Price discontinuities in an online market for used cars*

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Abstract

We examine empirically whether individuals evaluating used cars efficiently aggregate all relevant information on its constituent characteristics. Based on detailed field data on almost 90,000 used car offers in a large online marketplace, we provide evidence for biased information processing. While the precise date of first registration, i.e., its "age", is publicly and prominently stated for each car, we identify an amplified value adjustment for otherwise identical cars at year-count changes. These discontinuities indicate that individuals over-react to the figure displayed in the latter, while underrating the finer information on a car's age as conveyed through the month of first registration. Moreover, we are able to replicate the findings from Lacetera *et al.* (2012) and find discontinuous drops in prices at 10,000km odometer thresholds. While the latter finding, as suggested by Lacetera *et al.* (2012), is consistent with a left-digit bias in the processing of numerical information, the first finding cannot be explained by this. Our findings underline that information-processing heuristics might also matter in markets with large stakes and easily observed information.

Keywords: Complex Goods; Price Discontinuities; Information Neglect; Heuristics; Field Study

JEL classification: D12, D83, L 62

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1 Introduction

Motivation Economic theory suggests that a rational agent should incorporate all relevant pieces of information into his considerations and exclude any that are non-informative. However, at least since Simon (1955), economists have proposed models to relax this strong assumption. In these models, individuals simplify complex decisions, for example by processing only a subset of information. Recent empirical research convincingly documents that consumers fail to efficiently process the available relevant information but instead rely on heuristic evaluation rules.[1]

In particular the paper by Lacetera *et al.* (2012) on used car markets makes use of (literally) millions of datapoints from US used car auctions to find systematic and substantial price drops at 10,000mile odometer marks and to explain this pattern with a model of inattention and in particular left digit bias.

Data Based on detailed field data on used car offers from the German website *mobile.de*, one of Europe's largest online vehicle marketplaces, we add to this evidence. We show that there are clear threshold effects on prices[2] at year changes

[1]See, e.g. Lee and Malmendier (2011) and Brown *et al.* (2010) on internet auctions or Chetty *et al.* (2009) and Finkelstein (2009) on taxes and tolls.

[2]Our sample of used cars does not originate from an auction market, and, rather than on actual sales prices, our analysis is based on the asking prices stated by the individual sellers, which may be subject to negotiation once an interested buyer has been found. However, we have strong reasons to believe that the posted price is a sensible proxy for the final price in this market. First, *mobile.de* offers the seller an option to declare the stated price either as "fixed" or as "negotiable", and a substantial fraction of the sellers opts for the former rather than the latter. Second, with several thousand offers for each model series the market for used cars is highly competitive. Moreover, the cars within each of our subsamples can be regarded as close substitutes. Under the presumption, that the stated sales price reflects the willingness to accept of the respective seller, according to Hanemann (1991) and Shogren *et al.* (1994) in such an environment an endowment effect, i.e. a divergence of willingness to pay and willingness to accept, is unlikely to persist. Moreover, the services of *mobile.de* are widely used by professional car dealers who purchase cars for resale rather than use, where according to Kahneman *et al.* (1991) the endowment effect does not apply. As it turns out, the majority of offers in our sample is indeed made by commercial rather than private sellers. Hence, it stands to reason that the stated prices are closely related to the final prices. Finally, since advertising a car is costly, it seems plausible that the sellers exert considerable effort to elicit a reasonable price, at which prospective buyers are indeed willing to buy.In line with this argument, Englmaier and Schmöller (2009a) document that the sellers' reserve prices in a similar, but distinct, online-auctions market are similarly determined as the sales prices, i.e. from an evaluation of the individual attributes. Our intuition is that the same also applies to this context. For simplicity, in the following we use the term "price" to refer to the stated prices in our data.

in the date of first registration[3], i.e., a car's age. All else equal, the price differential between two cars, where one was first registered in January and the other in December of the previous year, is dramatically larger than that between two cars first registered in any two subsequent months of the same year, respectively. Stated differently, we find an amplified adjustment in the prices for otherwise identical cars to be located *across* different registration years, or "vintages", where the impact of a marginal month of age is *up to four times larger* relative to that *within* the same vintage. We are documenting our results by implementing a regression discontinuity design and these results are robust to applying differing sets of controls, controlling for polynomials of lower or higher order than suggested by the Akaike Information Criterion test, or using log-linearized data.

Our (German) data has the appealing feature that within one data set there are two natural candidates where one might expect price discontinuities to appear. In addition to the above described vintage effects, we are also able to replicate the findings in Lacetera *et al.* (2012) and to document discontinuous price changes around 10,000km marks of odometer readings. For example, cars with odometer values between 59,000 and 59,999km are offered only slightly cheaper than cars with odometer readings between 58,000 and 58,999 but the price drop to the 60,000-60,999 bin is substantially bigger.

Interpretation The discontinuities regarding to the odometer readings can be, as suggested by Lacetera *et al.* (2012), reconciled with a model of left-digit bias in information processing. However, this does not explain the discontinuities between a car fist registered in December (e.g., 12/2004) and January (e.g., 01/2005). We suggest that the design of the search interface where agents are led to search within pre-specified intervals related to prominent marks can explain (part of) the effect and we propose a model of (rational or heuristic) search costs trying to capture this.

The results in Englmaier and Schmöller (2009b) complement this explanation approach. In a different online market with similar features, Englmaier and Schmöller (2009b) can exploit an exogenous change in the search interface, amounting to a substantial reduction in search costs and find that the size of previously

[3]In Germany, every car has a legally mandated, official documentation record. Hence, the date of first registration, i.e. a car's birthdate for being on the road, is verifiable hard information. Moreover, in Germany there is no concept of "model year". I.e., there is no such thing as an 1998 BMW but there exists a certain BMW series that is produced without major changes for an extended period of several years.

existing price discontinuities is substantially reduced – while a significant discontinuity remains which, they argue, can be attributed to inattention.[4]

Related Literature Limited attention has also been documented for other purchase decisions in other markets. For instance, Lee and Malmendier (2011) analyze individual bidding behavior in auctions on eBay and find that people tend to anchor on an irrelevant outside retail price for a board game, if the seller chose to state that price in the description of the product details. At the same time, many of the winning bids exceed a more relevant outside option, the so called "buy-it-now" price, which is an ex-ante fixed strike price set by the seller as an alternative to the auction process. Analyzing stock market data, Gilbert *et al.* (2008) provide evidence that investors with limited attention have an incentive to focus on summary statistics rather than individual pieces of information. They analyze the market response to the U.S. Leading Economic Index (LEI), a macroeconomic release that is purely a summary statistic, and show that the LEI announcement has an impact on aggregate stock returns, return volatility, and trading volume. We add to these findings by demonstrating that inattentiveness effects pertain for complex goods and large stake purchase decisions, even though the concerned piece of information is provided at arm's length within the relevant market environment.

The remainder of the paper is structured as follows. Section 2 describes the structure and the relevant details of the data. Section 3 presents our graphical analysis and the regression analysis for vintage and mileage discontinuities. Section 4 presents a simple model to rationalize our results. Section 5 presents linear approximations of structural parameters to capture otherwise unexplained price drops. Section 6 concludes and the Appendix collects all Figures and Tables.

2 Data Description

2.1 Institutional Background

For the purpose of this study, we collected detailed information on almost 90,000 cars offered during July and August 2009 on the online vehicle market platform *mobile.de*. Founded in 1996, *mobile.de* takes the role of an intermediator between supply and demand within a two-sided market. The company itself is not involved at any stage in the purchase or sale of a vehicle and a successful sale does not

[4]The paramount role of information provision in online markets is underlined by Lewis (2011). Tadelis and Zettelmeyer (2011) document it for the used car markt also studied by Lacetera *et al.* (2012).

invoke any final value fees to *mobile.de*. It provides both a platform for sellers to place advertisements for new and used cars at a small cost and a free comprehensive search tool for prospective buyers to screen among the mass of on average about 1.3 million offers. According to the company's own statement, prospective buyers "*can limit search results by setting individual preferences and like this obtain customized offers with just a few clicks*", providing them "*... with an overview of the market and information about prices*".[5] The same is true for a seller who wants to evaluate his car before placing a sales advertisement.

`-- Include Figure 1 about here. --`

Figure 1 shows the interface a user is presented with upon entering *mobile.de*'s website. It displays a simple search form, which among other things allows to filter for makes, models, and a number of other basic details. A detailed search form, which can be directly reached by clicking the link to the lower left, provides a large additional set of filter options. Note however, that the drop down selector for the date of first registration only allows to filter for the vintage, i.e. the year of first registration.

The search returns a list of all vehicles matching the chosen filters. Per default they are sorted by price, where an abstract of their main features is displayed as shown in Figure 2. This preview explicitly states the precise date of first registration (e.g. "FR 01/2000") and additionally provides valuable information on the price, mileage, color, and power of the car, to name only a few. It is also possible to remember a specific car for later access ("Park vehicle"), which allows the user to directly compare the latter to other remembered cars.

`-- Include Figure 2 about here. --`

A typical profile page of an offered car, which is accessed from the search results list by clicking on the model name at the top of the respective entry, is depicted in Figure 3.

`-- Include Figure 3 about here. --`

For each car, a seller has to specify a preselected set of features and attributes, where most of the respective values are chosen from a drop down menu during the preparation of the advertisement. Conveniently, this data is thus standardized and ensures a sufficient degree of comparability across individual observations. We therefore focus on these standard attributes in our data, which in addition to the stated price and the date of FR include various extras and also some information on the sellers (see Table 2 below).

[5] Source: http://cms.mobile.de/en/company/portrait_mobile.html; last accessed: May 1, 2013

2.2 Sample selection

Our data includes details on the most widespread car models from four leading German makes[6], all ranked among the top seven of Germany's vehicle population according to the Kraftfahrt-Bundesamt (KBA).[7] More specifically, we collected information on 25,593 Volkswagen (VW) Golf (KBA-rank 1), 12,955 Opel Astra (KBA rank 2), 22,398 BMW 3 (KBA rank 4), 17,796 Audi A4 (KBA rank 7), and 10,394 Mercedes Class A (KBA rank 9), all advertised as accident-free and with their FR-dates between 01/1998 and 12/2008.[8] We focus on this subsample for two main reasons. First, a high stock is a good indicator for a considerable volume of used car offers for a specific model, which ensures a sufficiently large number of observations.[9] Second, we consider models from different makes to achieve a broad diversification within our identification strategy.

`-- Include Table 1 about here. --`

Since the introduction of a new series within a particular car model affects the sales prices substantially, we can only retrieve meaningful estimates of the influential attributes if we accurately control for potential model revisions. Clearly, this requires detailed knowledge of the exact dates of the respective market launches. Conveniently, for the four different models considered in our sample, this information is readily available. In particular, we identify the respective estimation windows for each model according to the information provided through the manufacturers' websites, the Schwacke-List (http://schwacke.de), and the Deutsche Automobil Treuhand (http://www.dat.de).[10] Since all models in consideration experienced at least one update or change of series between 2000 and 2008, we control for different model variants accordingly. See Table 1 for the details on these model updates. Depending on their extent, these updates, or "face-lifts", can invoke similar price effects as a change of series. In the estimation we therefore treat the information on a face-lift similar to the introduction of a new production line.

[6]We had to limit our search and we chose to focus on the most widespread brand of each of the four biggest car producers in Germany to avoid potential specifities in sub-markets related to certain brands.

[7]Source: http://www.kba.de.

[8]KBA ranks not reported were taken by other models of VW (Passat, Polo) and Opel (Corsa).

