not reject the hypothesis of consumers' full valuation of fuel costs. The discrepancy in these results could lie in both the methodologies applied and the characteristics of the dataset used. The estimation in Grigolon et al. (2017) was performed for several European countries and with recent observations that might lead to a higher valuation parameter. Furthermore, the authors included in their estimation the heterogeneity in consumers' driving patterns by drawing from the distribution of the aggregate mileage in the UK. In contrast, we use the expected annual kilometers to be driven with the chosen car as stated by the consumers themselves. Thus, for the sample analyzed in our study, we can directly relate the heterogeneity in mileage to the 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 consumers' tastes for car attributes, we allow for correlation in tastes, and we do not need to make assumptions on the total market size and consumer choice sets.

By exploring the effects of consumer- and purchase-related factors on the valuation of fuel costs, our study also contributes to the literature investigating the role of consumer heterogeneity in the discounting of future energy costs (e.g., Hausman, 1979, Coller and Williams, 1999; Newell and Siikamäki, 2015). These studies have typically been based on stated preferences from choice experiments. Our research provides empirical evidence based on revealed preferences from actual transactions. We found that a better financial ability, a higher level of education, and brand loyalty facilitate a better understanding of the benefits of investments in fuel-efficient vehicles. Some of the heterogeneity determinants we investigate have not yet been studied in the literature on the consumer valuation of energy costs. In this vein, we also address the avenue for future research proposed by Grigolon et al. (2017) by studying the reasons for consumer heterogeneity in the valuation of usage costs. This understanding is important to assist policymakers in assessing policy instruments to deal with the externalities related to car use. Data on car choices at the individual level with provided consumer characteristics and expectations regarding car usage allow us to accomplish this aim.

The remainder of this paper proceeds as follows. In section 2 we present the conceptual framework and the methodology applied. Section 3 describes the data and provides initial 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 the 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 valuations of 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 given by the consumer's income Y_n that is distributed among the purchase of a product and the consumption of all other goods (outside option). The utility function is assumed to have a known parametric functional form (Equation 1) for identification purposes (see also Bajari and Kahn, 2005).

$$U_{nj} = \beta_{n,PVFC}\text{PVFC}_{nj} + \sum_{k} \beta_{n,k} X_{kj} + \beta_{n,\xi}\xi_j + (Y_n - P_{nj}) \tag{1}$$

The utility depends on the present value of fuel costs (PVFC), other car characteristics observed (X_{kj}) and unobserved by the analyst (ξ_j), and the income (Y_n) net the paid price (P_{nj}). The coefficients $\beta_{n,PVFC}$, $\beta_{n,k}$, $\beta_{n,\xi}$ represent individual consumer tastes for the respective car characteristics, and $(Y_n - P_{nj})$ is a 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 a hedonic price function, i.e., $P_{nj} = \mathbf{p}(X_{kj}, \xi_j)$, which 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). From the first-order condition (FOC), the marginal rate of substitution between a product attribute k and the outside good equals to the partial derivative of the hedonic price function with regard to this attribute for the chosen product j^* (see Equation 2). The rate reflects the willingness-to-pay for marginal improvements in the attribute.

$$\frac{U_{nj}}{\partial X_{kj}} / \frac{\partial U_{nj}}{\partial (Y_n - P_{nj})} = \frac{\partial \mathbf{p}(X_{kj^*}, \xi_{j^*})}{\partial X_{kj}} \tag{2}$$

Our main focus is on the consumer valuation of the present-discounted value of expected fuel costs ($\beta_{n,PVFC}$). Formally, the value of PVFC depends on fuel prices (FP, €/liter), a vehicle's fuel consumption (FC, liter/100 km), the annual kilometers driven (KM), the length of car ownership (T, years), and the interest rate (r). We follow the previous literature and assume that consumers' expectations of future fuel prices follow a random walk for real fuel prices measured at the time of a car purchase (see e.g., Anderson et al., 2013). The interest 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 discuss the implications of this assumption below. 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 car specifications allows us to mitigate the possible effect of omitted car attributes on the estimation (more details are given in Section 3).

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

The utility specification in this setting is given in the "willingness-to-pay" space (see e.g., Train and Weeks, 2005). Hence, the individual's willingness-to-pay for marginal savings in PVFC is given by $\beta_{n,PVFC}$ after controlling for tastes for other product attributes, i.e. $\frac{\partial U_{nj}}{\partial PVFC_{nj}} / \frac{\partial U_{nj}}{\partial (Y_n - P_{nj})} = \beta_{n,PVFC}$. For a rational (cost-minimizing) consumer, $\beta_{n,PVFC}$ should equal -1. If $|\beta_{n,PVFC}|$ is less (more) than one, then consumers undervalue (overvalue) potential fuel savings. The parameter $\beta_{n,PVFC}$ is also referred to as "attention weight", "future valuation", or "valuation weight" in the literature (e.g., Allcott and Greenstone, 2012; Allcott and Wozny, 2014). Also note that the recovered valuation parameter is isomorphic to both the implicit discount rate at which consumers discount future costs and the consumers' required payback period. On one hand, a valuation weight for future fuel savings lower than one also implies a discount rate higher than the (assumed) market rate and a shorter required payback period. On the other hand, if we assume a higher interest rate (r) or a shorter ownership period (T) in our computation of PVFC, we will obtain a higher valuation parameter.

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 portion of data around the chosen bundles of product attributes, individual PVFC values, and purchase prices. We assume that locally the hedonic price function takes the semi-logarithmic functional form of dependency (Equation 4).

$$\ln P_{nj} = \mathbf{p}(PVFC_{nj}, X_{kj}, \xi_{nj}) \tag{4}$$

The local semi-logarithmic specification fits the data 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. Based on the utility and hedonic price specifications, individual willingness-to-pay values for savings in future fuel costs are computed as in Equation 5, where

$\dfrac{\partial \widehat{\mathbf{p}}(\cdot)}{\partial PVFC}$ is the estimate of the price gradient with respect to PVFC.

$$\widehat{\beta}_{n,PVFC} = \frac{\partial \widehat{\mathbf{p}}(\cdot)}{\partial PVFC} \tag{5}$$

In 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 preference shock at the individual level that is assumed to be exogenous and independent of other consumer-specific covariates, $E(\eta_n|Z_n) = 0$.

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

3 Data and Descriptive Evidence

3.1 Data sources and sample

For our analysis, we use a dataset that contains information on a sample of new vehicle models purchased in Germany over a period of seven years – from 2000 to 2006 (henceforth, transaction data). The data are collected by a German market research company through an anonymous survey of consumers who bought a new car within the previous three months (see Appendix A.1 for more details). The transaction data include the date of consumers' car purchase, the attributes of and prices paid for the chosen cars, and various consumer- and purchase-related characteristics for each respondent. Consumers stated values for their anticipated annual car use and their length of ownership of a previously owned car. We use these values to construct individual PVFC values for our analysis.

In the transaction data, the purchased vehicles are described by the car model name (e.g., VW Golf), the engine type (e.g., diesel), the transmission (e.g., manual), the horsepower (e.g., 125 HP), and displacement (e.g., 1997 cm^3) for each month-of-year observation. We additionally retrieve values for the fuel consumption (the weighted average between city and highway values), weight, and car class of the purchased vehicles from a web database of the largest automobile club in Germany, ADAC (http://www.adac.de/infotestrat/

autodatenbank). ADAC provides detailed information on the attributes of all unique car specifications available in Germany since the mid-1990s. We merge the additional information from ADAC to the transaction data for each observation. The month-of-year of the purchases serves as an additional condition for identifying a precise car match based on the dates of the production start and end given in the ADAC database. Information on fuel prices at the monthly level for 2000-2006 also comes from the ADAC web database. As an interest rate to discount future fuel costs, we take 3%, which is an average of the ECB interest rates for the main refinancing operations over 2000-2006 provided by the German Federal Bank (http://www.bundesbank.de/). Table 1 gives an overview of the fuel prices and interest rates over time. All monetary values in the data are inflation-adjusted by using the consumer price index (CPI), which is normalized to one in April 2010.

Table 1: Fuel prices and benchmark interest rates 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 the average annual fuel prices and interest rates from 2000 to 2006. Interest rate is the ECB rate for the main refinancing operations given by the German Federal Bank at http://www.bundesbank.de/. Information on fuel prices comes from the ADAC web database (http://www.adac.de/infotestrat/autodatenbank).

For the analysis, we use observations only on passenger cars with diesel or gasoline engines. Other types of cars are excluded because of their minimal representation among car purchases during the considered period ($< 2\%$). We also focus on consumers who purchased a car privately (in contrast to corporate purchases). For the analysis, we use observations with the price and PVFC values between the 1^{st} and the 99^{th} percentiles of their distributions within each car class and engine type. The final dataset contains 121313 observations. There are 38761 (31.95%) and 82552 (68.05%) observations for diesel and gasoline vehicles, respectively. We provide the detailed descriptive statistics for the attributes of the purchased cars in the Appendix (see Table B6).

3.2 Description of consumer heterogeneity

Buyers' differences can be described by socio-demographic and purchase-related characteristics, individual expectations of car utilization, and heterogeneous tastes for car attributes. In this study, we aim to understand how variation in consumers' valuation of the expected future fuel costs relates to the observed consumer- and transaction-specific characteristics.

First, we look at variations in both, the present values of fuel costs and individual prices paid by different consumers for the same car specifications. Additional information in our data on supplementary car features that the consumers individually selected at the time of a car purchase enables us to use very detailed product definitions. We distinguish the purchased vehicles by car class, engine type, model name, model year, transmission, horsepower, displacement, and a set of additional car features, including a sunroof, air conditioning, cruise control, leather seats, a GPS navigation system, and a park distance sensor. Accounting for these additional attributes is especially important for classes of larger cars, in which these features are more common (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 the average shares of choices for and the total amount of supplementary features of each car class over engine types.

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. Later, we also discuss the robustness of our results to this assumption. 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. 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 vast heterogeneity in consumers' willingness-to-pay values. The dispersion in purchase prices increases for more expensive cars. This finding might indicate a high heterogeneity in luxury car buyers' traits, preferences, and bargaining power with car dealers.

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
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
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. By first computing the values for the mean and standard deviation of the variables for each car specification, the averages of these values are then taken. A product specification is defined by the car model, engine type, transmission, horsepower, 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. The number of consumers is the total number of observations (not product-specific) within the engine type and car class.

In line with our expectations, buyers of diesel vehicles anticipate driving more annually than those of gasoline vehicles. The length of car ownership is greater among gasoline car owners, without significant variations across car classes. The holding length values are comparable to the average values of official statistics for Germany (6 years; see www.statista.com). Due to lower values for both diesel (fuel) prices and fuel consumption, the discounted values of fuel costs (PVFC) for diesel vehicles are significantly lower than those for gasoline vehicles (despite a higher average driving intensity) for all but the mini car classes. Dispersion of these values is significant over all car classes for both engine types. This finding indicates that some consumers expect to incur €2000-€4000 more or less in fuel expenses compared to the mean values for the car class. For our analysis, we also adjust the values of expected annual fuel expenses for the possibility that a person can use the vehicle for business trips. In Germany, individuals may deduct the value of fuel costs for a work-related car usage from their annual income tax values. The 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. These values are considered to better reflect a relationship between the individual fuel costs and the individual willingness to invest upfront in a more fuel-efficient car. Details on the construction of the net PVFC are given in Appendix.

