# HEURISTIC PRICING IN AN UNCERTAIN MARKET: ECOLOGICAL AND CONSTRUCTIVIST RATIONALITY*

FLORIAN M. ARTINGER AND GERD GIGERENZER

How do firms set prices when faced with an uncertain market? Analyzing the pricing strategies of used car dealers using online data and interviews, we find that dealers employ an aspiration level heuristic similar to a Dutch auction. At the same time, the aggregate market is well described by a model of equilibrium price dispersion. Unlike the equilibrium model, the heuristic correctly predicts systematic pricing characteristics such as high initial price, price stickiness, and the "cheap twin paradox." We also find first evidence that heuristic pricing can generate higher profits given uncertainty than the equilibrium strategy. *JEL* Codes D22, D80, L81.

Address for correspondence: Florian Artinger, Max Planck Institute for Human Development, Center for Adaptive Behavior and Cognition, Lentzeallee 94, 14195 Berlin, Germany, tel: +49 30 82406-361, fax: +49 30 82406-697, artinger@mpib-berlin.mpg.de.

## I. INTRODUCTION

At the largest BMW dealership worldwide for used cars, one of the authors was looking to buy a car. Among the offers were two cars both 20 months old, with the same mileage, and virtually identical in every other respect. Nevertheless, one was more than 10 percent cheaper than the other. How can two cars from the same dealer, as similar as identical twins, be priced several thousand euros apart? In this article we analyze the pricing strategies relied on by car dealers and find that virtually all use the aspiration level heuristic. We show that the "cheap twin paradox" is a logical consequence of this pricing strategy, absent differences between cars. By analyzing how dealers set prices, we provide a novel perspective on how their pricing strategies shape the market, creating price dispersion in equilibrium.

A central determinant of the pricing strategy of a firm is the reliability of information. Stigler (1961, 261) already pointed out that the ideal of the 'law of one price' rarely holds and that "price dispersion is a manifestation—and, indeed, it is the measure—of ignorance in the market." Even in markets with a clearing house, such as newspapers or online platforms, price dispersion persists and the market reveals an imprecise estimate of the value of a good to firms and consumers alike (Brynjolfsson and M. D. Smith 2000). Price dispersion can be due among others to firms' limited knowledge about demand and difficulty in learning about it, a dynamic market, highly differentiated products, or relatively few competing offers (Baye, Morgan, and Scholten 2004; Einav et al., in press). Given such an uncertain environment, the major challenge for firms is to determine the best pricing strategy to use.

Despite uncertainty that agents face, markets quickly converge to equilibrium even though agents operate under information conditions that are much weaker than specified in the theory as first shown by V. L. Smith in his classic 1962 work which initiated a very large stream of literature (for a review see V. L. Smith 2008). Addressing this gap, V. L. Smith (2008) distinguishes between two types of analyses[1]: The first, constructivist rationality, which is commonly used in economics, applies deductive reasoning from first principles. It commences with an analysis of the incentive structure of the environment, whereby a model is developed that abstracts and sufficiently simplifies the decision-making problem. This then allows deducing the equilibrium strategy that an agent uses and in turn the conditions that characterize the market. A second analysis, that of ecological rationality, is inductive in nature and allows for uncertainty as opposed to only risk[2]. It proceeds by first identifying the decision strategy that an agent uses. It then assesses the determinants of the performance of the strategy as a function of the structural properties of the environment. The term ecological rationality thereby refers to the degree to which a strategy is adapted to the environment, evaluated in terms of a fitness measure such as profit or accuracy (Gigerenzer, Todd, and the ABC Research Group 1999). Underlying the idea of ecological rationality is a form of a Darwinian selection process, where the best performing strategy survives competition.

Given sufficiently strong information conditions, analyses based on ecological and constructivist rationality may yield the same best performing strategy. Under weak information conditions such as noisy, little, or unreliable information, where the decision maker cannot precisely ascertain the structure of the environment, heuristics have been shown to perform surprisingly well compared to other more complex strategies (e.g., Gigerenzer, Todd, and the ABC Research Group 1999; Åstebro and Elhedhli 2006; DeMiguel, Garlappi, and Uppal 2007; Wübben and von Wangenheim 2008). The precise nature of the heuristics

---

1 The principal distinction between two rational orders can already be found in the writings of Adam Smith (1776; 1779), Hume (1739), and, later, Hayek (e.g., 1937; 1945), as well as in Savage (1951) and Simon (1955; 1956).

2 We use the terms risk and uncertainty in line with Knight (1921) and Keynes (1921). In situations of risk the decision maker knows all relevant elements of the decision space: the options, associated outcomes, and probabilities with which the outcomes obtain. In contrast, under uncertainty the decision maker lacks such complete knowledge; at least one or more of the elements of the decision space are unknown.

used for pricing in an uncertain market such as the used car market, however, has so far been unknown. This article investigates the heuristics dealers actually use, whether they are well adapted to the characteristics of the local environments of the dealerships, and whether the analysis of the ecological rationality of a heuristic can be integrated with a constructivist analysis of the aggregate market pattern.