[9]We do not consider cars that were first registered before January 1998, since their values are very low and these vintage brackets are only sparsely populated.

[10]The latter are commercial service providers who offer benchmark evaluations for all kind of cars at a small cost. In fact, they allow to account for the precise date of first registration in an individual evaluation of a car, which makes the discontinuities we are able to document in our data even more puzzling.

However, control for these model updates is not trivial because we only know when factories switched from producing the old to the new models but not precisely if a given car in our sample is truly a new model or rather an old model that has been sitting at the dealer's lot for a few months. Furthermore, some makes (e.g., BMW) have not introduced all their model variants at the same date but sequentially (e.g., station wagon 8 months after the introduction of the sedan etc.).

For our main specifications we classify a car as having undergone a model update if its date of first registration was > 3 months after the factories switched production. In Section 3.2 we document that our results are robust to differing definitions of these indicators.

Naturally, due to different variants offered within a model series, e.g. limousine, estate car, or compact car, the latter are not perfect substitutes. To account for such within-series variation, we add a large set of main attributes as controls, and exclude convertibles from the sample. In this way, we capture a substantial share of the variation in the price within a series and are thus able to obtain precise estimates of the influential factors.

`-- Include Table 2 about here. --`

2.3 Data description

Table 2 provides an overview of the collected details and shows the corresponding summary statistics. In general, the value of an individual car from a specific model series depends on numerous factors. Among others, this includes its age, its odometer reading, the power and fuel-type of its engine, and the different extras it is equipped with, e.g. an automatic gearbox, a sun-roof, seat-heating, or cruise control. Along with the stated prices and the month and year of first registration, we therefore collected a large number of features for each of the cars to control directly for quality differences. To measure their impact on the price of the car, we assign a dummy variable to each of the observed extras in our analysis. For instance, if a offered car has a sun-roof, the dummy variable *sun_roof* takes the value of 1 and 0 otherwise.[11]

For our vintage analysis, we leave out years 1999 and 1998 because we only have very few observations. The information on the month and year of the first registration is stored in the variables $fr\_month \in [1, 12]$ and $fr\_year \in [2000, 2008]$, respectively. For our empirical analysis, we combine the latter to construct the

[11] In the following, we use italics to denote the variable name in our data corresponding to an attribute.

measure *totalage* $\in [1, 108]$, which displays the precise age of a car in units of months:

$$totalage \equiv 12 \cdot (2008 - fr\_year) + (13 - fr\_month),$$

where the normalization is such that a car's age is measured relative to the most recent FR-date included within our dataset, i.e. 12/2008, which corresponds to the minimum age of 1 month.

When inspecting Table 2 note that a large majority of offers originates from professional car dealers, as indicated by the dummy *private_seller* being equal to zero.

As we would expect, a correlation analysis for *price* yields a strong negative correlation coefficient with *totalage* ($\rho = -0.85$) and with *mileage* ($\rho = -0.78$). Conversely, *power* ($\rho = 0.45$), *diesel* ($\rho = 0.11$), *five-door* ($\rho = 0.16$), and all of the considered extras are significantly positively related to the price of a car.[12]

While not listed in Table 2, another important determinant for the price of a car is its color. We therefore additionally include a set of color-dummies to control for their impact on price, where the effects are measured relative to *black*. We find that the prices are indeed somewhat responsive to different colors. For the sake of clarity, however, in the discussion below the respective coefficients for the color-dummies are not reported, but are available from the authors upon request.

`-- Include Figure 4 about here. --`

`-- Include Figure 5 about here. --`

`-- Include Figure 6 about here. --`

Next, consider the age distribution of the cars, which are depicted in Figure 4. We find some fluctuation across registration months but conclude that our sample contains a sufficient number of observations for each FR-date in the estimation period. The highest frequency of offers is observed for relatively new cars, i.e. around an age of 7 to 15 months relative to 12/2008. These refer to so called "Jahreswagen", i.e. cars given for a year to employees as part of their compensation package. This pattern is not surprising given the high number of professional car dealers that is active in this market segment. Mileage is pretty much evenly distributed with a plateau below 30,000km and another fairly stable but substantially lower plateau above 30,000km (Figure 5). Finally, the distribution of prices is somewhat right skewed, but approximately normally distributed (Figure 6).

[12]Among the explanatory variables, we find that *totalage* and *mileage* co-move at a degree of $\rho = 0.77$. While in general collinearity among the explanatory variables can be problematic, our sample size is sufficiently large to produce precise parameter estimates.

3 Empirical Analysis

3.1 Vintage Discontinuities

Note that for the vintage analysis, we have to exclude years 1999 and 1998 for lack of sufficiently many observations.

Graphical Analysis We begin the empirical analysis by simply plotting the raw price data as a function of car age. In Figures 7, each dot shows the average sale price for all cars first registered in a given month of a given year starting December 2008 and counting backwards until January 2000.

`-- Include Figure 7 about here. --`

As one would expect, average prices decrease with increasing age. Within each year, monthly average prices decline almost linearly, but there are discontinuities between years (Figure 7). These patterns are systematic and substantial for all cars at least 2 years old. The "youngest" cars are a specific sub-sample. Namely so called "Jahreswagen". For these cars, there is also a marked discontinuity upon the year change, but in the "wrong" direction. However, inspecting the plotted (adjusted) residuals – i.e., average prices after controlling for age polynomial, mileage, horsepower, model update, and other car features – show substantially more structure. See Figure 8 where we observe marked drops in priced between January cars and December cars. Again, the one exception is the apparent lack of discontinuities for young cars (Jahreswagen).

`-- Include Figure 8 about here. --`

Figure 9, excluding these Jahreswagen, gives an even clearer picture of these price discontinuities.

`-- Include Figure 9 about here. --`

Regression Analysis The preceding graphical analysis suggested the existence of systematic price discontinuities at year changes for the month of first registration. To augment this approach, we turn now to regression analysis to establish numerical estimates of these price discontinuities. We implement regression discontinuity designs - see Lee and Lemieux (2010) for an overview of this literature - where the dependent variable in our regressions is the price for the cars stated on the website.

To establish the effect of crossing a year threshold, we control for the actual age - by means of a fifth-order polynomial[13] - , the mileage and other relevant characteristics of the particular car being sold like make, model, special equipment, etc..

The regression also includes a series of indicator variables for whether the car has crossed a given year threshold. The coefficients of these indicator variables can be interpreted as the discontinuous changes in price (all else constant) that occur as cars cross a particular year threshold. Hence, the specification allows us to estimate the price discontinuities separately at each year threshold.

`-- Include Table 3 about here. --`

Table 3 presents the regression results for the above described specification. Column (1) controls only for a fifth-order age polynomial and the full set of indicator variables for whether the car has crossed a given year threshold and provides estimates of the price discontinuities before any further controls on observables. However, this specification suffers from uncontrolled model changes and updates. hence the (unsystematic) results should be read cautiously.

Columns (2) through (5) in the table add increasingly restrictive fixed effects to the model. Column 2 adds controls for car features which increases R^2 and affects significance, size, and even sign of the coefficients. In Column (3) we control for model updates while in Column 4 we add car model fixed effects. Column (5) is our preferred specification as it controls for the age polynomial, car features, model updates, and includes car model fixed effects. With the controlled estimates, most of the coefficients are significant, negative and for 2006, 2005, and 2004 rather big (on average EUR 400).

These regression results closely mirror the graphical analysis above: there are no detectable discontinuities for the “noisy” Jahreswagen-Sample, and diminishing discontinuities for old cars. Though the pattern is not perfect, by and large we conclude that there are sizeable and systematic negative price discontinuities upon passing a year threshold even after controlling for the exact age and a host of observable characteristics.

3.2 Robustness – Vintage Discontinuities

3.2.1 Potential Empirical Pitfalls

Do other car features change at vintage thresholds? In particular we check here whether January and December cars are actually comparable with respect to

[13] The specific functional form was chosen based on the Akaike Information Criterion test. Our results are robust to the specific order of the polynomial; see Section 3.2.

their average mileage, see Figure 10, the type of cars on offer in terms of their average horsepower, see Figure 11, or their fuel type, see Figure 12, or finally whether the seller types (dealer/private) differ, see Figure 13. These raw data plots show somewhat erratic and certainly unsystematic patterns. Hence we conclude that our effects are not driven by changing car populations at year's end.

`-- Include Table 10 about here. --`

`-- Include Table 11 about here. --`

`-- Include Table 12 about here. --`

`-- Include Table 13 about here. --`

Are there discontinuities in the density of cars at thresholds? I.e., we question whether the price drops could be explained by supply "shocks" for certain car types. Note, that we should not see systematic patterns here: There is no incentive to sell the car prior to reaching a threshold because the registration of the car is an inherent feature that does not change (and cannot be changed) over time (in contrast to the case of mileage). Indeed, while the distribution looks jumpy and is subject to seasonality, there are no discontinuities at the year thresholds but during the years (see Figure 14). These data follow the seasonal pattern of first registrations that the Federal Office for Motor Vehicles (Kraftfahrtbundesamt) records since 1970: There are generally few registrations in January/February, then the number picks up in spring and starts to decrease again in July to finally reach low levels again in December.

`-- Include Table 14 about here. --`

Are there discontinuities at other arbitrary month thresholds? We perform the placebo test of picking arbitrary month thresholds (e.g., March/April) and checking whether we find discontinuities or not. Though, in a few cases we do get significant threshold coefficients they do, however, not appear to be systematic neither in size nor in sign. Moreover, these significant coefficients come about mostly for Jahreswagen. Results for the other three end-of quarter months – March, June, and September – are in Table 6.

`-- Include Table 6 about here. --`

3.2.2 Robustness of the Analysis

Log-linearization Results are robust to log-linearizing prices; see Figure 4. In fact, results in this specification look even cleaner and more systematic than in our main specification.

`-- Include Table 4 about here. --`

Controlling for model updates For our main specifications we classify a car as having undergone a model update if its date of first registration was > 3 months after the factories switched production. However, the results from our main specification are robust to varying these model update dummies. This suggests that the measurement error in model generation is unlikely to be harmful. Table 5 collects the results for the following dummies that have been used for the robustness analysis[14]:

- D1: model generation dummy for each model generation, imposing no insecurity (i.e. we treat all cars registered 1 month after official model switch as new model.
- D2: model generation dummy for each model generation, with 5-months insecurity windows: Like D1 but we treat model status of cars registered within the three months after a model switch as "unknown". Effectively, these cars are not used to identify our model.
- D3: model update dummy, imposing no insecurity: Takes on the value of 1 if and only if a given month saw a model update.
- D4: model update dummy, with 5-months insecurity windows: Like D3 but the three months after the introduction are also labelled as a model update month.

`-- Include Table 5 about here. --`

Higher- and lower-order age polynomials The RD design literature – see e.g., Lee and Lemieux (2010) – stresses that results should be robust to different polynomials in order to be credible. As can be seen from Table 7 this is the case in our case.

`-- Include Table 7 about here. --`

[14]We have also experimented with smaller and larger insecurity windows (3 to 6 months) but omitted these results to save space as results are very similar.

3.3 Mileage Discontinuities

3.3.1 Graphical Analysis

Next we plot the raw price data as a function of car mileage.In Figure 15, each dot shows the average sale price for cars in a 1,000Km mileage bin. There is a dot for the average price of cars with 1,000 through 1,999Km, then a dot for cars with 2,000 to 2,999Km, and so on. The vertical lines in the graph indicate each 10,000Km mark. As one would expect, average prices decrease with increasing mileage. Within each 10,000-mile band, average prices decline quite smoothly. Excluding the Jahreswagen segment of the market, there are systematic (small but visible) drops in average prices at the 10,000Km marks.