The descriptive statistics for consumer- and transaction-specific characteristics that are used in the later analysis to determine their roles in the degree of consumers' valuation of future fuel costs are given in Table 4 (see also Appendix for more details on the variables). To facilitate the following discussion, all determinants are grouped into three types – characteristics related to demographics, car usage, and capital constraints. We discuss the effects of the investigated determinants on the individual valuations of fuel costs when we present the empirical results in Subsection 4.3.

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 for six different car classes of two engine types (diesel and gasoline) separately. The main motivation for undertaking separate estimations

Table 4: Consumer- and purchase-related characteristics

		Diesel vehicles (N = 38761)		Gasoline vehicles (N = 82552)	
Characteristics	Units	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 a 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 or 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: The table presents summary statistics (means and standard deviation) for the consumer- and transaction-specific characteristics used in the analysis. Averages for group variables (hometown size and income) are computed without the "not answered" option. Hometown size has 8 categories ranging from "$<$ 2,000" to "$\geq$ 500,000", with the median for both engine types being group 4 (20,000-49,999). Income has 15 categories ranging from "$<$€1,000" to "$\geq$€15,000", with the median for both engine types being group 8 ("€2,500-€2,999"). See Table A5 for more details.

is that the equilibrium conditions in each of these twelve markets (6 car classes $\times$ 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 determine these differences within a class. Additionally, we 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 coefficients from the pooled regressions differ significantly from those for car classes in the separate regressions (see Table B5 for the robustness check estimates). Thus, we find it important to conduct estimations by car class to correctly investigate the extent of the valuation of future fuel expenses.

To recover individual tastes for PVFC (and other car attributes), we estimate the hedonic price regression using the local-linear nonparametric method described in Li and Racine (2004). Equation 7 presents a hedonic price specification, where α_ns are locally-estimated consumer-specific coefficients on the included car attributes.

$$\ln(\mathrm{Price}_{njt}) = \mathbf{p}(\mathrm{PVFC}_{njt}, \mathrm{HPW}_{jt}, \mathrm{W}_{jt}, \mathrm{Disp}_{jt}, \mathrm{Automatic}_{jt}, \mathrm{Extras}_{sjt}, \mu_j, \tau_t, q_t, r_n, \xi_{njt}) \tag{7}$$

Our primary interest is the estimate of the price gradient with respect to PVFC, i.e. $\frac{\partial \widehat{\mathbf{p}}}{\partial PVFC}$. The identified variation in the relationship between transaction car prices and PVFC comes from differences in these values among consumers and over time (net any seasonal variations controlled by year and quarter fixed effects) after controlling for preferences for other car attributes. Horsepower related to weight (HPW) and displacement ($Disp$) control for the car performance (e.g., Berry et al., 1995), and car weight (W) refers to the size of a car (e.g., Arguea et al., 1994). $Extras$ contains dummy variables that indicate whether the purchased car has any supplementary features of those presented in Table 2.

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

Because there are too many observations for most car classes to directly use a commonly applied cross-validation method in selecting smoothing parameters (the computational time necessary for the cross-validation methods is proportional to the squared number of observations), we apply an approach outlined in Racine (1993). 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. By taking the median value over the scale factors from these subsets, one can proceed 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 (without repetition), each with 230 observations, to select the smoothing parameters. The results are robust to the amount of resamples and the number of observations higher than 230. We use 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, 2004; Hayfield and Racine, 2008).

Table 5 provides fit statistics for the estimated hedonic price regression. Overall, the results indicate a moderate to good fit of the hedonic regressions. We exclude observations for diesel vehicles from the smallest car class (minis) from our estimation because of too few observations (only 42 products; see Table 3). Summary statistics for the parameter estimates from the nonparametric hedonic price regression for all car attributes are presented in Table B.

Table 5: Fit statistics for the nonparametric hedonic price regression

	Diesel vehicles					**Gasoline vehicles**				
Car Class	N used	MSE	MAPE	SE	R2	N used	MSE	MAPE	SE	R2
Minis						3924	0.0107	0.0087	0.0017	0.7078
Superminis	4134	0.0076	0.0069	0.0014	0.6648	19824	0.0103	0.0081	0.0007	0.6896
Compact Class	14884	0.0067	0.0063	0.0007	0.7492	33232	0.0072	0.0066	0.0005	0.7749
Middle Class	14328	0.0057	0.0057	0.0006	0.8184	20832	0.0054	0.0055	0.0005	0.8738
Upper Middle Class	4869	0.0055	0.0054	0.0011	0.8784	4383	0.0051	0.0051	0.0011	0.9279
Upper Class	312	0.0077	0.0061	0.0050	0.9146	357	0.0088	0.0063	0.005	0.8666

NOTE: The table shows fit statistics for the local-linear hedonic price regression with a Gaussian kernel for continuous variables and a Li-Racine kernel for discrete variables. MSE is the mean square error; MAPE is the mean absolute percentage error; SE refers to standard errors; and R^2 is a pseudo-R^2.

4.2 Recovered consumer valuation of fuel costs

Individual valuation of fuel costs ($\widehat{\beta}_{n,PVFC}$) is given by the estimate of the price gradient with respect to PVFC that is evaluated at the prices consumer paid for the purchased vehicles. The cost-minimizing trade-off between PVFC and purchase price by a "rational" consumer requires that the willingness-to-pay for a €1 reduction in PVFC equal €1. Table 6 provides summary statistics for the estimates of this value. Here, the mean values along with the standard deviation, median, 10^{th} percentile, and 90^{th}-percentiles give an overview of the distribution of individual estimates. All price gradient values are statistically significant (not shown) and, as expected, are mainly negative (between 70% and 90% of the observations). The summary statistics are shown only for observations that have a negative price gradient of PVFC. A positive price gradient estimate implies that consumers have a greater preference for higher fuel costs, which is counter-intuitive. A higher number of positive price gradient estimates for larger car classes can be driven by both the variability common to nonparametric estimates and the presence of other factors that are not considered but important for luxury car buyers.

Overall, a high degree of undervaluation is evident. Only 0.26% of observations exhibit an overvaluation of fuel savings. On average, consumers' willingness-to-pay for a €1 reduction

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							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)
Over car classes	31481 (81.33)	0.17	0.15	0.04	0.14	0.33	68091 (82.60)	0.13	0.13	0.03	0.10	0.26	0.04 (p<0.001)

NOTE: The table displays summary statistics for the valuation parameter $\beta_{n,PVFC}$ for a subset of observations with 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 consumers. N(%) is the number and percentage of observations (compared to the full sample) with a negative price gradient of PVFC. Mean differences are the differences in the average valuation parameters for diesel versus gasoline vehicles. The price gradient is estimated by a local-linear hedonic price regression with a Gaussian kernel for continuous variables and a Li-Racine kernel for discrete variables. All price gradient values are statistically significant.

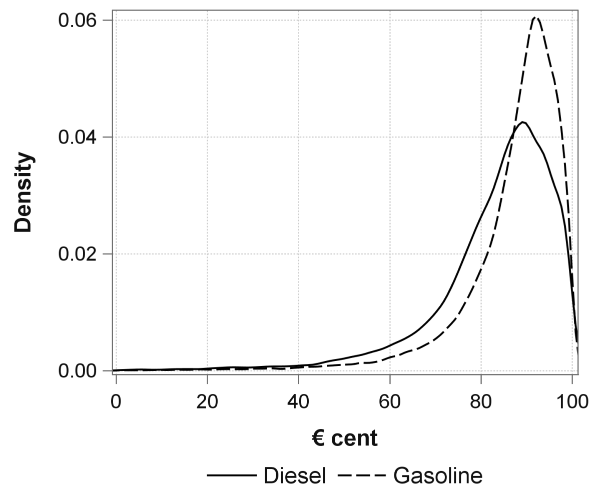
in future fuel costs is below €0.20. Buyers of diesel cars are characterized as having a lower degree of myopia on average than those of gasoline vehicles. Differences between the estimated willingness-to-pay for diesel and gasoline cars are statistically significant over all car classes. The valuation parameter that we recover in our analysis can also be used to determine individual implicit interest rates or payback periods. Our results suggest implicit interest rates of 109% and 144% over car classes on average for diesel and gasoline car owners respectively. The payback period for investments in fuel efficiency is less than one year on average. These values imply that consumers are very impatient in their decision-making and value savings in upfront costs more than savings in ongoing fuel expenses. As a robustness check, we also use different assumptions for the interest rate and the length of car ownership when computing the individual PVFC values (the results are in Table B5). A higher interest rate leads to a higher valuation weight on future fuel costs due to the interdependence of these two measures in describing consumer intertemporal preferences. As in previous studies, under a fixed time horizon (for example, 10 and 15 years), we find differences in the results in an expected direction, with a longer time period resulting in a lower valuation parameter. We also reestimate the hedonic price regression for only those consumers whose previous car was a new car. In our data, 67.86% of respondents previously possessed a newly bought car. On average, the length of ownership for a previously owned car is approximately 6 months longer if it was bought new (see Table B1). However, we did not find statistically significant differences in the estimation results for the valuation parameters from those of our base model. Relatively high standard deviation values for the valuation parameter reflect high heterogeneity among consumers. In the next section, we aim at investigating how various factors can help to explain this heterogeneous degree of fuel cost undervaluation.

4.3 Determinants of the undervaluation of fuel costs

We regress the derived individual willingness-to-pay values for a reduction in the discounted future fuel costs on the consumer- and purchase-related characteristics to understand these values' role in consumers' valuations of energy-saving technology. A 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 fuel savings and use it as our dependent variable. The variable is defined as 1 (€) less the derived individual valuation parameter ($\beta_{n,PVFC}$). Figure 1 shows that the distribution of the constructed dependent variable is negatively skewed. To obtain a comprehensive understanding of the effects for the selected heterogeneity determinants at different points along the conditional distribution of undervaluation, we apply quantile regression. In contrast to the conventional least squares regression, quantile regression estimates all 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). Quantile regression is also robust to distributional assumptions regarding the error terms.