`-- Include Figure 15 about here. --`

Inspecting the plotted (adjusted) residuals – i.e., average prices after controlling for age polynomial, age, horsepower, model update, and other car features – show these patterns slightly more clearly. See Figure 16 where these price drops at the 10,000Km marks are more systematic and even better in Figure 17 that excludes the Jahreswagen (<20,000Km).

`-- Include Figure 16 about here. --`

`-- Include Figure 17 about here. --`

With no other explanation for the importance of 10,000Km thresholds, these result suggest a role for heuristic decision making in this market.

3.3.2 Regression Analysis

The preceding graphical analysis suggested the existence of systematic price discontinuities around 10,000km thresholds of odometer readings. To augment this visual evidence, we again turn to regression analysis to establish numerical estimates of these price discontinuities. As before we implement regression discontinuity designs where the dependent variable in our regressions is the price for the cars stated on the website.

Though the graphical evidence looked less clear cut than in the case of vintage discontinuities, the results of our regression analysis look very encouraging.

To establish the effect of crossing a mileage threshold, we control for the actual mileage - by means of a second-order polynomial[15] - , the age and other relevant

[15] The specific functional form was chosen based on the Akaike Information Criterion test. Our results are locally robust to the specific order of the polynomial; see Section 3.4.

characteristics of the particular car being sold like make, model, special equipment, etc..

The regression also includes a series of indicator variables for whether the car has crossed a given 10,000km mileage threshold. The coefficients of these indicator variables can be interpreted as the discontinuous changes in price (all else constant) that occur as cars cross a particular 10,000km mileage threshold. Hence, the specification allows us to estimate the price discontinuities separately at each mileage threshold.

`-- Include Table 8 about here. --`

Table 8 presents the regression results for the above described specification. The Column (1) controls only for a second-order age polynomial and the full set of indicator variables for whether the car has crossed a given year threshold and provides estimates of the price discontinuities before any further controls on observables. However, this specification suffers from uncontrolled model changes and updates. Hence the results should be read cautiously.

Columns (2) through (5) in the table add increasingly restrictive fixed effects to the model. Column 2 adds controls for car features which increases R^2 and affects significance and size of the coefficients. In Column (3) we control for model updates while in Column 4 we add car model fixed effects. Column (5) is our preferred specification as it controls for the age polynomial, car features, model updates, and includes car model fixed effects. With the controls, all the coefficients are significant, negative and sizeable. We conclude that there are sizeable and systematic negative price discontinuities upon passing a 10,000km mileage threshold even after controlling for the exact mileage and a host of observable characteristics.

3.4 Robustness – Mileage Discontinuities

Supply Side Effects In Figure 18 we find indirect evidence that sellers do at least believe that the mileage thresholds are important for the car's price or, alternatively, the likelihood of it being sold: Clearly, cars are brought to the market just before the odometer passes a 10,000Km threshold. However, a positive supply "shock" *before* the mileage threshold is passed should rather depress prices for these types of cars. Hence, a simple supply shock argument should not be able to fully explain the price discontinuities.

`-- Include Figure 18 about here. --`

Placebo Test – US miles threshold For our placebo test we employ our most preferred specification from Table 8 were we convert odometer readings from Km to US miles and then check for discontinuities in the converted data at 10,000 mile thresholds. All the (placebo) thresholds for the non-Jahreswagen sample are insignificant; see Table 9.

`-- Include Table 9 about here. --`

Alternative Specifications Unfortunately, overall the mileage discontinuity results are not as robust as those for vintage. For instance, log linearization reverses (!) results for the first four 10,000Km thresholds (i.e. the estimates here are significantly positive) and results are sensitive to using polynomials of orders higher than three (while orders of 1, 2, and 3 are fine). This is somewhat surprising as discontinuities in the mileage dimension have been documented to be systematic and sizeable by Lacetera *et al.* (2012). Our data suffer more from measurement than theirs, however in particular the inversion of signs for log-linearized data is somewhat troubling.

3.5 A Horserace

Finally, we implement a horserace idea of controlling for mileage and vintage thresholds at the same time. Results in Table 10 are, again, encouraging: Both discontinuities survive and the vintage discontinuities become even somewhat more pronounced.

`-- Include Table 10 about here. --`

4 A simple Model

In light of a rather sophisticated behavior as displayed with respect to other attributes, the main finding we are able to document in our data seems even more puzzling. If people are careful enough to check out numerous details of the attribute vector of a car, why do they systematically pay too little attention to the valuable information conveyed through the month of first registration (or the exact mileage)?

Though they do not disregard the impact of precise age as indicated by the evidential continuous decline *within* a vintage, they fail to recognize the connection to subsequent or previous vintages. Our intuition is that individuals evaluate cars relative to the average car from the same vintage, while the more relevant and informative peer group consists of cars of close-by actual age, irrespectively of the vintage the latter belong to.

Neither in the simple nor the expanded form it is possible to adjust the search inquiry for the precise month of the first registration (FR).

To illustrate what we have in mind, consider an agent who has to evaluate a car with given attributes first registered in 12/2006. All else equal, to elicit how much to bid for this car, she should look up and compare the prices for a car of a similar total age, say, roughly from 3 months younger (09/2006) to three months older (03/2007).

Note that neither in the simple nor the expanded form of the search interface it is possible to adjust the search inquiry for the precise month of the first registration (FR). Hence, in the example to get the desired information the agent has to screen a large number of cars on the market platform, namely all 2006 and 2007 cars on offer, to find enough falling into the age-range of interest, thus involving a time consuming and thus costly search. See Table 11 for the respective population in these coarse bins.

`-- Include Table 11 about here. --`

This implies that one possible explanation for the inattentiveness effect lies within the design of the user interface of the search engine, which is used to screen the market: It may be physical search costs that prevent an agent from efficient information aggregation.

Consider a risk-neutral agent j who wants to evaluate a particular car $i = (y_i, m_i, X_i)$, where $y_i \in \{2000, ..., 2008\}$ denotes its vintage, $m_i \in \{0, ..., 12\}$ the month of first registration, and X_i all other attributes of the car, respectively. Normalize by $a_i = 12 \cdot (2008 - y_i) + (13 - m_i)$ the total age in days. For given values of $X_i = \overline{X}$, individual j's value estimate for car i in dependence of its age attribute is described by the function $E_j[v_i] : (y_i, m_i) \to \mathbb{R}^+$.[16] More specifically, let

$$E_j[v_i] := (1 - \pi(c_j)) \cdot \overline{v}_y^j + \pi(c_j) \cdot v_{a_i}^j,$$

where $\overline{v}_y^j$ is the value of an average car in age-group y, and $v_{a_i}^j$ denotes her precise value of car i. For simplicity, assume that $\overline{v}_y^j$ is commonly available free of cost. Her value estimate is a convex combination of the average value and her true value, where the relative weight $\pi(c_j)$ is a function of her search costs c_j. By screening the market for otherwise identical cars within an age-range around a_i, she can learn their values and thus increase the weight $\pi(\cdot)$ on her true value for

[16] To simplify the notation we suppress $\overline{X}$ in the expressions.

car i and thereby obtains a more precise estimate.[17] Generally, the intensity of this search will depend on how costly, or time consuming, it is to find appropriate cars in the respective age interval. Formally, assume that the convex weighting function $\pi(c_j)$ has the following properties:

$$\begin{aligned}
\lim_{c_j \to \infty} \pi(c_j) &= 0 \\
\lim_{c_j \to 0} \pi(c_j) &= 1 \\
\pi'(c_j) &< 0 \quad \forall \ c_j \in R_0^+.
\end{aligned}$$

First, consider that the search costs are sufficiently large such that $\pi(c_j) = 0$. Then manager j's valuation will reflect the average value $\overline{v}_y^j$. Second, for a given c_j suppose that $\pi(c_j) < 1$. If $v_{a_i}^j > \overline{v}_y^j$, the agent values the car too low, though her true value for the car would be higher than her estimate. Conversely, if $v_{a_i}^j < \overline{v}_y^j$, she will be willing to pay a price above her true valuation for car i. While the former case is unproblematic, in the latter the agent with the least precise estimate will affect the posted final price. Third, in the absence of search costs, agent j will fully learn her precise value, i.e. $\pi(0) = 1$. These cases are illustrated in Figure 19.

-- Include Figure 19 about here. --

For lower search cost $c_j' < c_j$, the estimates of any individual agent j should become more accurate in the sense that they become closer to her precise value $v_{a_i}^j$ since $\pi(c_j) < \pi(c_j')$. Our data are thus consistent with a model that includes intermediate search costs, $0 < \pi < 1$, which suffice to cause discontinuities between two consecutive vintages. Obviously, a similar reasoning can be applied to explain the price drops around 10,000Km odometer marks where the search mask also offers natural break points.

5 A first take at "Structurally" Estimating Discontinuities

If we assume in the above model a linear value function, the size of the estimated price discontinuity at a vintage (or 10,000Km) threshold should be approximately equal to $\alpha * (1 - \pi) * \Delta$ where α is the slope of the value function, Δ is the width

[17] The underlying rationale may be best explained by assuming that for any c_j, the agent solves an optimal search problem, which determines the number of cars she optimally screens. In turn, this implicitly determines the extent to which she learns $v_{a_i}^j$.

of the bracket, i.e., one year or 10,000Km, and $(1-\pi)$ is the friction. The friction could be interpreted (as above) as caused by search costs or – as in Lacetera *et al.* (2012) – as an inattention parameter. Hence, $1-\pi$ gives the fraction of the discontinuous (unexpected) price reduction that occurs at vintage or 10,000-mile thresholds.

By imposing linearity we simplify the problem and force the discontinuity to be constant across thresholds. This is clearly false for our data, but estimates like this have been prominently documented in the literature; see, e.g., DellaVigna (2009) or Lacetera *et al.* (2012).

If we estimate this model for the vintage discontinuities the results suggest that approximately 20% of the depreciation that a car experiences due to aging occurs discontinuously at year changes while for the mileage discontinuities the results suggest that approximately 30% of the depreciation that a car experiences due to increases in mileage occurs discontinuously at 10,000Km thresholds. These numbers fall well within the range of such parameters that have been documented in the literature for inattention parameters; see DellaVigna (2009).

However, note that our search cost based model would make more subtle predictions in fact predicting *differing discontinuities* for differing search costs. If one proxies for the search costs by the direct effect of including a "neighboring bin" into the search, the bin sizes as shown in Table 11 would guide predictions of where we should expect the starkest discontinuities: namely where adding a neighboring bin adds the most cars to sift through. However, this "testing the theory part" is still research in progress.

6 Discussion and Conclusion

We examine empirically to what extent the stated prices for used cars reflect available and relevant information. Based on detailed field data on used car offers from the online vehicle market platform *mobile.de*, we find strong evidence for biased information processing. Despite the large monetary stakes involved, our findings suggest that people in this market systematically fail to aggregate the information provided on specific attributes of the items on sale. In particular, although the precise date of first registration is clearly stated, the pattern of observed prices exhibits sizeable discontinuities, indicating that a substantial fraction of the value adjustment due to the age of a car is located where the FR-year changes. As a consequence, across two consecutive vintages the price differential for cars with otherwise close-by registration dates is significantly larger than rationally justified, given that they only marginally differ in their precise age. This finding proves robust. Moreover, we are able to replicate the findings from Lacetera *et al.* (2012) and find discontinuous drops in prices at 10,000km odometer thresholds.

The fact that we are able to provide suggestive evidence for a systematic friction in an otherwise highly competitive market, where in addition individual choices are conceivably subject to profound deliberations, naturally raises two closely related questions. First, what are the driving forces behind this effect? And second, what are the economic consequences of this finding?

Regarding the first question: While the latter finding, as suggested by Lacetera *et al.* (2012), is consistent with a left-digit bias in the processing of numerical information, the first finding cannot be explained by this. We suggest a model of (rational or heuristic) search costs that is capable of explaining both price patterns.

Regarding the second question, these price discontinuities might entail that from the perspective of rational buyers a substantial fraction of cars will be overpriced, potentially leading to too little trade. Or, from the perspective of rational sellers, cars from some segments will appear underpriced, potentially leading to too little trade from the supply side.

Several extensions to this research suggest themselves. One potential source for this effect may be linked to the design of the filter mechanism, which people can use to screen and cross compare different offers. Due to the fact that it is not possible to directly filter for the FR-month on platforms like *mobile.de*, it may be tempting to perceive this information as unimportant and to overly focus one's attention on the more salient FR-year. It would therefore be interesting to see whether the size of the discontinuities is affected by including this feature in the filter mechanism. In a different online market with similar features but for small stakes items, Englmaier and Schmöller (2009b) can exploit an exogenous change in the search interface, amounting to a substantial reduction in search costs and find that the size of previously existing price discontinuities is substantially reduced.

In his seminal contribution to information economics, Akerlof (1970) employs the information asymmetries between buyers and sellers of used cars as his prime example to illustrate the famous "lemons-problem". Although adverse selection due to asymmetric information with respect to unobservables is undeniably still a major problem within this market, our findings suggest that inefficiencies may also arise with respect to observable characteristics. People seem to be inattentive to subtle, but nevertheless valuable details of the *available* information.

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A Figures and Tables

Figure 1. *Website www.mobile.de*

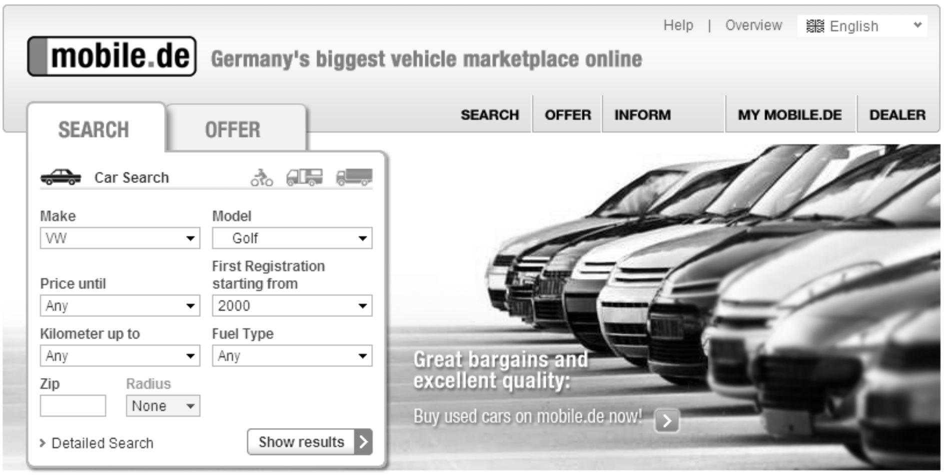

Figure 2. *Search Results Listing – www.mobile.de*

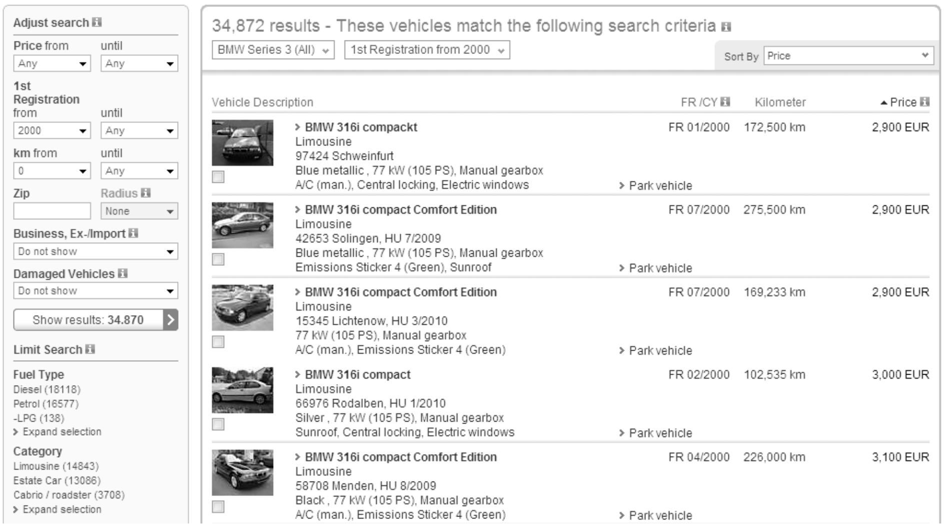

Figure 3. *Car Details – www.mobile.de*

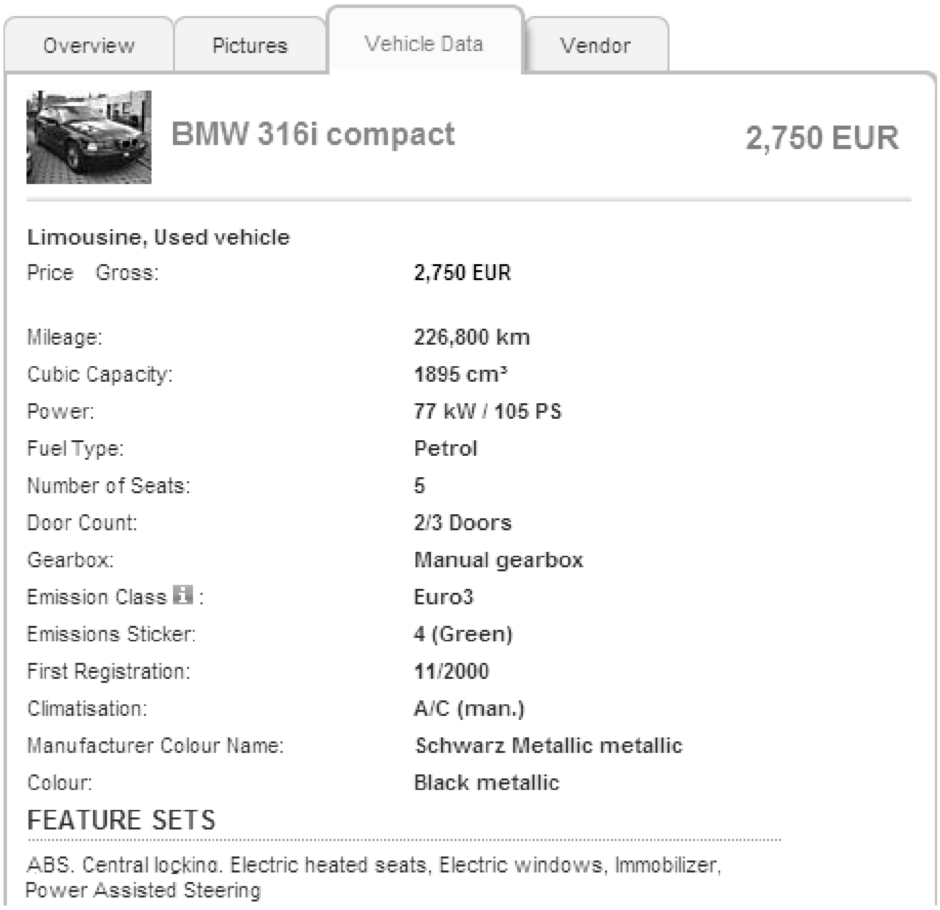

Table 1. *Models Series and Estimation Periods*

Make & Model	Name of Series		Production period
VW Golf	IV		10/1997 - 09/2003
	V		10/2003 - 07/2008
BMW 3	E46		04/1998 - 11/2004
	E90	(limousine)	12/2004 - 09/2008*
		(estate)	06/2005 - 09/2008*
Audi A4	B6	(limousine)	10/2000 - 11/2004
		(estate)	09/2001 - 11/2004
	B7	(limousine)	11/2004 - 11/2007
		(estate)	11/2004 - 03/2008
Opel Astra	G		02/1998 - 01/2004
	H		02/2004 - 10/2007*

Notes: Entries with an asterisk indicate an upgrade of the current production series. If there were different introduction dates within a model series, we use the later date to determine the estimation period.