A specification of the quantile regression in Equation 8 is estimated for each quantile τ of the conditional undervaluation distribution given all covariates, where $\gamma_0(\tau)$ and $\gamma_d(\tau)$ are the intercept and the corresponding estimate for each covariate in Z_d, respectively. The error term $\eta_n(\tau)$ is interpreted as an individual-specific taste shock. Heterogeneity determinants (Z_d) include gender, age, the number of children under 18, an indicator for university degree, hometown size, net monthly income, an indicator for considering the purchase of a

Figure 1: Distribution of consumers' undervaluation of future fuel costs



NOTE: The figure presents the kernel density function of the undervaluation distribution for both diesel and gasoline vehicles. Undervaluation is computed as 1 - (individual) willingness-to-pay for a €1 reduction in the discounted future fuel costs. The values are given in € cents.

used car, the financing method (savings versus loans), indicators for frequent holiday and weekend driving, the number of cars in use, and an indicator for purchasing the same car make as purchased previously. For the estimation we use the Frisch-Newton interior point method with standard errors obtained via the Markov chain marginal bootstrap (MCMB). It is recommended as a robust and computationally tractable estimation procedure for large datasets (Portnoy et al., 1997).

$$\text{Undervaluation}_n = \gamma_0(\tau) + \sum_d \gamma_d(\tau) Z_{dn} + \eta_n(\tau) \tag{8}$$

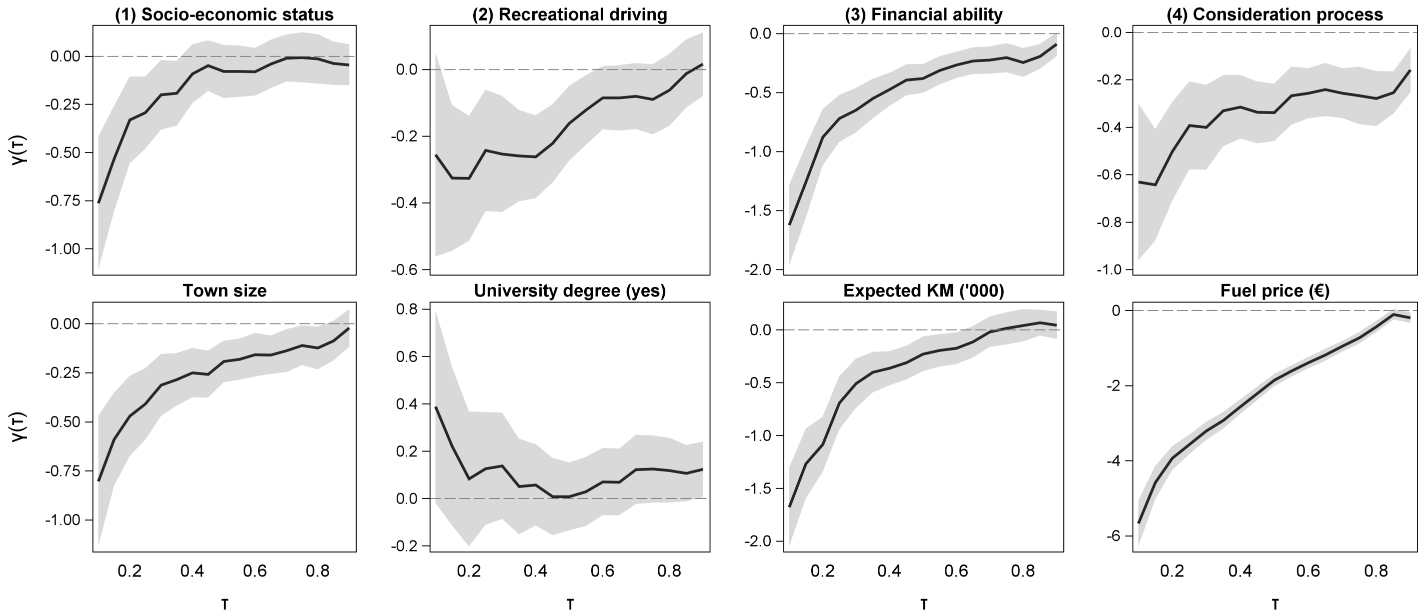
We estimate the quantile regression by including fixed effects for engine types and car classes. For the estimation, we replace missing values in the categorical variables with "NA" and treat this value as a separate category. The detailed results for all determinants can be found in Appendix (Table B3). Along with values for the covariate effects on the conditional undervaluation distribution, we report the ordinary least-squares (OLS) estimates. In our investigation, the conditional mean (OLS) estimates tend to under- or over-estimate the effects of the covariates. To assess the relative importance of each variable in explaining the undervaluation distribution, we standardize all variables prior to the estimation by subtracting their means and dividing by two standard deviations. This type of standardization allows the coefficients on continuous variables to be comparable with those on binary ones, as by construction, the latter have a standard deviation of one-half (in the case of equal probabilities). Thus, each coefficient $\gamma_d(\tau)$ shows a change in the conditional quantile of the undervaluation (in € cents) when the explanatory variable increases by two standard deviations, ceteris paribus.

Because many determinants are interrelated and may thus refer to the same underlying component, we also arrange all heterogeneity determinants into homogeneous clusters. For this purpose, we apply an oblique principal component cluster analysis (e.g., Rey et al., 2012; Enki et al., 2013), which groups together variables that are strongly related to one another and yet allows the clusters to be correlated. We should note that score values for clusters of variables are not always unequivocally interpretable, as the same score value can result from different combinations of the weighted variables. In our analyses, the resulting four clusters of variables have a relatively clear interpretation and yield results that are in line with the effects from a regression with non-clustered variables. The retained clusters have low-to-moderate inter-cluster correlations between 0.06 and 0.24 in absolute values. We include all details on the clustering procedure in Appendix.

The effects of the clustered and standardized determinants are presented in Figure 2 (see also Table B4), which depicts the changes in the coefficients over quantiles of the undervaluation distribution. Negative $\gamma_d(\tau)$ values for the effects indicate a lower myopia in terms of the expected future fuel costs. Overall, the estimated effects are found to be more pronounced at lower and average quantiles of the undervaluation distribution. The values for the standardized coefficients indicate that determinants that reflect capital constraints and consumers' financial ability make a greater contribution to the explanation of the valuation of future fuel expenses than other types of variables (such as the purposes of car use and the characteristics of the decision process). Expected annual driving and fuel prices both 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 decreases.

The effects of socio-demographic characteristics indicate that male and older drivers,

Figure 2: Effects of determinants on undervaluation of future fuel costs



NOTE: The figure depicts the quantile processes for each covariate based on the quantile regression. Explanatory variables are standardized to have means of zero and standard deviations of 0.5. Each coefficient shows a change in the undervaluation (in € cents) as the explanatory variable increases by two standard deviations. Negative $\gamma_d(\tau)$ values correspond to lower myopia. The number of observations used is 98873.

and those with more minors in the family can better assess the potential savings in future fuel costs. This phenomenon can be linked to a reduced uncertainty in one's own driving preferences due to these consumers' longer experience with cars, their better assessment of car information, and the importance of any marginal changes in expenditures for consumers with larger families. For example, De Borger et al. (2016) found that an increase in the number of children in the household raises the demand for driving. Additionally, due to the lower disposable wealth for these consumers, the importance of making the "right" car choice should increase. These effects are summarized in the first cluster of variables as **"socio-economic status"**. Higher score values for this cluster correspond to being male, older, and having more children drivers. This cluster also includes a variable that indicates the financing method for the car purchase (own savings versus loans), with higher scores being linked to the use of savings. Educational level does not yield a significant effect in the model with clustered variables. However, in the model that includes all determinants separately, holding a university degree results in lower myopia as well. The significant negative effect of hometown size shows that buyers from larger cities have lower myopia regarding fuel expenditures. This pattern may be explained by relatively lower income levels or a worse availability of various car specifications in smaller towns.

Previous studies have demonstrated that low-income households consistently place lower values on future fuel costs (e.g., Berkovec and Rust, 1985). In our study, we confirm this pattern. The cluster of variables that we label **"financial ability"** has higher values for buyers with higher incomes and for those who have more than one car in regular use. A better assessment of fuel costs for these consumers is explained by these consumers' better ability to invest in improved car quality and their greater experience with cars.

While some previous studies have shown that the purpose of car use significantly affects the choice of car type (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 that a higher expected car use for recreational purposes (holiday and weekend driving) improves consumers' recognition of the value of fuel economy, resulting in less bias. The combined effect of the holiday and weekend driving variables is given by the cluster component **"recreational driving"**.

Our last cluster of variables includes indicators for whether a consumer has considered purchasing a used car and whether the make of a previously owned car was purchased again. We refer to this cluster as the **"consideration process"**. Consumers with higher scores for this cluster are those who have considered purchasing new cars and those who have purchased the same car make. We link the negative effect of this group of variables on undervaluation to the complexity of the decision process. A smaller bias for brand-loyal consumers may be explained by the costs of processing and searching 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 preselected brand. Information on product attributes may also be more easily available and more reliable for new rather than used cars. Thus, the results for these variables provide support for the theory of choice overload (e.g., Iyengar and Lepper, 2000) and are in line with the findings of studies on consumers' strategies to deal with information overload (e.g., Walsh et al., 2007; Foxman et al., 1992). Consumers' consideration of a used car can also be motivated from an economic perspective. If a consumer has restricted financial resources, the second-hand market becomes a valid alternative to search for a vehicle (e.g., Guiot and Roux, 2010). In our sample, consumers with the lowest incomes tend to consider used vehicles more often (on average 1.5 times more often). Thus, being indicative of consumer financial ability, both variables – income and the consideration of used cars – have an impact on the valuation of fuel savings in the same direction.

5 Policy Implications

Our findings of a low valuation weight of future fuel costs and high implicit interest rates for buyers of new vehicles in Germany suggest that consumers value savings in upfront costs much more than savings in ongoing fuel expenses. In this case, consumers do not choose cost-effective, energy-efficient technology despite its lower fuel costs at current energy prices – a pattern defined in the literature as the "energy-efficiency paradox" (Jaffe and Stavins, 1994). Many studies discuss potential explanations for this phenomenon (e.g., Allcott, 2011; Gillingham and Palmer, 2014; Gerarden et al., 2015; Metcalf and Hassett, 1999; and Tietenberg, 2009, to name a few). All factors have been related either to market failures (insufficient information provision and capital constraints) or behavioral anomalies (inconsistent time preferences, cognitive limitations, choice inertia, and usage uncertainty). The recommendations for policy implementations depend on the prevailing explanations. A Pigouvian tax on energy that optimally deals with energy use externalities under the full valuation of energy costs would not provide the first-best outcome if agents are imperfectly informed or exhibit behavioral anomalies (e.g., Allcott and Greenstone, 2012).