Figure 4. *Distribution of Car Age*

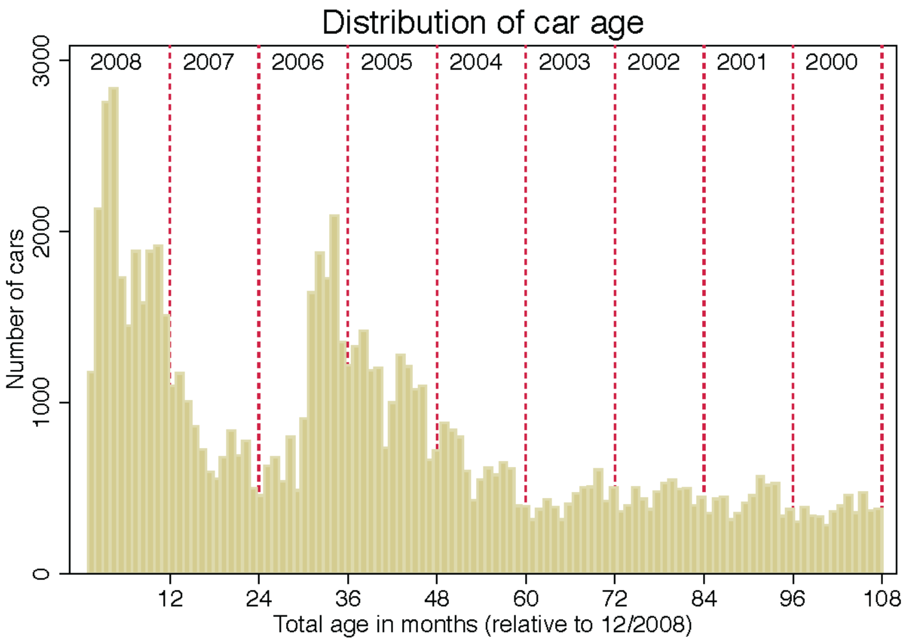

Figure 5. *Distribution of Car Mileage*

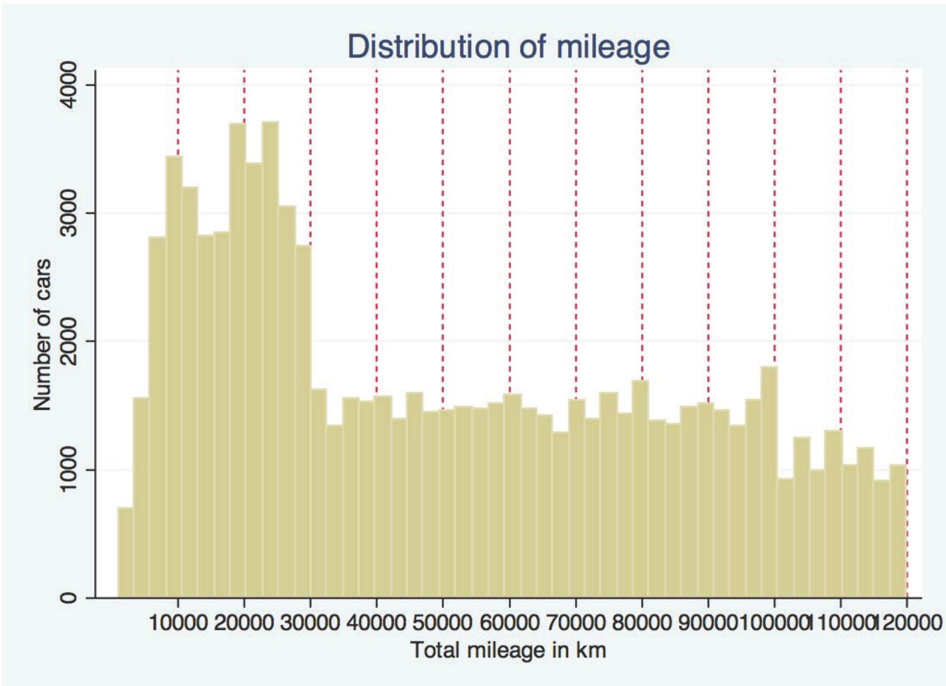

Figure 6. *Distribution of Car Prices*

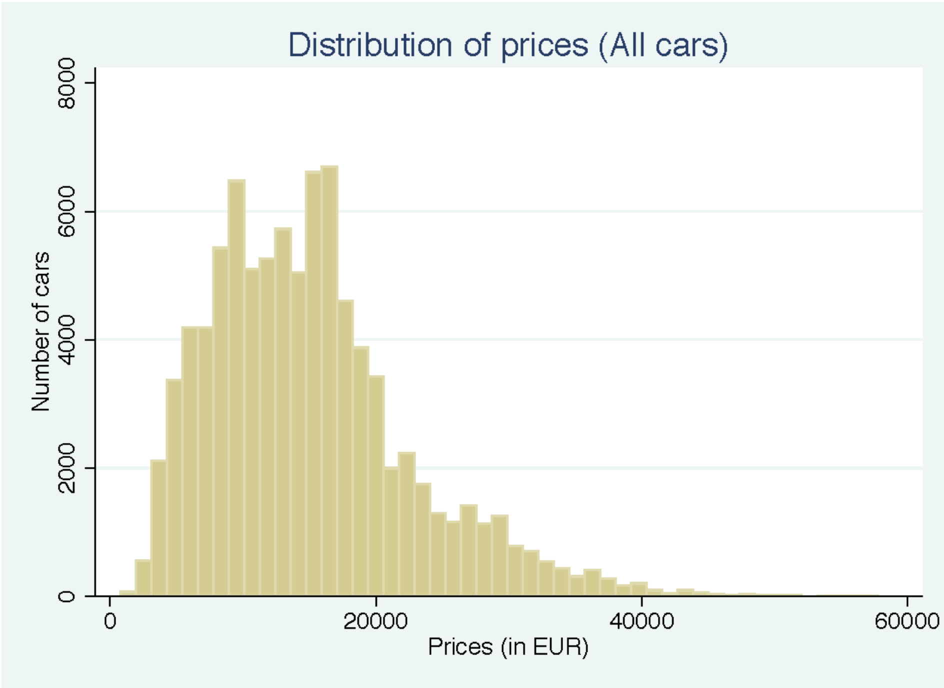

Figure 7. *Avg. Car Prices by Age (monthly averages)*

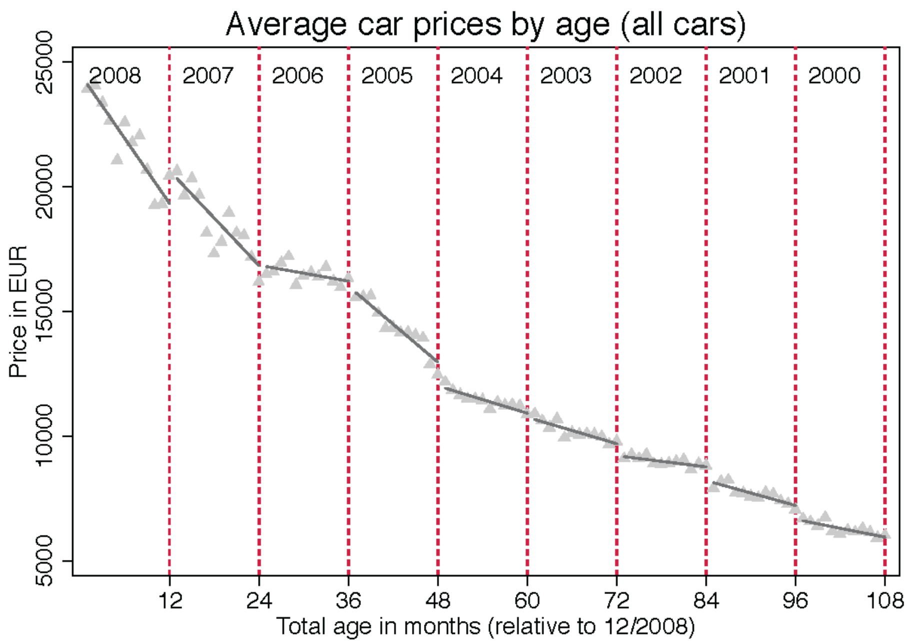

Figure 8. *Avg. Adj. Residual Car Prices - all cars*

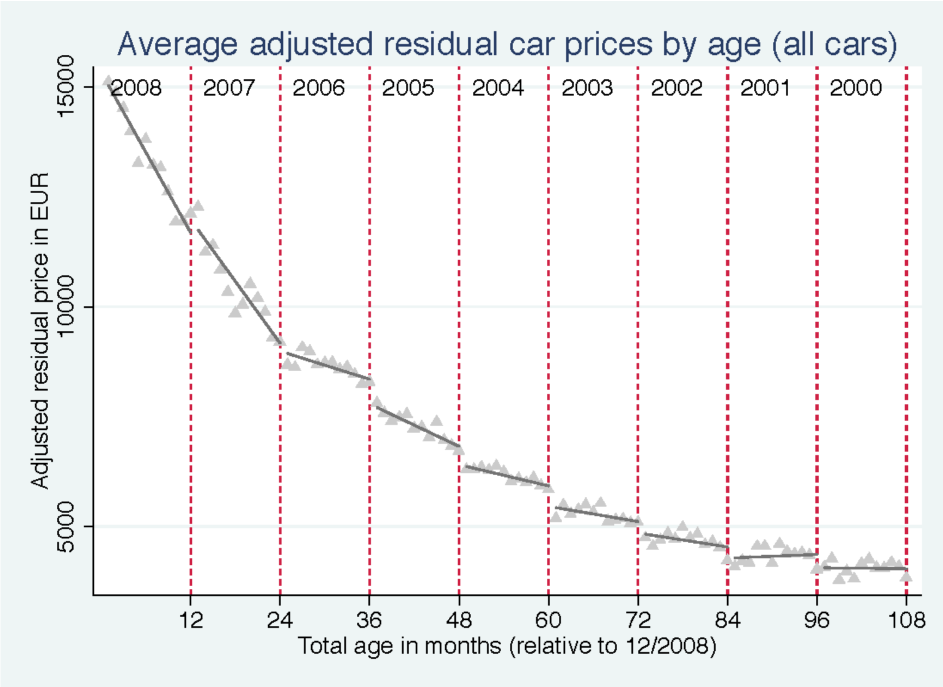

Figure 9. *Avg. Adj. Residual Car Prices - cars older than 2 yrs.*

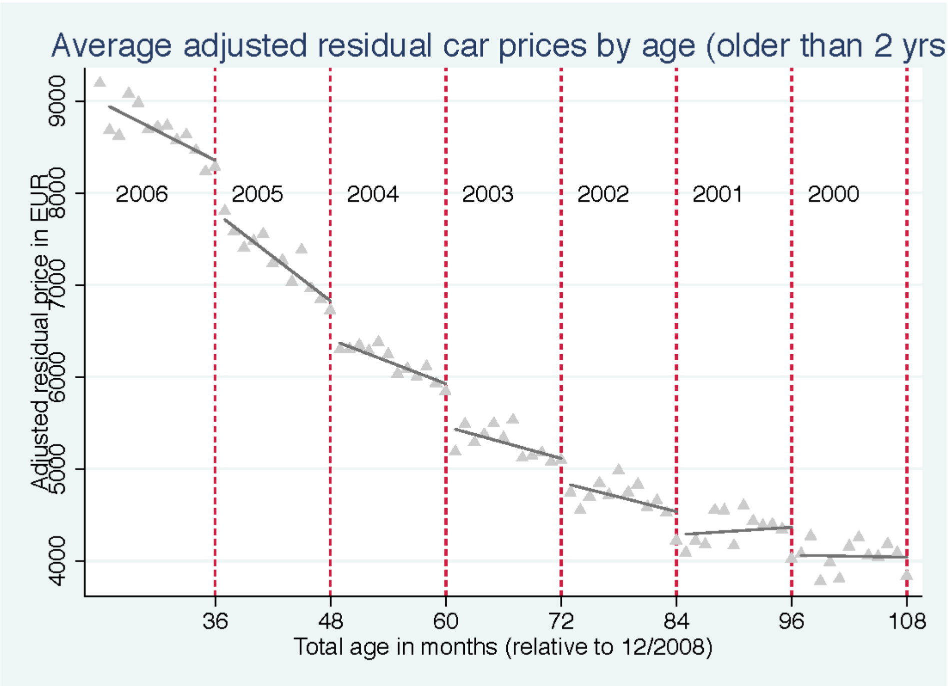

Figure 10. *Avg. Car Mileage by Age (monthly averages)*

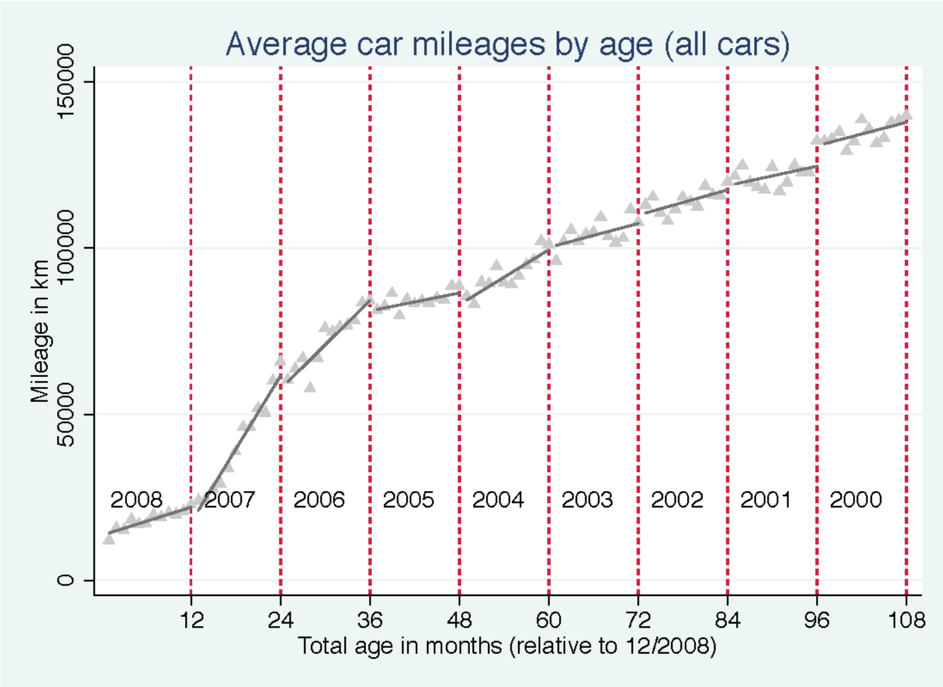

Figure 11. *Avg. horsepowers by age (monthly averages)*

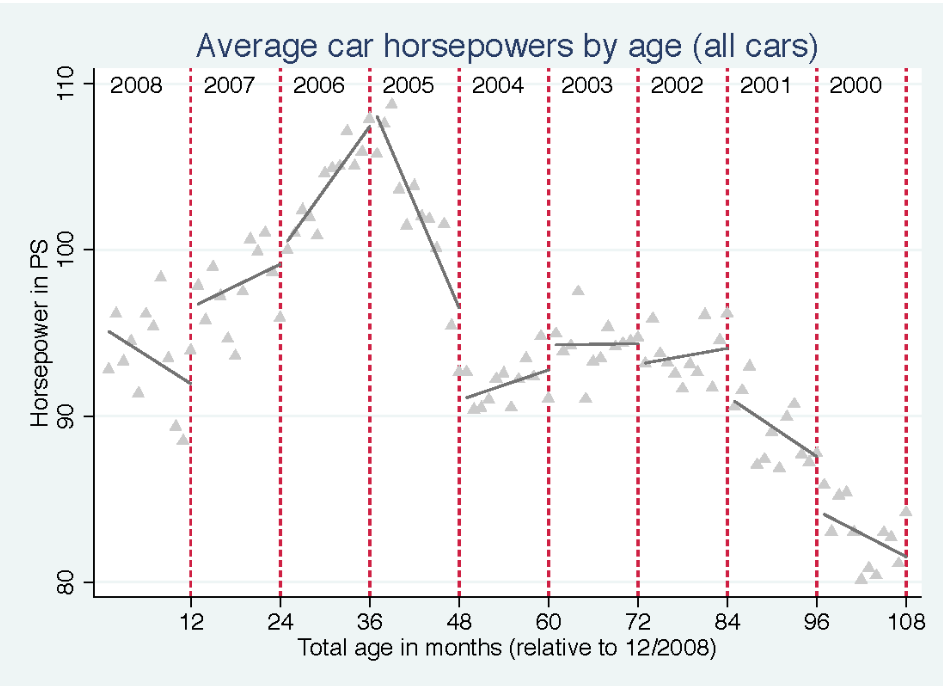

Figure 12. *Share of regular gasoline cars on offer (monthly averages*

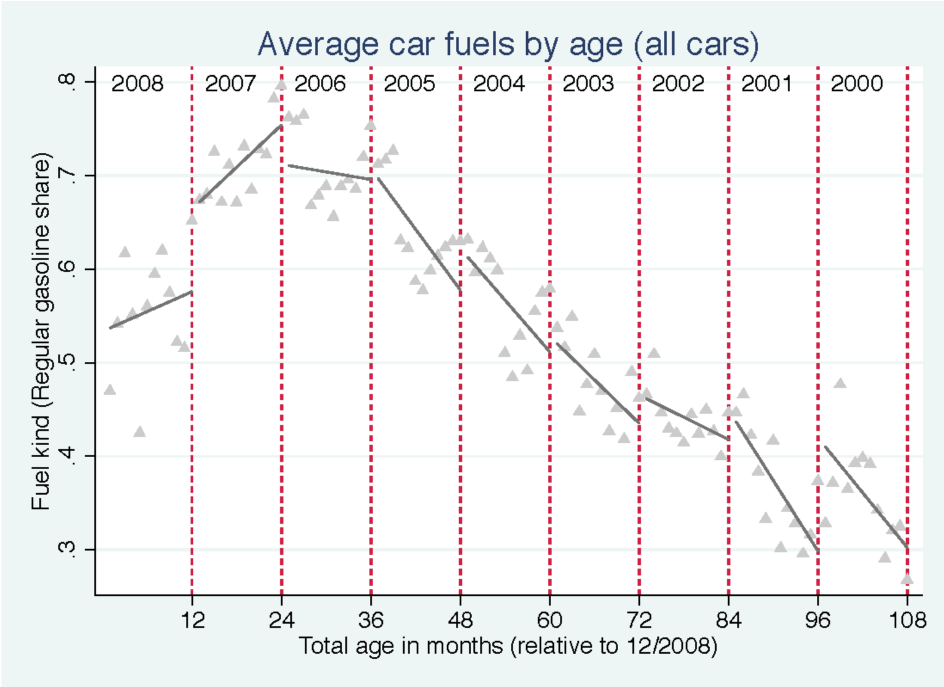

Figure 13. *Avg. Share of Private Sellers by car age*

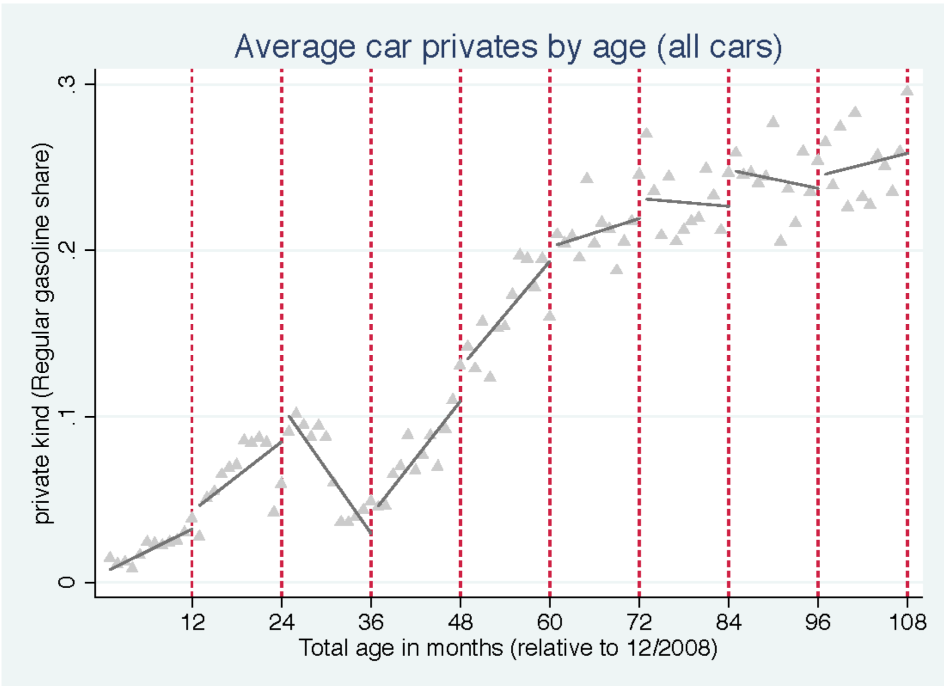

Figure 14. *Avg. Number of Cars offered – monthly averages*

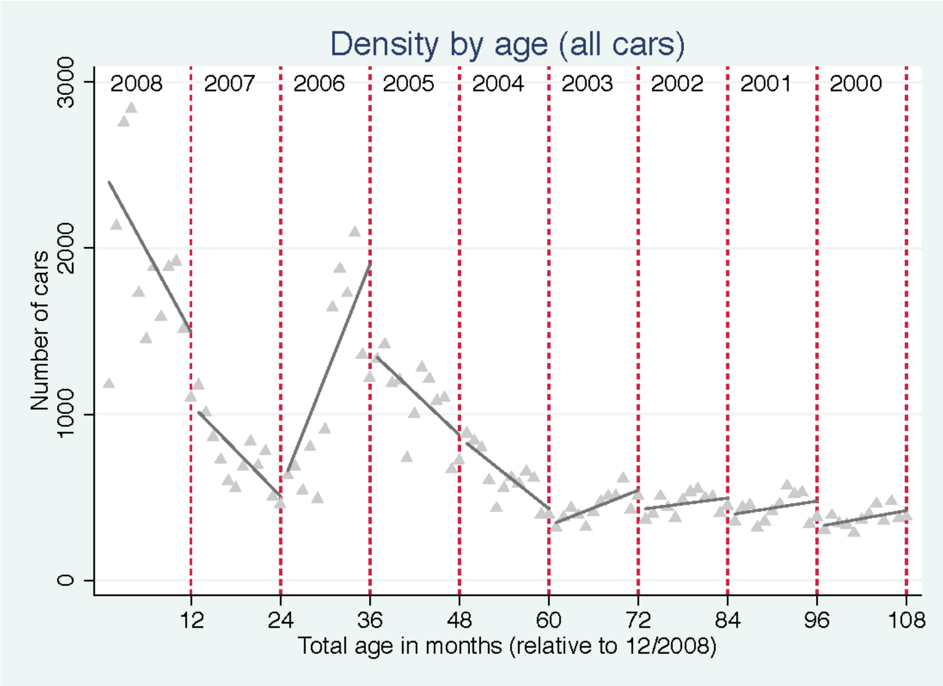

Table 2. *Summary statistics*

Dep. Variable: Car price Variable	N	Mean	StDev	Min	Max
Price (in EUR)	89136	14973,74	7544,360	800	57880
Mileage (in km)	89136	72600,13	56422,780	1000	493300
Total age (in months*)	89136	43,03	33,430	1	108
Horsepower (in PS)	89049	95,15	28,430	44	309
Indicators					
Diesel engine	89136	0,560	0,496	0	1
Automatic gearbox	89136	0,195	0,396	0	1
Metallic paint	89136	0,808	0,394	0	1
Air condition	89136	0,961	0,194	0	1
Leather trim	89136	0,157	0,364	0	1
Airbag	89136	0,501	0,500	0	1
Power windows	89136	0,936	0,245	0	1
Sunroof	89136	0,183	0,387	0	1
Four-wheel drive	89136	0,041	0,490	0	1
Seat heating	89136	0,504	0,197	0	1
Cruise control	89136	0,470	0,500	0	1
Private seller	89136	0,108	0,310	0	1

Notes: *Total age in months measured relative to December 2008.