In our investigation, we find that socio-economic conditions explain many differences among consumers in terms of their degree of fuel cost valuation. Factors that relate to car buyers' financial ability and the importance of capital constraints make a significant contribution to reducing consumers' myopia. Consumers with a lower level of financial stability may not be able to afford cars with better fuel economy and therefore must make suboptimal choices. Because investment inefficiencies in consumers' decisions may discourage manufacturers from developing cars with better fuel economy, it is also crucial to provide economic incentives on the supply side. Proper functioning of the capital market and the provision of subsidies to consumers and/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 consumers' limited attention to fuel expenses or insufficient information to identify economically optimal choices. Insufficient information refers to a market failure, whereas limited attention refers to a behavioral failure. The latter is also linked to nonstandard decision-making directly or nonstandard beliefs indirectly through consumers' cognitive limitations (Gillingham and Palmer, 2014; DellaVigna, 2009). It is difficult to disentangle these causes empirically. However, several insights can be inferred from the present research. For our data, information on car fuel efficiency during the sample period (2000-2006) may have been costly for consumers to obtain. The national German regulation regarding energy efficiency labeling for new passenger cars came into force only after November 2004. Although a re-estimation of the hedonic price regression for the 2005-2006 period does not yield significantly different valuation parameters (see Table B5), data on recent years may indeed lead to a higher valuation parameter, as information provision has improved over time. However, for example, in their recent study on the U.S. automobile market, Allcott and Knittel (2017) found no statistically significant effect of information on the average fuel economy of purchased vehicles.

In addition to the costs of acquiring information, limited attention to energy cost savings can also result from cognitive limitations and the difficulty of processing all information correctly. One of the errors that consumers can make in their perceptions of total energy costs is presented by the "MPG Illusion" (Larrick and Soll, 2008; Allcott, 2011), which suggests a systematic misperception of improvements in fuel efficiency when expressed in miles per gallon (MPG). Although this perceptual error does not indicate the undervaluation of fuel cost savings per se, it highlights computational difficulties that consumers may encounter. Because in Germany, cars' fuel economy is presented in liters per kilometer, a measure linearly linked to fuel costs, it should have been easy for consumers to assess potential fuel savings from more fuel-efficient vehicles. Therefore, the recovered undervaluation of energy cost savings in our study is explained by other market and behavioral failures.

Because we observe only one point of consumers' investment decisions, we cannot interpret the high implicit discount rate (or high degree of myopia) as being a result of time-inconsistent preferences. For this, one must observe discount rates of the same consumers over time. However, a lack of self-control (Thaler and Shefrin, 1981), which is also related to the time-inconsistency of preferences, may still be an explanation for our findings. A less-fuel-efficient vehicle with a lower purchase price may appear "tempting" to consumers despite its relatively high operating costs. Thus, as Tsvetanov and Segerson (2013) proposed, energy efficiency standards that limit the supply of cheap but fuel-inefficient vehicles could serve as a commitment device to address investment inefficiencies in consumer choices.

The role of uncertainty in consumers' expectations regarding car usage should have a lower impact on the results of our investigation than on those of previous studies because the sample of consumers used in the current analysis consists of those who had previously possessed a car. Experience with a car should help consumers understand their own driving preferences. Additionally, we control for the purpose of car use as an indicator of 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 reduction in fuel costs increases.

The recovered consumer heterogeneity in the degree of investment inefficiency also highlights the importance of designing targeted policies to motivate 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) indicated, "welfare gains will be larger from a policy that preferentially affects the decisions of consumers subject to investment inefficiencies" (p.5). Our results suggest that capital constraints and the potential complexity of car choice tasks are important determinants of the recovered undervaluation of car fuel efficiency. A set of complementary policies could help to reduce the energy-efficiency gap. In conjecture with information provision policies that contribute to a better understanding of potential savings in future fuel costs, financial incentive schemes could efficiently support consumers with tighter capital constraints. In addition to tools that address market failures, the development of social preferences could help to overcome certain behavioral failures. For example, consumer attention could be shifted to fuel efficiency as a signal of pro-environmental behavior to peers (Gsottbauer and van den Bergh, 2011). Hence, policy tools should aim at developing intrinsic (inner motivation) and extrinsic (external financial and non-financial) incentives for consumers to embrace better fuel efficiency.

6 Conclusion

Using observed choices of new cars by a sample of consumers in Germany within the 2000-2006 period, the present study first quantified the direction and magnitude of these 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, this study explained the recovered heterogeneity in consumers' valuation with the help of observed consumer- and purchase-related characteristics.

During our analysis, we controlled for various dimensions of consumer heterogeneity. Along with heterogeneity in tastes for car attributes, we accounted for consumer differences in the expected car usage intensity and car ownership length. These additional sources of consumer heterogeneity allowed us to contrast the variation in the individual values for present-discounted fuel expenses with that in the prices individually paid by buyers of identical cars. This process constituted our identification strategy to recover consumers' valuation of potential fuel savings from better fuel economy. A detailed definition of car specifications enabled the analysis to control for many car attributes (including supplementary features such as leather seats or a sunroof), thus reducing a potential source of omitted variable bias.

We recovered individual values for the present-discounted fuel costs 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 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 accounts for correlation in consumer tastes for car attributes without needing to model the variance-covariance matrix.

In our study, we found that consumers do not fully recognize the value of cost-effective, energy-efficient technology at the time of purchasing a car. The results remain robust to various assumptions on the interest rate, the length of ownership, and the time period under investigation. The rate at which consumers undervalue future energy costs varies significantly across buyers of various engine technologies and car classes. We also explored the effects of various determinants on the extent of consumers' valuation of future fuel savings from a more fuel-efficient car. Some of these factors have not yet been discussed in the literature on consumers' valuation of energy costs (e.g., considering the purchase of a used car and recreational driving). Using quantile regression, we recovered the covariate effects for various quantiles of the conditional distribution for the valuation parameter.

There are several possible concerns and extensions of the present analysis. First, the current paper did not account for potential rebound effects of reduced fuel costs, either direct (impact on car usage) or indirect (impact on the consumption of other energy-consuming goods). We assumed that annual kilometers driven remain constant over the entire car ownership period and are equal to the consumers' stated expected driving intensity. We found this assumption justifiable for the present research because we aimed at recovering the value of fuel costs for consumers at the time of car purchase conditional on their expected driving. Additionally, in our application, we do not consider a PVFC measurement error.

If PVFC is measured with error, the recovered undervaluation may partially be a result of attenuation bias rather than a bias in the consumer decision-making. However, the noise-to-signal ratio should be unrealistically large (around six) to be the only reason for the low valuation weight we obtain. Furthermore, the results of our second-stage analysis of the effects of heterogeneity determinants on the valuation distribution should not be affected by the PVFC measurement error.

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

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A Data Appendix

A.1 Survey details

The dataset used in the study is provided by a market research company for (non-commercial) scientific research. A sample of new car buyers in Germany was surveyed briefly after the purchase (within the first 3 months). The survey was conducted by phone (CATI). We do not have information on the response rate. The dataset contains information on the car models purchased by a sample of consumers along with the car attributes, prices paid for the chosen cars, and various consumer- and purchase-related characteristics. We use a sample of private buyers of cars with gasoline or diesel engines from six car classes over a time period of 7 years (see Table A1).

The sample of respondents we use in our analysis is comparable to new car buyers and the population, with only slight differences in certain characteristics (e.g., there are only repeat car buyers in the sample; Table A2). The sources of information for new car buyers and the population are given in Table A4. The representation of car classes in the survey is also similar to those shares in new car registrations in Germany (Table A3).

Table A1: 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	$\in [1; 99]$ percentiles for each car class
PVFC	$\in [1; 99]$ percentiles for each car class
Car ownership	Private

Table A2: Characteristics of the data sample compared to the population and new car buyers in Germany (average values for 2000-2006)

			Survey	Population	New car buyers
Number of persons			121313	82.54×10^6	3.33×10^6
Gender	(Male=1; Female=0)		0.75	0.49	0.71
Age	(number)		50.89	41.81	49.27
Net monthly income	(€)		2500-2999 ([a])	1467.43	2910.71
	Not answered	(%)	12.99	NA	5.00
	Under 1000	(%)	1.06	NA	1.80
	1000 - 1249	(%)	2.48	NA	3.00
	1250 - 1499	(%)	4.39	NA	6.40
	1500 - 1749	(%)	5.91	NA	7.40
	1750 - 1999	(%)	7.26	NA	8.40
	2000 - 2499	(%)	16.91	NA	16.20
	2500 - 2999	(%)	10.40	NA	15.20
	3000 - 3499	(%)	12.08	NA	12.40
	3500 - 3999	(%)	11.63	NA	7.80
	4000 and more	(%)	14.89	NA	16.40
Number of kids under 18	(number)		0.40	0.38	NA
Family size	(number)		2.47	2.11	NA
Region	(East=1; West=0)		0.20	0.16	NA
Two and more cars in use	(share)		0.44	0.34	NA
First acquirers	(share)		0	0.22	0.13
Repeating car buyers ([b])	(share)		1	0.78	0.87
Previous car was new	(share)		0.68	NA	0.64
Annual distance driven (Diesel)	(kilometers)		18555	19389	NA
Annual distance driven (Gasoline)	(kilometers)		12199	11537	NA
Diesel cars in new registrations	(%)		31.95	39.12	
Gasoline cars in new registrations	(%)		68.05	60.63	

NOTE: "NA" stands for "not available".
([a]) The average income of the sample corresponds to group 8 (the precise average is 7.72).
([b]) The share for repeat car buyers includes both buyers of an additional car and buyers of a car as a replacement for the previous one.

Table A3: Car class shares in the survey sample and new car registrations in Germany (average values for 2000-2006)

Car class	Sales shares, %	Survey shares, %
Minis	4.94	3.43
Superminis	21.02	19.75
Compact class	36.86	39.66
Middle class	28.20	28.98
Upper middle class	7.89	7.63
Upper class	1.08	0.55
Number of observations	3.33×10^6	121313

NOTE: Average car class shares in new car registrations are based on information at www.kba.de.

Table A4: Sources of data for the population and new car buyers (2000-2006)

		Source
Number of HH	Population	https://de.statista.com/statistik/daten/studie/156950
	New car buyers	https://www.statista.com/statistics/587730
Gender	Population	https://www.destatis.de/DE/Publikationen/WirtschaftStatistik/Bevoelkerung/Bevoelkentwicklung2006.pdf
	New car buyers	https://de.statista.com/statistik/daten/studie/385492
Age	Population	https://www.destatis.de/DE/Publikationen/WirtschaftStatistik/Bevoelkerung/Bevoelkentwicklung2006.pdf
	New car buyers	https://de.statista.com/statistik/daten/studie/215576
Net monthly income	Population	https://de.statista.com/statistik/daten/studie/370558
	New car buyers	DAT-Reports 2001-2007 (https://www.dat.de/angebote/verlagsprodukte/dat-report.html)
Number of kids under 18	Population	https://de.statista.com/statistik/daten/studie/197783
	New car buyers	NA
Family size	Population	Federal Institute for Population Research (http://www.bib-demografie.de)
	New car buyers	NA
Region	Population	http://www.vgrdl.de/VGRdL/tbls/tab.jsp?rev=RV2014&tbl=tab20&lang=de-DE
	New car buyers	NA
Cars in use	Population	DAT-Reports 2001-2007
	New car buyers	NA
First acquirers/ Repeating car buyers	Population	DAT-Reports 2001-2007
	New car buyers	DAT-Reports 2001-2007
Previous car was new	Population	NA
	New car buyers	DAT-Reports 2001-2007
Annual distance driven	Population	https://www.diw.de/documents/publikationen/73/diw_01.c.433448.de/13-50-3.pdf
	New car buyers	NA
New car registrations by fuel type	Population	www.kba.de
	New car buyers	www.kba.de

A.2 Construction of the key variables

A.2.1 Net PVFC

For our analysis, we additionally adjust the values of expected annual fuel expenses by accounting for the possibility that a person can use a vehicle for business trips. Individuals may deduct the value of fuel costs for work-related car usage from their annual income tax values. According to §9 of the Income Tax Act (Einkommensteuergesetz), the German government sets a fixed deduction rate per kilometer driven for business purposes at €0.30. 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 kilometers driven above the set limits is multiplied by €0.15 (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.