Figure 15. *Distribution of Car Prices by Mileage (1,000Km bins)*

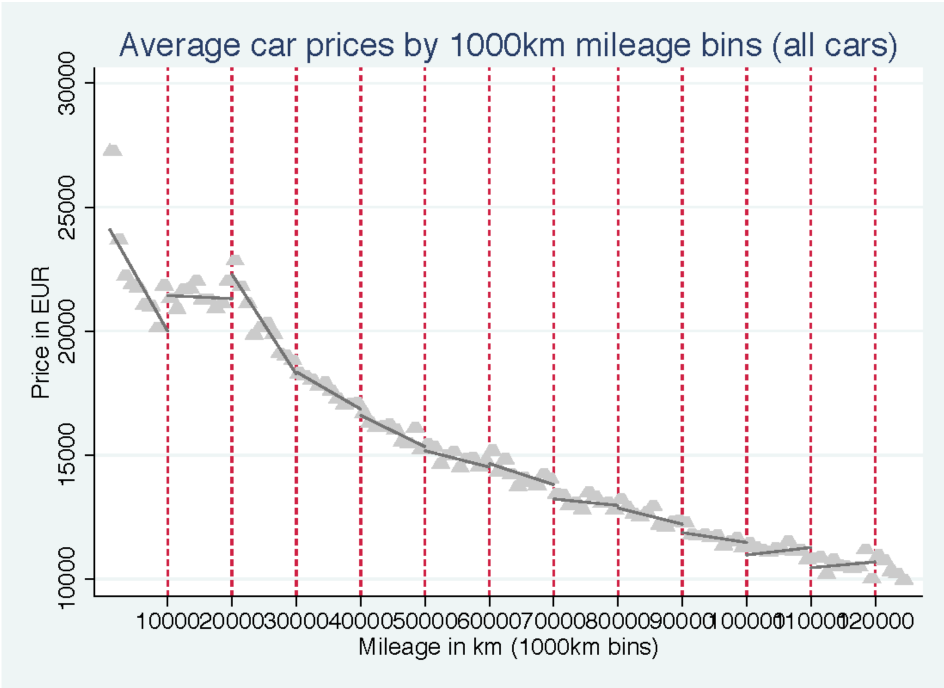

Figure 16. *Avg. Adj. Residual Car Prices - all cars*

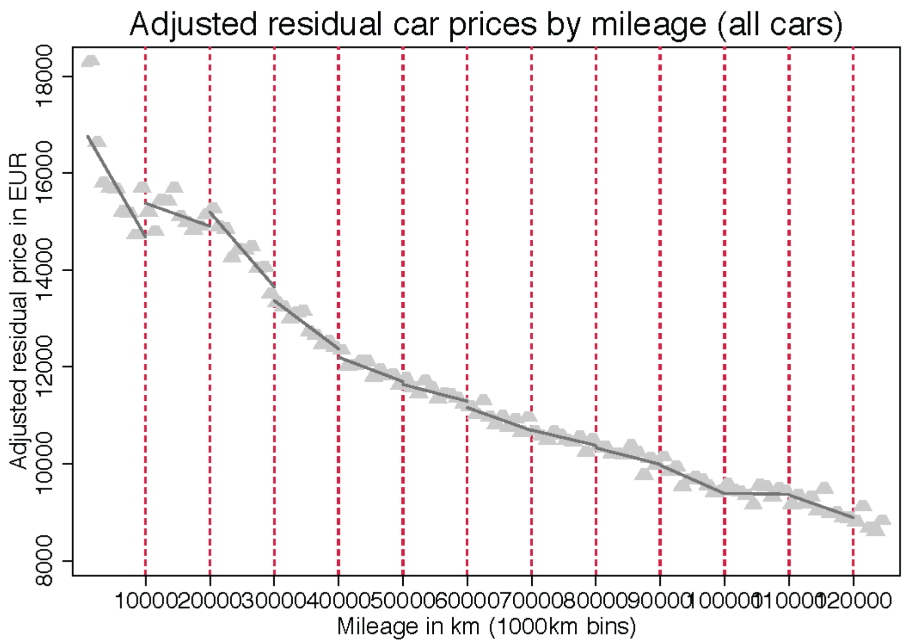

Figure 17. *Avg. Adj. Residual Car Prices - cars older than 2 yrs.*

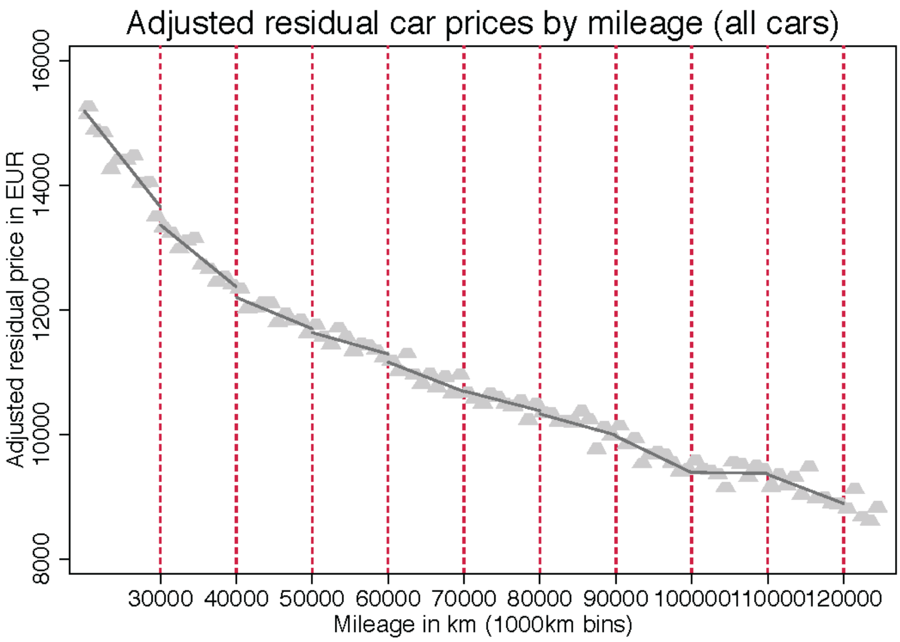

Figure 18. *Avg. Number of Cars offered – 1,000Km bin averages*

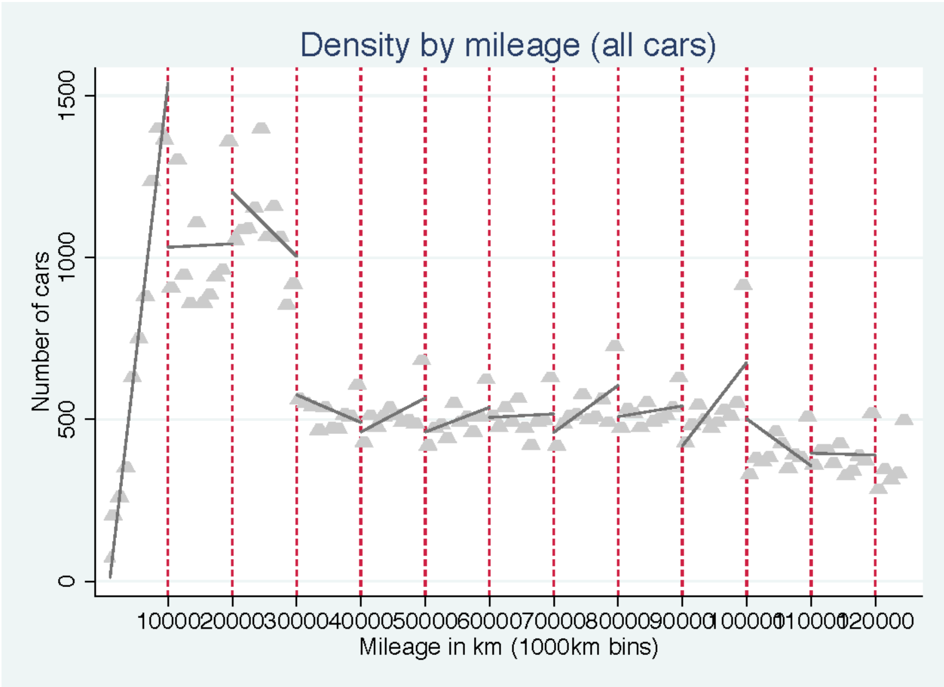

Figure 19. *Expected Valuation in Dependence of Search Costs*

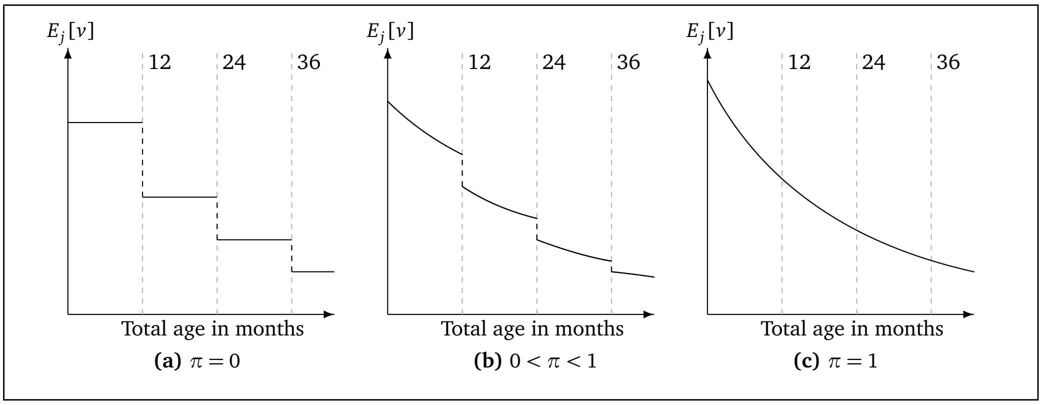

Table 3. *The impact of vintage discontinuities on price*

Dep. Variable: Car price	(1)	(2)	(3)	(4)	(5)
Indicator for...					
...older than 2008	891.0***	68,1	3,9	-34,9	-60.9
	(154.5)	(99.2)	(99.0)	(84.4)	(84.7)
...older than 2007	515.4**	-41,5	-142,5	-167.3*	-213.4*
	(177.8)	(104.9)	(104.7)	(86.2)	(86.0)
...older than 2006	-296.9**	-402.7***	-512.4***	-332.3***	-382.5***
	(104.1)	(61.8)	(61.9)	(52.5)	(52.5)
...older than 2005	-1297.1***	-479.5***	-554.1***	-335.0***	-388.9***
	(99.6)	(72.2)	(72.9)	(65.7)	(66.3)
...older than 2004	263.8*	-425.3***	-450.2***	-439.0***	-450.3***
	(117.3)	(94.1)	(93.9)	(90.0)	(89.7)
...older than 2003	-171,7	-256.9**	-306.2**	-52,3	-75,5
	(95.3)	(90.6)	(90.7)	(88.3)	(88.5)
...older than 2002	-692.8***	-130.2	-195.2	20,7	-10.0
	(110.0)	(107.6)	(107.3)	(106.0)	(106.1)
...older than 2001	-792.6***	-231.1*	-230.2*	-80,0	-80.3
	(91.4)	(113.7)	(113.7)	(114.9)	(115.3)
5th-order age polynomial	X	X	X	X	X
Controls for car features		X	X	X	X
Controls for model updates			X		X
Car model fixed effects				X	X
R-squared	0,4913	0,8281	0,8284	0,8703	0,8703
N	85295	67785	67785	67785	67785

Notes: Robust standard errors in brackets. ***p<0.001; **p<0.01; *p<0.05

Table 4. *Robustness analysis: Log-linearization*

Dep. Variable: ln(Car price)	(1)	(2)	(3)	(4)	(5)
Indicator for...					
...older than 2008	0.032***	-0.009*	-0.019***	-0.020***	-0.023***
	(0.008)	(0.004)	(0.005)	(0.004)	(0.004)
...older than 2007	0.03**	-0.007	-0.028***	-0.026***	-0.031***
	(0.010)	(0.006)	(0.006)	(0.005)	(0.005)
...older than 2006	-0.014*	-0.025***	-0.036***	-0.024***	-0.029***
	(0.007)	(0.004)	(0.004)	(0.003)	(0.003)
...older than 2005	-0.092***	-0.045***	-0.046***	-0.032***	-0.036***
	(0.008)	(0.005)	(0.005)	(0.005)	(0.005)
...older than 2004	-0.004	-0.038***	-0.038***	-0.034***	-0.036***
	(0.010)	(0.007)	(0.007)	(0.006)	(0.006)
...older than 2003	-0.023*	-0.023**	-0.026**	-0.008	-0.011
	(0.011)	(0.007)	(0.008)	(0.006)	(0.006)
...older than 2002	-0.073***	-0.044***	-0.049***	-0.038***	-0.042***
	(0.013)	(0.009)	(0.009)	(0.008)	(0.008)
...older than 2001	-0.100***	-0.070***	-0.073***	-0.068***	-0.068***
	(0.013)	(0.009)	(0.010)	(0.009)	(0.009)
5th-order age polynomial	X	X	X	X	X
Controls for car features		X	X	X	X
Controls for model updates			X		X
Car model fixed effects				X	X
R-squared	0,5956	0,8751	0,8659	0,9111	0,8703
N	85295	67785	67785	67785	67785