A.2.2 Heterogeneity determinants

Table A5 provides the number of observations for each group of the categorical consumer- and purchase-related characteristics. For the analysis, answer options for the variables that characterize how frequently a consumer expects to use a car for weekend and/or holiday trips have been grouped into two categories "frequent" and "infrequent" usage using the median-split methodology (Iacobucci et al., 2015). A variable for frequent car use for holiday trips equals one if the usage frequency was stated at the levels of "at least once a year" or more frequently (82.51% of the sample); a variable for frequent car use for weekend driving is unity if the usage frequency was stated as "at least once a month" or more frequently (60.89% of the sample).

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

		N	Percent			N	Percent
	Hometown size				**Net monthly income, €**		
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
	Children under 18			11	€4000 - €4999	10091	7.90
				12	€5000 - €7499	6478	5.07
1	None	90211	74.36	13	€7500 - €9999	1411	1.16
2	One	16228	13.38	14	€10000 - €14999	662	0.55
3	≥Two	14874	12.26	15	≥€15000	557	0.46
	Overall	121313	100		Overall	121313	100
	Financing				**Number of cars in use**		
0	Not answered	5628	4.64	1	One	67569	55.70
1	Savings	75652	62.36	2	Two	44310	36.53
2	Loan	39869	32.86	3	Three	7679	6.33
3	Lease	164	0.14	4	≥Four	1755	1.45
	Overall	121313	100		Overall	121313	100

Table A6: Consumer- and purchase-related characteristics (cont'd)

	Initial response	Recoded response	N	Percent
	Weekend driving			
0	Not answered	NA	13843	11.41
1	Almost Every Day	Frequent	15245	12.57
2	At Least Once A Week	Frequent	58544	48.26
3	At Least Once A Month	Infrequent	26313	21.69
4	At Least Once A Year	Infrequent	7368	6.07
5	Never/Not Applicable	Infrequent	372	0.31
		Overall	121313	100
	Holiday driving			
0	Not answered	NA	8315	6.85
3	At Least Once A Month	Frequent	5969	4.92
4	At Least Once A Year	Frequent	94079	77.55
5	Never/Not Applicable	Infrequent	12950	10.67
		Overall	121313	100

A.2.3 Clustering of variables

To uncover the underlying structure of the determinants, we apply oblique principal component cluster analysis. Associated with each cluster is a linear combination of the variables in the cluster. We use the first principal component as a weighted average of the variables that explains as much variance as possible. The procedure begins with a single cluster and recursively divides existing clusters into two sub-clusters until it reaches the stopping criteria, producing a hierarchy of disjoint clusters. The cluster procedure stops splitting when every cluster has only one eigenvalue greater than one. In the analysis, the procedure stops after four clusters of variables. Approximately 54.4% of the total variation is accounted for by the four cluster components (column (3) in Table A7). The cluster summary (Table A8) gives the number of variables in each cluster and the variation explained by the cluster component. Table A9 provides an overview of variables that belong to each of four clusters. Here, the column labeled "R^2 with Own Cluster" gives the squared correlation of the variable with its own cluster component. This value should be higher than the squared correlation with any other cluster. A larger squared correlation is better. The column "R^2 with Next Closest" contains the next-highest squared correlation of the variable with a cluster component, and low values here suggest that the clusters are well separated. The column labeled "$1 - R^2$ Ratio" gives the ratio of one minus the "Own Cluster" R^2 to one minus the "Next Closest" R^2. A small "$1 - R^2$ Ratio" indicates good clustering. The cluster components are oblique. The intercluster correlation is presented in Table A10. The cluster structure in Table A11 contains the correlations between each variable and each cluster component, which are used to interpret the cluster components. The standardized scoring coefficients in Table A12 are used to compute the first principal component of each cluster. Since each variable is assigned to one and only one cluster, each row of the scoring coefficients contains only one nonzero value (zero values are removed for better readability).

Education level and hometown size were not included in the final clustering procedure because a cluster procedure with them resulted in these two determinants to be in their own cluster components. For ease of interpretation of the regression results, we multiplied the score values for the first and second cluster components by -1.

Table A7: Statistics for the clustering procedure

(1) Number of clusters	(2) Total variation explained	(3) Proportion of variation explained	(4) Minimum proportion explained	(5) Maximum second eigenvalue	(6) Minimum R-squared	(7) Maximum $1-R^2$ ratio
1	2.183	0.218	0.218	1.265	0.067	
2	3.391	0.339	0.244	1.160	0.073	0.934
3	4.476	0.448	0.296	1.017	0.143	0.861
4	5.440	0.544	0.400	0.959	0.215	0.804

Table A8: Cluster summary for 4 clusters

Cluster	Members	Cluster variation	Variation explained	Proportion explained	Second eigenvalue
1	4	4	1.602	0.400	0.959
2	2	2	1.439	0.720	0.561
3	2	2	1.261	0.631	0.739
4	2	2	1.138	0.569	0.862

Table A9: Cluster description

Cluster	Variable		R^2 with own cluster	R^2 with next closest	$1-R^2$ ratio
Cluster 1	Gender	(Male=1, Female=2)	0.215	0.024	0.804
	Age	(number)	0.683	0.075	0.342
	Children under 18	(number)	0.408	0.032	0.612
	Financing method	(Savings=1, Loan=2)	0.295	0.005	0.708
Cluster 2	Frequent holiday trips	(Yes=1, No=2)	0.720	0.036	0.291
	Frequent weekend trips	(Yes=1, No=2)	0.720	0.044	0.293
Cluster 3	Net monthly income	(group)	0.631	0.007	0.372
	Two cars or more	(Yes=1, No=2)	0.631	0.077	0.400
Cluster 4	Considered a used car	(Yes=1, No=2)	0.569	0.047	0.452
	Same make as previous	(Yes=1, No=2)	0.569	0.022	0.441

Table A10: Inter-cluster correlations

Cluster	1	2	3	4
1	1	0.234	0.219	-0.241
2	0.234	1	0.143	-0.063
3	0.219	0.143	1	-0.067
4	-0.241	-0.063	-0.067	1

Table A11: Cluster structure

Variable		Cluster 1	Cluster 2	Cluster 3	Cluster 4
Gender	(Male=1, Female=2)	0.464	0.153	0.065	-0.065
Age	(number)	-0.827	-0.250	-0.207	0.273
Children under 18	(number)	0.639	0.094	0.179	-0.149
Net monthly income	(group)	0.071	0.083	0.794	-0.014
Financing method	(Savings=1, Loan=2)	0.543	0.068	0.066	-0.065
Considered a used car	(Yes=1, No=2)	-0.216	-0.050	-0.041	0.754
Frequent holiday trips	(Yes=1, No=2)	0.189	0.848	0.120	-0.044
Frequent weekend trips	(Yes=1, No=2)	0.209	0.848	0.123	-0.063
Two cars or more	(Yes=1, No=2)	-0.277	-0.145	-0.794	0.092
Same make as previous	(Yes=1, No=2)	0.148	0.045	0.060	-0.754

Table A12: Standardized scoring coefficients

Variable		Cluster 1	Cluster 2	Cluster 3	Cluster 4
Gender	(Male=1, Female=2)	0.290			
Age	(number)	-0.516			
Children under 18	(number)	0.399			
Net monthly income	(group)			0.630	
Financing method	(Savings=1, Loan=2)	0.339			
Considered a used car	(Yes=1, No=2)				0.663
Frequent holiday trips	(Yes=1, No=2)		0.589		
Frequent weekend trips	(Yes=1, No=2)		0.589		
Two cars or more	(Yes=1, No=2)			-0.630	
Same make as previous	(Yes=1, No=2)				-0.663

B Additional Tables

Table B1: The number of observations and length of ownership by type of previous car

	N	New			Used	
		Share	Length, months		Length, months	
			Mean (SD)	Median	Mean (SD)	Median
			Diesel vehicles			
Minis	234	0.57	71.00 (43.10)	60	56.90 (35.09)	52
Superminis	4134	0.58	67.72 (40.94)	60	55.67 (35.22)	48
Compact class	14884	0.64	65.20 (38.29)	59	59.46 (36.03)	51
Middle class	14328	0.67	63.66 (36.83)	56	60.30 (35.01)	54
Upper middle class	4869	0.72	62.77 (38.52)	54	62.38 (37.58)	56
Upper class	312	0.75	63.35 (42.15)	52	54.33 (39.10)	48
Over car classes	38761	0.65	64.53 (38.13)	57	59.50 (35.78)	51
			Gasoline vehicles			
Minis	3924	0.52	81.01 (48.36)	72	63.13 (40.80)	54
Superminis	19824	0.63	79.87 (44.43)	72	66.41 (39.68)	60
Compact class	33232	0.70	73.05 (39.41)	64	66.77 (37.82)	60
Middle class	20832	0.74	66.60 (36.48)	60	66.31 (37.07)	60
Upper middle class	4383	0.79	65.20 (35.08)	60	65.03 (37.41)	60
Upper class	357	0.82	62.50 (32.63)	60	57.51 (31.08)	54
Over car classes	82552	0.69	72.54 (40.23)	62	66.22 (38.42)	60

NOTE: The share of previous cars that are used is one minus the share of previous vehicles that are new.

Table B2: Overview of the selected studies on consumer valuation of future fuel costs 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

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Study	Framework	Dependent Variable	Market	Data level	Time period	Fuel efficiency measure	Transaction prices	Taste heterogeneity	KM heterogeneity	Holding heterogeneity	Results on valuation
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	new	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 B3: Quantile regression results for undervaluation of fuel savings on a set of consumer-related characteristics

Variable	OLS	Q10	Q25	Q50	Q75	Q90
Intercept	83.95***	71.76***	81.04***	82.84***	86.98***	94.14***
	(1.09)	(3.20)	(1.48)	(1.05)	(0.84)	(0.86)
Gender (NA)	-0.94	-0.57	-0.82	-0.59	-1.18	-0.88
	(1.19)	(4.55)	(1.00)	(0.84)	(0.85)	(1.10)
Gender (Male)	-0.26***	-0.78***	-0.52***	-0.15**	0.00	-0.04
	(0.09)	(0.19)	(0.11)	(0.07)	(0.07)	(0.05)
Age	-0.01***	-0.02***	-0.02***	-0.01***	-0.01***	-0.01***
	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)
Children under 18	0.00	0.17*	-0.07	-0.12***	-0.14***	-0.11***
	(0.05)	(0.10)	(0.07)	(0.05)	(0.04)	(0.04)
Town size	-0.10***	-0.15***	-0.06***	-0.04**	-0.03**	-0.01
	(0.02)	(0.04)	(0.02)	(0.02)	(0.01)	(0.01)
University degree (NA)	-6.33	2.66	-9.39	-5.86	-2.66	-6.59
	(8.16)	(134.08)	(17.75)	(16.54)	(13.57)	(26.43)
University degree (yes)	-4.33***	-5.69*	-3.55*	-3.67***	-2.75***	-2.47***
	(1.13)	(3.32)	(2.04)	(1.07)	(1.01)	(0.78)
Financing (NA)	0.30	0.55	0.39**	0.18	-0.02	0.02
	(0.18)	(0.37)	(0.19)	(0.14)	(0.12)	(0.12)
Financing (Savings)	0.49***	0.85***	0.47***	0.31***	0.15**	0.07
	(0.08)	(0.17)	(0.09)	(0.07)	(0.06)	(0.06)
Cons. used car (NA)	-0.85**	-1.58*	-1.00**	-0.57**	-0.27	-0.56***
	(0.34)	(0.82)	(0.48)	(0.27)	(0.27)	(0.19)
Cons. used car (yes)	0.68***	1.56***	0.71***	0.39***	0.20***	0.04
	(0.08)	(0.17)	(0.09)	(0.06)	(0.06)	(0.05)
Income (NA)	0.38	1.06	0.66	-0.27	0.12	-0.05
	(0.81)	(2.03)	(1.14)	(0.68)	(0.51)	(0.59)
Income (under 1000)	0.52	1.52	0.89	-0.42	-0.02	-0.04
	(0.88)	(2.16)	(1.12)	(0.70)	(0.57)	(0.66)
Income (€1000-€1249)	0.65	1.48	1.00	-0.36	0.10	-0.24
	(0.84)	(2.03)	(1.13)	(0.68)	(0.54)	(0.58)
Income (€1250-€1499)	0.86	1.64	1.12	0.01	0.21	-0.05
	(0.83)	(1.98)	(1.09)	(0.68)	(0.51)	(0.61)
Income (€1500-€1749)	0.81	1.59	0.86	-0.03	0.17	-0.07
	(0.82)	(2.03)	(1.14)	(0.68)	(0.51)	(0.60)
Income (€1750-€1999)	0.93	2.10	1.37	0.00	0.20	-0.07
	(0.82)	(1.98)	(1.13)	(0.68)	(0.49)	(0.58)
Income (€2000-€2249)	0.50	1.02	0.70	-0.39	0.03	-0.01
	(0.82)	(2.01)	(1.12)	(0.67)	(0.51)	(0.61)
Income (€2250-€2499)	0.55	1.06	0.92	-0.23	0.03	-0.12
	(0.82)	(2.01)	(1.14)	(0.69)	(0.51)	(0.59)
Income (€2500-€2999)	0.09	0.46	0.38	-0.54	-0.20	-0.11
	(0.81)	(2.03)	(1.11)	(0.68)	(0.51)	(0.59)
Income (€3000-€3499)	0.21	0.51	0.50	-0.43	-0.01	-0.10
	(0.81)	(2.03)	(1.14)	(0.69)	(0.52)	(0.60)
Income (€3500-€3999)	0.02	-0.15	0.34	-0.18	0.13	0.04
	(0.81)	(2.03)	(1.13)	(0.68)	(0.51)	(0.58)
Income (€4000-€4999)	-0.95	-1.98	-0.61	-1.02	-0.33	-0.10
	(0.82)	(2.04)	(1.15)	(0.68)	(0.52)	(0.59)
Income (€5000-€7499)	-1.33	-3.03	-0.98	-0.96	0.01	-0.08
	(0.84)	(2.30)	(1.22)	(0.73)	(0.54)	(0.62)
Income (€7500-€9999)	-2.49***	-4.78	-3.29**	-2.11*	-0.81	0.04
	(0.95)	(3.01)	(1.50)	(1.10)	(0.70)	(0.79)
Income (€10000-€14999)	-1.72	-7.49*	-1.52	-1.78	-0.59	0.48
	(1.13)	(4.40)	(1.61)	(1.26)	(1.07)	(0.92)
Income (NA) x Uni (NA)	6.06	-3.72	9.29	5.74	2.74	6.21
	(8.17)	(133.98)	(17.77)	(16.52)	(13.57)	(26.41)
Income (NA) x Uni (yes)	4.36***	5.50	3.48*	3.82***	3.14***	2.92***
	(1.16)	(3.36)	(2.07)	(1.11)	(1.05)	(0.80)
Income (under €1000) x Uni (NA)	2.21	-15.81	6.07	2.30	2.87	5.40
	(8.60)	(135.14)	(19.13)	(16.86)	(13.71)	(27.68)

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Variable	OLS	Q10	Q25	Q50	Q75	Q90
Income (under €1000) x Uni (yes)	4.74***	7.03*	3.34	4.25***	1.91	1.85
	(1.70)	(4.15)	(2.28)	(1.31)	(1.35)	(1.20)
Income (€1000-€1249) x Uni (NA)	2.09	-23.29	1.91	3.62	4.56	8.90
	(8.56)	(134.14)	(18.98)	(17.02)	(13.59)	(26.52)
Income (€1000-€1249) x Uni (yes)	4.00***	5.89	2.75	3.08**	3.00**	2.97***
	(1.44)	(3.87)	(2.29)	(1.20)	(1.26)	(0.90)
Income (€1250-€1499) x Uni (NA)	5.92	-5.25	8.20	5.32	1.99	5.14
	(8.43)	(133.42)	(17.66)	(16.44)	(13.38)	(26.36)
Income (€1250-€1499) x Uni(yes)	4.22***	5.14	3.74*	3.77***	3.37***	2.73***
	(1.29)	(3.34)	(2.06)	(1.11)	(1.09)	(0.95)
Income (€1500-€1749) x Uni (NA)	2.99	-11.62	6.05	3.80	1.43	6.57
	(8.40)	(133.74)	(17.93)	(16.46)	(13.63)	(26.35)
Income (€1500-€1749) x Uni (yes)	4.09***	5.02	2.92	3.25***	2.21**	2.57***
	(1.24)	(3.38)	(2.18)	(1.11)	(1.05)	(0.82)
Income (€1750-€1999) x Uni (NA)	6.81	-3.47	9.94	6.18	3.00	7.69
	(8.32)	(134.10)	(17.68)	(16.51)	(13.60)	(26.32)
Income (€1750-€1999) x Uni (yes)	4.31***	5.42	3.29	3.45***	2.53**	2.40***
	(1.19)	(3.32)	(2.06)	(1.09)	(1.01)	(0.83)
Income (€2000-€2249) x Uni (NA)	6.45	-3.49	9.24	3.31	1.73	6.04
	(8.33)	(133.54)	(17.75)	(16.54)	(13.62)	(26.45)
Income (€2000-€2249) x Uni (yes)	4.59***	6.27*	3.68*	3.87***	2.81***	2.49***
	(1.18)	(3.31)	(2.04)	(1.09)	(1.01)	(0.82)
Income (€2250-€2499) x Uni (NA)	4.02	-4.70	5.90	3.32	2.10	5.48
	(8.31)	(134.10)	(17.97)	(16.40)	(13.63)	(26.15)
Income (€2250-€2499) x Uni (yes)	4.57***	5.43	3.65*	3.68***	3.16***	2.67***
	(1.18)	(3.41)	(2.08)	(1.14)	(1.05)	(0.79)
Income (€2500-€2999) x Uni (NA)	8.62	-2.18	12.20	6.49	3.77	7.31
	(8.30)	(133.49)	(17.88)	(16.42)	(13.39)	(26.30)
Income (€2500-€2999) x Uni (yes)	4.61***	6.41*	4.38**	4.12***	3.27***	2.81***
	(1.16)	(3.33)	(2.07)	(1.09)	(1.02)	(0.80)
Income (€3000-€3499) x Uni (NA)	4.12	-11.05	4.86	3.37	3.06	6.89
	(8.27)	(133.26)	(17.82)	(16.72)	(13.56)	(26.39)
Income (€3000-€3499) x Uni (yes)	4.79***	6.94**	3.96*	3.91***	2.89***	2.61***
	(1.15)	(3.33)	(2.04)	(1.09)	(1.00)	(0.81)
Income (€3500-€3999) x Uni (NA)	6.06	-3.16	9.25	6.02	2.28	7.09
	(8.32)	(134.61)	(17.69)	(16.24)	(13.42)	(26.26)
Income (€3500-€3999) x Uni (yes)	4.79***	7.10**	4.03*	3.62***	2.83***	2.58***
	(1.15)	(3.32)	(2.06)	(1.06)	(1.02)	(0.78)
Income (€4000-€4999) x Uni (NA)	8.35	3.44	11.44	6.30	3.05	6.17
	(8.48)	(133.67)	(17.69)	(16.70)	(13.58)	(26.22)
Income (€4000-€4999) x Uni (yes)	5.52***	8.21**	4.82**	4.29***	3.23***	2.72***
	(1.16)	(3.45)	(2.12)	(1.10)	(1.05)	(0.80)
Income (€5000-€7499) x Uni (NA)	10.79	5.15	8.21	9.41	5.17	9.05
	(8.72)	(133.24)	(17.24)	(17.07)	(14.09)	(28.25)
Income (€5000-€7499) x Uni (yes)	4.73***	7.40**	3.71*	3.24***	2.52**	2.30***
	(1.18)	(3.62)	(2.13)	(1.10)	(1.01)	(0.83)
Income (€7500-€9999) x Uni (NA)	5.78	14.33	14.16	2.34	-2.39	-3.09
	(11.52)	(710.55)	(90.14)	(54.90)	(53.32)	(168.40)
Income (€7500-€9999) x Uni (yes)	4.60***	5.61	5.40**	3.76**	3.49***	2.00**
	(1.33)	(4.06)	(2.28)	(1.56)	(1.23)	(0.95)
Income (€10000-€14999) x Uni (NA)	-5.85	-18.28	-17.06	-6.58	3.12	5.86
	(10.01)	(317.22)	(47.36)	(36.40)	(29.22)	(45.11)
Income (€10000-€14999) x Uni (yes)	2.61*	10.52	3.85	3.04	2.08	0.02
	(1.54)	(6.55)	(2.40)	(1.95)	(1.53)	(1.23)
Multiple cars	-0.21**	-0.22	-0.18	-0.03	-0.06	-0.10*
	(0.09)	(0.20)	(0.11)	(0.07)	(0.06)	(0.06)