Notes: Robust standard errors in brackets. ***p<0.001; **p<0.01; *p<0.05

Table 5. *Robustness analysis: Varying controls for model updates*

Dep. Variable: ln(Car price)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Indicator for...								
...older than 2008	153,9	6,7	145,2	-42,3	85,7	-19,4	4,5	-53,2
	(97.7)	(78.6)	(97.5)	(79.9)	(98.2)	(84.0)	(98.2)	(84.5)
...older than 2007	-30,8	11,1	66,0	-133,6	-37,6	-163.5*	-134,9	-199.2*
	(105.3)	(83.7)	(105.8)	(84.3)	(104.7)	(86.1)	(104.7)	(86.0)
...older than 2006	-354.0***	-437.5***	-291.9***	-321.2***	-398.6***	-328.8***	-535.1***	-377.8***
	(62.7)	(50.7)	(63.4)	(51.6)	(61.6)	(52.4)	(61.8)	(52.3)
...older than 2005	-609.0***	-61.9	-386.5***	-189.0***	-471.2***	-347.1***	-471.8***	-352.7***
	(73.5)	(60.0)	(78.4)	(66.5)	(72.7)	(65.9)	(71.9)	(65.6)
...older than 2004	-643.7***	-338.8***	-453.4***	-517.5***	-425.4***	-438.7***	-330.1***	-406.6***
	(94.1)	(83.3)	(100.4)	(92.4)	(94.2)	(90.1)	(93.2)	(89.3)
...older than 2003	-349.0***	-527.8***	-317.5***	-493.3***	-253.5***	-49.2	-271.6**	-58.0
	(88.5)	(87.8)	(90.4)	(90.2)	(90.6)	(88.3)	(90.4)	(88.3)
...older than 2002	-54.1	144.3	-122.7	264.4*	-124.1	26.2	-220.1*	-11.1
	(105.2)	(105.6)	(107.3)	(108.2)	(107.4)	(105.9)	(107.1)	(106.1)
...older than 2001	-96.9	392.5***	-197.4	-375.3	-224.2*	-73.5	-204.9	-71.8
	(110.9)	(112.1)	(119.3)	(128.0)	(113.7)	(114.8)	(113.6)	(115.4)
5th-order age polynomial	X	X	X	X	X	X	X	X
Controls for car features	X	X	X	X	X	X	X	X
Controls for model updates	D1	D1	D2	D2	D3	D3	D4	D4
Car model fixed effects		X		X		X		X
R-squared	0,8306	0,8817	0,8659	0,8781	0,8281	0,8703	0,8287	0,8703
N	67785	67785	65485	65485	67785	67785	67785	67785

Notes: Robust standard errors in brackets. ***p<0.001; **p<0.01; *p<0.05

Table 6. *Placebo tests: Other month thresholds*

Dep. Variable: Car price	(1)	(2)	(3)
Indicator for...			
...older than 2008	-145,5	45,7	-581.8***
	(95.0)	(103.7)	(111.0)
...older than 2007	319.8***	454.2***	360.9***
	(55.0)	(72.8)	(87.1)
...older than 2006	95.5	-77,3	-107.0
	(62.6)	(64.0)	(59.0)
...older than 2005	-59,3	-182.6*	-92.0
	(89.9)	(90.3)	(80.1)
...older than 2004	-41,5	-66,2	139.0
	(96.9)	(112.2)	(112.0)
...older than 2003	-124,8	-12,6	220.8*
	(107.4)	(114.9)	(107.3)
...older than 2002	-112,1	-2,1	326.1*
	(107.9)	(122.5)	(118.7)
...older than 2001	-19,0	162,0	90,9
	(166.3)	(154.1)	(140.8)
5th-order age polynomial	X	X	X
Controls for car features	X	X	X
Controls for model updates	X	X	X
Car model fixed effects	X	X	X
Placebo month	March	June	September
R-squared	0,8704	0,8705	0,8706
N	67785	67785	67785

Notes: All regressions also include the original non-placebo December months, for which estimates do not significantly change. Robust standard errors in brackets. ***p<0.001; **p<0.01; *p<0.05

Table 7. *Robustness analysis: Varying age polynomials*

Dep. Variable: Car price	(1)	(2)	(3)	(4)	(5)
Indicator for...					
...older than 2008	-387.1**	21,0	118,9	189,7	188,9
	(140.9)	(95.1)	(110.8)	(121.6)	(125.7)
...older than 2007	-55,9	-94,7	-50,7	-108,7	-107,1
	(79.3)	(87.2)	(107.1)	(106.5)	(114.7)
...older than 2006	-244.1***	-511.5***	-457.7***	-488.8***	-489.4***
	(51.1)	(62.3)	(64.1)	(67.5)	(66.6)
...older than 2005	-345.2***	-593.0***	-472.2***	-401.8***	-402.3***
	(69.2)	(66.3)	(73.2)	(77.0)	(79.1)
...older than 2004	-780.7***	-524.5***	-329.1**	-286.7**	-284.7*
	(88.2)	(85.4)	(102.2)	(105.4)	(114.0)
...older than 2003	-263.3***	-292.3***	-173.0	-270.3*	-270.2*
	(74.8)	(91.0)	(99.5)	(106.0)	(106.2)
...older than 2002	-16.9	-91.3	-192.3	-226.5*	-228.3*
	(85.9)	(95.3)	(108.6)	(110.5)	(117.3)
...older than 2001	143.0	-208.4	-344.5*	-220.5	-218.3
	(112.0)	(111.7)	(121.6)	(133.2)	(142.02)
Order of age polynomial	3rd	4th	6th	7th	8th
Controls for car features	X	X	X	X	X
Controls for model updates	X	X	X	X	X
Car model fixed effects	X	X	X	X	X
R-squared	0,8718	0,8308	0,8306	0,8306	0,8306
N	67785	67785	67785	67785	67785

Notes: Robust standard errors in brackets. ***p<0.001; **p<0.01; *p<0.05

Table 8. *The impact of mileage discontinuities on price*

Dep. Variable: Car price	(1)	(2)	(3)	(4)	(5)
Indicator for...					
...more than 10K km	304.9**	-193.2*	-132.7	-184.1**	-146.9*
	(114.3)	(75.1)	(75.5)	(66.0)	(66.3)
...more than 20K km	-562.6***	-487.2***	-466.4***	-659.1***	-643.6***
	(105.7)	(68.3)	(68.1)	(58.5)	(58.4)
...more than 30K km	-2316.4***	-1540.9***	-1549.2***	-1440.3***	-1445.2***
	(115.3)	(73.4)	(72.7)	(61.3)	(61.0)
...more than 40K km	-1237.1***	-807.7***	-808.9***	-893.8***	-893.8***
	(121.3)	(72.8)	(72.2)	(61.1)	(60.9)
...more than 50K km	-699.7***	-323.0***	-318.5***	-361.4***	-358.5***
	(116.0)	(63.3)	(63.1)	(54.2)	(54.1)
...more than 60K km	-194,1	-330.5***	-332.9***	-390.9***	-392.3***
	(113.4)	(59.8)	(59.8)	(51.6)	(51.5)
...more than 70K km	-730.2***	-210.8***	-209.9***	-253.5***	-252.8***
	(107.4)	(57.4)	(57.5)	(49.7)	(49.7)
...more than 80K km	-158.0	-176.1**	-177.2**	-274.0***	-274.1***
	(103.6)	(55.1)	(55.2)	(49.0)	(49.0)
...more than 90K km	-469.4***	-286.8***	-282.0***	-283.3***	-280.5***
	(100.7)	(53.1)	(53.3)	(48.4)	(48.4)
...more than 100K km	-179.3	-103.6	-101.0	-173.6**	-172.0**
	(103.2)	(56.1)	(56.3)	(52.0)	(52.0)
2nd-order mileage polynomial	X	X	X	X	X
Controls for car features		X	X	X	X
Controls for model updates			X		X
Car model fixed effects				X	X
R-squared	0,3991	0,8298	0,8305	0,8685	0,8688
N	89136	71142	71142	71142	71142

Notes: Robust standard errors in brackets. ***p<0.001; **p<0.01; *p<0.05

Table 9. *Placebo tests: US mile thresholds*

Dep. Variable: Car price	(1)
Indicator for...	
...more than 10K miles	-284.0**
	(103.6)
...more than 20K miles	-489.2***
	(131.0)
...more than 30K miles	-87.5
	(112.2)
...more than 40K miles	-144.0
	(83.2)
...more than 50K miles	-27.2
	(165.8)
...more than 60K miles	-41,4
	(78.2)
...more than 70K miles	-15.3
	(93.2)
...more than 80K miles	26.2
	(138.4)
...more than 90K miles	-165.2
	(108.2)
...more than 100K miles	111.6
	(96.6)
2nd-order mileage polynomial	X
Controls for car features	X
Controls for model updates	X
Car model fixed effects	X
R-squared	0,8328
N	71142

Notes: All regressions also include the original non-placebo 10,000Km thresholds, for which estimates do not significantly change. Robust standard errors in brackets. ***p<0.001; **p<0.01; *p<0.05

Table 10. *The joint impact of vintage and mileage discontinuities on price*

Dep. Variable: Car price	(1)	(2)	(3)
Indicator for...			
...older than 2008	-60.9		-80,3
	(84.7)		(83.6)
...older than 2007	-213.4*		-240.2**
	(86.0)		(84.4)
...older than 2006	-382.5***		-462.0***
	(52.5)		(50.6)
...older than 2005	-388.9***		-393.9***
	(66.3)		(65.8)
...older than 2004	-450.3***		-353.0***
	(89.7)		(85.5)
...older than 2003	-75,5		-19,2
	(88.5)		(86.9)
...older than 2002	-10.0		-63.0
	(106.1)		(105.4)
...older than 2001	-80.3		-172.5
	(115.3)		(114.2)
...more than 10K km		-146.9*	204.3**
		(66.3)	(63.8)
...more than 20K km		-643.6***	-374.9***
		(58.4)	(54.6)
...more than 30K km		-1445.2***	-263.7***
		(61.0)	(59.2)
...more than 40K km		-893.8***	-318.1***
		(60.9)	(56.6)
...more than 50K km		-358.5***	-149.9**
		(54.1)	(52.1)
...more than 60K km		-392.3***	-264.6***
		(51.5)	(50.6)
...more than 70K km		-252.8***	-177.8***
		(49.7)	(49.9)
...more than 80K km		-274.1***	-268.0***
		(49.0)	(49.8)
...more than 90K km		-280.5***	-282.0***
		(48.4)	(49.8)
...more than 100K km		-172.0**	-213.1***
		(52.0)	(54.1)
5th-order age polynomial	X		X
2nd-order mileage polynomial		X	X
Controls for car features	X	X	X
Controls for model updates	X	X	X
Car model fixed effects	X	X	X
R-squared	0,8703	0,8298	0,8750
N	67785	71142	67785

Notes: Robust standard errors in brackets. ***p<0.001; **p<0.01; *p<0.05

Table 11. *Number of cars on sale in coarse categories*

Cars on sale per vintage year	
2008	25.763
2007	11.450
2006	16.473
2005	14.916
2004	8.614
2003	6.251
2002	6.532
2001	5.898
2000	5.281
1999	2.768
1998	2.130
Cars on sale per 10,000Km bin	
0 – 10,000km	7.857
10,000 – 20,000km	12.730
20,000 – 30,000km	13.261
30,000 – 40,000km	6.435
40,000 – 50,000km	6.227
50,000 – 60,000km	6.084
60,000 – 70,000km	6.017
70,000 – 80,000km	6.157
80,000 – 90,000km	6.013
90,000 – 100,000km	0
100,000 – 110,000km	4.569
110,000 – 120,000km	4.495

Notes: Table gives the number of cars on sale in our data broken up by coarse categories of interest.