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Variable	OLS	Q10	Q25	Q50	Q75	Q90
Holiday (NA)	-0.03	0.06	-0.17	-0.20	-0.29**	-0.07
	(0.21)	(0.41)	(0.22)	(0.13)	(0.14)	(0.14)
Holiday (Frequent usage)	-0.29**	-0.65***	-0.54***	-0.35***	-0.21**	-0.09
	(0.13)	(0.24)	(0.13)	(0.09)	(0.09)	(0.08)
Weekend (NA)	0.00	-0.02	0.11	0.01	0.14	0.20*
	(0.15)	(0.35)	(0.18)	(0.12)	(0.11)	(0.10)
Weekend (Frequent usage)	-0.24***	-0.55***	-0.31***	-0.07	-0.04	0.04
	(0.09)	(0.17)	(0.11)	(0.06)	(0.06)	(0.05)
Same make as previous (NA)	0.19	-0.17	-0.59	-0.54	0.37	-0.38
	(0.86)	(1.59)	(0.68)	(0.63)	(0.67)	(0.45)
Same make as previous (yes)	0.15*	0.69***	0.06	-0.07	-0.20***	-0.20***
	(0.08)	(0.16)	(0.09)	(0.06)	(0.05)	(0.05)
Expected KM (000)	-0.04***	-0.11***	-0.04***	-0.02**	0.00	0.00
	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.00)
Fuel price	-10.09***	-22.22***	-13.66***	-7.10***	-2.73***	-0.72**
	(0.41)	(1.10)	(0.53)	(0.34)	(0.33)	(0.30)
Engine type dummies	Yes	Yes	Yes	Yes	Yes	Yes
Car class dummies	Yes	Yes	Yes	Yes	Yes	Yes

NOTE: The table reports the results of a quantile regression on the initial (non-standardized) consumer-specific determinants. Each coefficient, $\gamma_d(\tau)$, shows a change in the conditional quantile of the undervaluation (in € cents) as the explanatory variable increases by one unit, ceteris paribus. The reference category is female; upper class; university degree (no); financing (loan); considered a used car (no); one car in the household; same make as previous (no); holiday trips (infrequent usage); and weekend trips (infrequent usage). Standard errors are in parentheses. The number of observations used is 98873. *p<0.1; **p<0.05; ***p<0.01.

Table B4: Quantile regression results for undervaluation of fuel savings on clustered variables

Variable	OLS	Q10	Q25	Q50	Q75	Q90
Cluster 1	-0.27***	-0.76***	-0.30***	-0.08	-0.01	-0.04
(Socio-economic status)	(0.08)	(0.18)	(0.10)	(0.07)	(0.07)	(0.05)
Cluster 2	-0.14*	-0.26	-0.24***	-0.16***	-0.09*	0.02
(Recreational diving)	(0.08)	(0.16)	(0.09)	(0.06)	(0.05)	(0.05)
Cluster 3	-0.89***	-1.62***	-0.72***	-0.38***	-0.20***	-0.09*
(Financial ability)	(0.08)	(0.17)	(0.10)	(0.06)	(0.06)	(0.05)
Cluster 4	-0.31***	-0.63***	-0.39***	-0.34***	-0.27***	-0.16***
(Consideration process)	(0.08)	(0.17)	(0.09)	(0.06)	(0.06)	(0.05)
Town size	-0.51***	-0.80***	-0.41***	-0.19***	-0.11**	-0.02
	(0.07)	(0.17)	(0.09)	(0.05)	(0.05)	(0.05)
University degree (NA)	-0.66*	-2.07***	-1.00**	-0.42	0.00	-0.28
	(0.34)	(0.77)	(0.46)	(0.33)	(0.27)	(0.20)
University degree (yes)	0.14	0.39*	0.13	0.01	0.12*	0.12**
	(0.09)	(0.21)	(0.12)	(0.07)	(0.07)	(0.06)
Expected KM ('000)	-0.62***	-1.67***	-0.69***	-0.23***	0.01	0.04
	(0.09)	(0.19)	(0.13)	(0.08)	(0.08)	(0.07)
Fuel price	-2.66***	-5.67***	-3.57***	-1.85***	-0.73***	-0.19***
	(0.10)	(0.31)	(0.13)	(0.08)	(0.08)	(0.07)
Intercept	69.58***	40.14***	61.60***	72.13***	82.68***	92.82***
	(0.53)	(2.11)	(1.07)	(0.80)	(0.68)	(0.51)
Engine type dummies	Yes	Yes	Yes	Yes	Yes	Yes
Car class dummies	Yes	Yes	Yes	Yes	Yes	Yes

NOTE: The table reports the results of a quantile regression on the clustered and standardized variables. Each coefficient, $\gamma_d(\tau)$, shows a change in the conditional quantile of the undervaluation (in € cents) as the explanatory variable increases by two standard deviations, ceteris paribus. The reference category is given by upper class; diesel; and no university degree. Standard errors are in parentheses. The number of observations used is 98873. *p<0.1; **p<0.05; ***p<0.01.

Table B5: The valuation parameter under alternative assumptions

			Diesel		Gasoline	
			β	SD	β	SD
Parametric regression						
Over car classes, base		(1)	0.09	0.03	0.09	0.04
By car class, base		(2)	0.09	0.02	0.09	0.02
Nonparametric regression						
Over car classes, base		(3)	0.15	0.12	0.11	0.10
By car class, base		(4)	0.17	0.15	0.13	0.13
By car class, interest rate						
	r=10%	(5)	0.20	0.17	0.16	0.15
	r=15%	(6)	0.22	0.20	0.19	0.18
By car class, length of ownership						
	T=10 years	(7)	0.11	0.14	0.11	0.14
	T=15 years	(8)	0.08	0.10	0.08	0.10
	T for only new prev.car	(9)	0.16	0.13	0.12	0.11
By car class, Grigolon et al. (2017)'s assumptions	T=15; r=6%	(10)	0.08	0.09	0.07	0.08
By car class, time period	2005-2006	(11)	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 the case of separate estimations by car class, the weighted averages are displayed. "Base" corresponds to the assumptions of the length of ownership being approximated by that of the previous car in possession and an interest rate of 3%. Unless otherwise stated, all specifications include 121313 observations. For (9), there are 82317 observations. For (11), there are 37001 observations.

Table B6: 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
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
Examples of vehicles			Citroen C1 Ford Ka Opel Agila Toyota Aygo VW Lupo	Audi A2/S2 Citroen C2 Ford Fiesta Opel Corsa Toyota Yaris VW Polo	Audi A3/S3 BMW 1 Series Citroen C4 Ford Focus Mercedes A, B Opel Astra Toyota Corolla VW Golf	Audi A4/RS4/S4 BMW 3 Series Citroen C5 Ford Mondeo Mercedes C Opel Vectra Toyota Avensis VW Passat	Audi A6/S6 BMW 5 Series Mercedes E Opel Signum Toyota Camry VW Touareg	Audi A8 BMW 7 Series Mercedes S VW Phaeton

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			Minis	Superminis	Compact class	Middle class	Upper middle class	Upper class
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
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 Ford Ka Opel Agila Toyota Aygo VW Lupo	Audi A2/S2 Citroen C2 Ford Fiesta Opel Corsa Toyota Yaris VW Polo	Audi A3/S3 BMW 1 Series Citroen C4 Ford Focus Mercedes A, B Opel Astra Toyota Corolla VW Golf	Audi A4/RS4/S4 BMW 3 Series Citroen C5 Ford Mondeo Mercedes C Opel Vectra Toyota Avensis VW Passat	Audi A6/S6 BMW 5 Series Mercedes E Opel Signum Toyota Camry VW Touareg	Audi A8 BMW 7 Series Mercedes S VW Phaeton

NOTE: Fuel consumption, weight, and car class are retrieved from the ADAC web database (http://www.adac.de/infotestrat/autodatenbank) and matched to the transaction data. All monetary values in the data are inflation-adjusted by using the consumer price index (CPI), which is normalized to one in April 2010.

Table B7: Descriptive statistics for the nonparametric hedonic price regression estimates

		Diesel vehicles					Gasoline vehicles				
		Mean	SE	P10	Median	P90	Mean	SE	P10	Median	P90
PVFC (Estimate)	Minis	-2.09E-06	8.05E-07	-1.70E-05	1.76E-06	8.97E-06	-8.65E-06	1.18E-07	-1.80E-05	-8.70E-06	3.84E-07
PVFC (SE)		2.22E-09	8.22E-11	1.18E-09	1.92E-09	3.47E-09	1.21E-10	8.80E-13	6.92E-11	1.07E-10	1.87E-10
PVFC (Estimate)	Superminis	-6.08E-06	8.73E-08	-1.22E-05	-5.80E-06	-8.24E-08	-4.52E-06	3.78E-08	-9.40E-06	-4.78E-06	8.36E-07
PVFC (SE)		3.99E-11	3.07E-13	2.39E-11	3.39E-11	6.38E-11	2.99E-11	1.55E-13	1.53E-11	2.25E-11	5.41E-11
PVFC (Estimate)	Compact class	-3.84E-06	4.49E-08	-9.63E-06	-4.02E-06	2.11E-06	-4.16E-06	3.10E-08	-1.03E-05	-3.93E-06	1.59E-06
PVFC (SE)		1.72E-11	9.16E-14	6.67E-12	1.38E-11	3.27E-11	1.48E-11	5.63E-14	6.02E-12	1.14E-11	2.85E-11
PVFC (Estimate)	Middle class	-3.93E-06	5.04E-08	-1.06E-05	-4.05E-06	2.73E-06	-3.57E-06	4.40E-08	-1.03E-05	-3.48E-06	3.03E-06
PVFC (SE)		2.25E-11	1.05E-13	9.58E-12	1.96E-11	4.02E-11	1.59E-11	7.83E-14	5.26E-12	1.23E-11	3.20E-11
PVFC (Estimate)	Upper middle class	-3.23E-06	7.97E-08	-9.22E-06	-3.10E-06	2.77E-06	-2.57E-06	7.61E-08	-8.36E-06	-2.49E-06	2.88E-06
PVFC (SE)		3.22E-11	2.17E-13	1.72E-11	2.82E-11	5.21E-11	4.14E-11	3.55E-13	1.74E-11	3.57E-11	7.19E-11
PVFC (Estimate)	Upper class	-3.33E-06	3.96E-07	-1.25E-05	-3.47E-06	4.48E-06	-3.64E-06	3.65E-07	-1.04E-05	-3.24E-06	9.83E-07
PVFC (SE)		2.33E-10	6.94E-12	1.12E-10	1.98E-10	3.98E-10	2.23E-10	6.36E-12	1.19E-10	1.69E-10	3.44E-10
HPW (Estimate)	Minis	-1.26E-02	4.43E-03	-1.21E-01	-8.80E-04	5.67E-02	9.69E-03	5.18E-05	6.25E-03	9.39E-03	1.35E-02
HPW (SE)		2.85E-06	1.06E-07	1.52E-06	2.47E-06	4.46E-06	1.67E-08	1.21E-10	9.52E-09	1.47E-08	2.57E-08
HPW (Estimate)	Superminis	5.85E-03	3.68E-05	2.74E-03	6.15E-03	8.28E-03	9.18E-03	1.20E-05	7.25E-03	9.28E-03	1.10E-02
HPW (SE)		2.20E-08	1.69E-10	1.32E-08	1.87E-08	3.52E-08	8.32E-09	4.31E-11	4.24E-09	6.25E-09	1.51E-08
HPW (Estimate)	Compact class	6.17E-03	1.75E-05	4.00E-03	6.25E-03	8.27E-03	7.28E-03	1.17E-05	5.00E-03	7.22E-03	9.72E-03
HPW (SE)		5.37E-09	2.86E-11	2.09E-09	4.32E-09	1.02E-08	7.01E-09	2.67E-11	2.86E-09	5.41E-09	1.35E-08
HPW (Estimate)	Middle class	7.51E-03	2.04E-05	4.64E-03	7.45E-03	1.04E-02	7.45E-03	1.78E-05	4.70E-03	7.37E-03	1.06E-02
HPW (SE)		5.35E-09	2.50E-11	2.28E-09	4.66E-09	9.56E-09	5.34E-09	2.63E-11	1.76E-09	4.14E-09	1.08E-08
HPW (Estimate)	Upper middle class	8.44E-03	4.89E-05	3.73E-03	8.34E-03	1.29E-02	7.03E-03	3.10E-05	4.83E-03	6.92E-03	9.56E-03
HPW (SE)		1.24E-08	8.30E-11	6.59E-09	1.08E-08	2.00E-08	1.54E-08	1.32E-10	6.45E-09	1.32E-08	2.67E-08
HPW (Estimate)	Upper class	-2.49E-04	1.39E-03	-4.60E-02	5.17E-03	2.08E-02	7.80E-03	1.07E-04	5.54E-03	8.33E-03	9.73E-03
HPW (SE)		3.35E-01	9.95E-03	1.61E-01	2.85E-01	5.71E-01	1.10E-07	3.15E-09	5.88E-08	8.35E-08	1.71E-07
Weight (Estimate)	Minis	-4.21E-04	1.79E-04	-4.56E-03	-7.09E-04	2.64E-03	1.22E-03	4.18E-06	8.82E-04	1.19E-03	1.59E-03
Weight (SE)		3.46E-02	1.28E-03	1.85E-02	3.00E-02	5.41E-02	2.06E-09	1.49E-11	1.17E-09	1.81E-09	3.17E-09
Weight (Estimate)	Superminis	3.61E-04	4.49E-06	4.64E-05	4.08E-04	6.66E-04	7.03E-04	1.55E-06	4.79E-04	6.78E-04	9.81E-04
Weight (SE)		1.94E-09	1.49E-11	1.16E-09	1.65E-09	3.10E-09	1.83E-09	9.48E-12	9.32E-10	1.37E-09	3.31E-09
Weight (Estimate)	Compact class	4.51E-04	1.95E-06	1.55E-04	4.67E-04	7.28E-04	5.23E-04	1.58E-06	2.65E-04	5.36E-04	8.44E-04
Weight (SE)		1.20E-09	6.39E-12	4.65E-10	9.64E-10	2.28E-09	3.59E-04	1.37E-06	1.47E-04	2.78E-04	6.94E-04
Weight (Estimate)	Middle class	3.93E-04	1.32E-06	1.87E-04	4.01E-04	5.78E-04	4.68E-04	1.44E-06	2.43E-04	4.59E-04	6.99E-04
Weight (SE)		6.01E-10	2.81E-12	2.55E-10	5.23E-10	1.07E-09	5.40E-10	2.66E-12	1.78E-10	4.19E-10	1.09E-09
Weight (Estimate)	Upper middle class	3.41E-04	2.08E-06	1.41E-04	3.60E-04	5.07E-04	6.22E-04	4.13E-06	3.11E-04	6.19E-04	9.39E-04
Weight (SE)		6.84E-10	4.60E-12	3.65E-10	6.00E-10	1.11E-09	1.50E-03	1.29E-05	6.30E-04	1.29E-03	2.61E-03

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		Diesel vehicles					Gasoline vehicles				
		Mean	SE	P10	Median	P90	Mean	SE	P10	Median	P90
Weight (Estimate)	Upper class	3.16E-04	2.40E-05	-8.95E-05	2.89E-04	9.08E-04	7.63E-05	1.76E-05	-3.04E-04	1.28E-04	4.16E-04
Weight (SE)		4.60E-09	1.37E-10	2.21E-09	3.91E-09	7.84E-09	4.86E-08	1.39E-09	2.59E-08	3.67E-08	7.50E-08
Displacement	Minis	3.95E-06	3.14E-06	-3.46E-05	4.05E-06	4.06E-05	-5.83E-05	3.46E-05	-1.61E-03	-2.14E-05	1.45E-03
	Superminis	6.75E-04	1.38E-04	-6.76E-03	-3.57E-04	7.54E-03	-2.99E-05	5.38E-05	-6.73E-03	-3.48E-04	7.07E-03
	Compact class	8.92E-04	3.68E-05	-1.31E-03	4.40E-04	4.00E-03	-3.47E-04	5.35E-05	-1.07E-02	7.54E-05	9.72E-03
	Middle class	-2.69E-03	1.34E-04	-1.65E-02	-2.22E-03	1.06E-02	-6.24E-04	8.71E-05	-1.15E-02	-5.04E-04	1.02E-02
	Upper middle class	-2.13E-03	2.37E-04	-1.60E-02	-9.72E-04	9.22E-03	2.29E-05	2.69E-04	-1.52E-02	9.01E-04	1.25E-02
	Upper class	-8.96E-05	2.94E-05	-6.62E-04	-2.04E-05	4.93E-04	4.09E-05	3.96E-05	-3.31E-04	5.82E-06	2.67E-04
Transmission	Minis	1.11E-04	1.57E-05	9.37E-05	9.62E-05	1.42E-04	2.14E-02	2.01E-03	-8.83E-03	1.59E-02	6.64E-02
	Superminis	1.48E-02	1.49E-03	1.03E-03	1.12E-02	3.79E-02	2.20E-02	6.15E-04	-8.90E-03	2.15E-02	5.04E-02
	Compact class	3.16E-02	7.57E-04	2.95E-03	2.82E-02	6.77E-02	4.10E-02	6.36E-04	-5.95E-04	3.91E-02	8.90E-02
	Middle class	5.15E-02	1.13E-03	-9.25E-03	5.42E-02	1.10E-01	2.47E-02	4.69E-04	-9.09E-03	2.33E-02	6.49E-02
	Upper middle class	1.54E-02	3.06E-04	-2.00E-03	1.32E-02	3.74E-02	1.75E-02	4.75E-04	-7.03E-03	1.39E-02	5.03E-02
	Upper class	2.00E-02	2.85E-03	-2.85E-03	1.71E-03	8.61E-02	2.74E-04	6.01E-05	-5.23E-04	5.75E-05	1.01E-03
Sunroof	Minis	4.42E-02	1.11E-02	-3.20E-02	2.79E-02	1.31E-01	8.42E-03	6.47E-04	-1.10E-02	6.25E-03	3.01E-02
	Superminis	1.32E-02	8.98E-04	-7.01E-03	1.10E-02	3.55E-02	1.73E-02	6.00E-04	-4.69E-03	1.18E-02	4.71E-02
	Compact class	1.57E-02	6.02E-04	-8.35E-03	1.25E-02	4.65E-02	1.88E-02	5.46E-04	-1.10E-02	1.60E-02	5.96E-02
	Middle class	2.10E-02	7.05E-04	-1.72E-02	1.94E-02	6.16E-02	2.98E-02	7.78E-04	-1.55E-02	2.79E-02	8.06E-02
	Upper middle class	1.62E-02	5.23E-04	-5.60E-03	1.51E-02	4.32E-02	1.17E-02	4.81E-04	-9.54E-03	1.23E-02	3.29E-02
	Upper class	2.93E-02	1.95E-03	-1.37E-03	2.55E-02	6.29E-02	1.10E-03	2.33E-04	-2.22E-03	1.42E-03	5.15E-03
Air conditioning	Minis	1.35E-01	1.05E-02	3.83E-02	1.38E-01	3.03E-01	2.92E-02	7.32E-04	-1.37E-03	3.17E-02	5.64E-02
	Superminis	-5.54E-03	3.01E-04	-2.57E-02	-4.89E-03	1.29E-02	5.63E-03	1.64E-04	-1.24E-02	5.23E-03	2.44E-02
	Compact class	-6.62E-03	1.89E-04	-3.05E-02	-4.47E-03	1.26E-02	-1.19E-02	2.28E-04	-4.71E-02	-9.53E-03	1.91E-02
	Middle class	-2.08E-02	3.00E-04	-5.38E-02	-1.85E-02	7.46E-03	-1.25E-02	2.90E-04	-4.46E-02	-9.05E-03	1.38E-02
	Upper middle class	-7.88E-03	3.40E-04	-3.00E-02	-5.05E-03	8.38E-03	-9.58E-03	5.04E-04	-3.38E-02	-9.05E-03	1.38E-02
	Upper class	9.21E-05	1.31E-04	-1.84E-03	-5.01E-09	2.15E-03	-2.00E-03	2.31E-04	-5.02E-03	-3.08E-03	2.28E-03
Cruise control	Minis	6.46E-02	7.12E-02	-2.85E-02	1.77E-02	2.05E-01	4.53E-03	2.77E-03	-1.33E-02	5.04E-03	2.24E-02
	Superminis	9.11E-03	7.24E-04	-9.22E-03	6.69E-03	2.92E-02	5.67E-03	8.94E-04	-2.92E-02	5.08E-03	4.40E-02
	Compact class	1.06E-02	2.40E-04	-6.83E-03	8.62E-03	2.99E-02	1.41E-02	3.40E-04	-1.53E-02	1.37E-02	4.31E-02
	Middle class	9.30E-03	2.64E-04	-1.58E-02	7.32E-03	3.73E-02	1.61E-02	3.10E-04	-1.09E-02	1.27E-02	5.00E-02
	Upper middle class	2.85E-02	6.55E-04	-1.42E-02	2.22E-02	8.35E-02	1.27E-02	3.94E-04	-8.20E-03	8.52E-03	4.31E-02
	Upper class	5.20E-04	8.18E-05	-3.81E-04	6.68E-10	2.33E-03	2.57E-04	6.84E-05	-6.88E-04	7.02E-05	1.05E-03

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		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 a Gaussian kernel for continuous variables and a Li-Racine kernel for discrete variables. Effects for make, year, quarter, and region fixed effects are not shown. For the 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.