A prominent candidate rule formally developed by Simon (1955) is the aspiration level heuristic, where an object is evaluated with regards to a reference point or threshold: if the object does not meet or exceed the threshold, the decision maker continues search, engaging in a sequential sampling process. If, after a certain amount of search, no adequate object has been encountered, the aspiration level is adapted accordingly. Simon (1955) cites the real estate market as one relevant domain where uncertainty about the asking price looms large due to highly differentiated products with relatively few offers of the same good. A given price serves as an aspiration level for evaluating whether there are any customers with a sufficiently high willingness to pay. Aspiration level pricing implies the possibility of price stickiness. If prices of twins do not adapt synchronously, price stickiness results in price dispersion even within one firm, as the introductory example with the cheap twin paradox illustrates. We would like to point out that aspiration adaptation closely resembles a Dutch auction, where the price starts high and is sequentially adapted downwards until one customer's willingness to pay meets or exceeds the asking price. Given uncertainty about demand, auctions are more frequently used than posted prices, which is in line with the incentives provided by the market environment (Einav et al., in press).

This is the first paper to apply an analysis of both constructivist and ecological rationality using field data. The data set is from the largest online market platform for used cars in Europe, where we tracked the market for two types of cars and the pricing of dealers who offered them over a period of 15 months. Online platforms are of central importance to the used car market because they provide the primary source of information for the vast majority of customers: after identifying a sufficiently attractive car online, many buyers visit only this one dealership to make the purchase, a pattern observed across Europe and the US (Mohr et al. 2015). We used a grouping method to obtain matching cars and thereby analyze the pricing strategy that dealers employ: on a given day and for all cars posted online, those with identical advertised attributes apart from the price were grouped together. To verify and add to the conclusions from the online data, we independently conducted interviews with 55 dealers about their pricing strategies.

This paper reports three major results: First, faced with weak information conditions, including uncertainty about demand, a dynamic market, and relatively small samples of matching cars, virtually all dealers use an aspiration level heuristic for pricing. Dealers' pricing exhibits three characteristics that derive from the use of the heuristic: high initial price, price stickiness, and the cheap twin paradox. Second, the aggregate market pattern produced by the heuristic best fits an equilibrium model of price dispersion (Varian, 1980) in the tradition of a constructivist analysis. Finally, due to competitive pressure in the market, dealers adapt the parameters of the heuristic pricing strategy to their local environment and thus can make more profit than if they had used the equilibrium strategy underlying the aggregate market model.

Section II presents a general strategy of heuristic pricing as first proposed by Simon (1955) and introduces the concept of ecological rationality, with a focus on when and why heuristic strategies can perform well. Section III briefly discusses the concept of constructivist rationality and introduces the relevant literature on models of price dispersion. This is followed by the methods and results in sections IV and V, respectively. Finally, the discussion in section VI centers on the role of adaptive heuristics in generating aggregate market phenomena.

## II. HEURISTIC PRICING

*II.A. Aspiration adaptation*

Aspiration levels are at the heart of a range of decision strategies and their use has been widely documented in empirical research. Aspiration levels feature, for instance, in the behavioral theory of the firm (Cyert and March 1963), in modeling the evolution of industries and economies (Nelson and Winter 1973), and in research on adaptive expectations (Chow 1989) and adaptive learning (Jacobs and Jones 1980). In rational expectation models, aspiration levels are subsumed in the overall function. Relying on them can converge in the long run with rational expectations (Lucas 1986; Lant 1992; Conlisk 2003). Empirical evidence on the use of aspiration levels in the context of firm decision making stems primarily from management (for a review see Argote and Greve 2007), but also from marketing (Wübben and von Wangenheim 2008) and finance (Åstebro and Elhedhli 2006). In the context of price setting, the use of aspiration levels, as proposed by Simon (1955), has not been investigated so far.

Pricing according to an aspiration level heuristic where prices are adjusted in regular time intervals can be summarized by a three-parameter strategy:

$$p(t) = \begin{cases} (1+\alpha)p_{g,min,t} & if\ t \leq \beta \\ (1+\alpha)p_{g,min,t}\,\gamma^{m-1} & if\ \beta < t \leq m\beta \end{cases} \tag{1}$$

where the price of a car $p(t)$ at time $t$ is initially equal to the minimum price $p_{g,min,t}$ in a group of matching cars $g$ at time $t$ multiplied by the firm's specific parameter for the initial price $\alpha \in [0;1]$. With $\alpha = 0$ the firm's price is the cheapest in the group of matching cars. This price is kept constant up to a time threshold $\beta$. If the car is not sold by time $t > \beta$, the firm changes the price by $\gamma \in [0, \infty]$. This process is repeated until the car stops being on offer, where $m \geq 1$ is the count of prices per car. The strategy assumes that there is a sequence of consumers who inspect the car, which is sold to the first consumer whose willingness to pay $r$ meets or exceeds the price $p(t)$, $r \geq p(t)$. Note that the strategy requires relatively little information and does not make any assumptions about the nature of customers or how competitors respond. Instead, it is similar in spirit to reinforcement learning models where the strategy and its parameters adapt via a trial-and-error process (Erev and Roth 1998). Given the market setting, such a search process for the best parameter values can be aided by making intelligent use of a few relevant and robust environmental features such as the number of competing firms and population density in the local environment. Unlike in reinforcement learning models, the price does not change at every time step, unless $\beta$ is equal to one time step.

The cheap twin paradox is a logical consequence of this pricing strategy: at a given dealership, if one of the twin cars has been offer longer than time $\beta$ but not the other, twins are priced differently. In general, price dispersion in the market among matching cars exists if dealers use a different $\alpha$ to set the initial price, a different $\beta$ to set the duration of a given price, or a different $\gamma$ that sets the amount by which a price changes.

*II.B. Ecological rationality: When and why heuristics work*

Heuristics, such as the aspiration level strategy, are simple strategies that have often been assumed to always yield suboptimal performance (Tversky and Kahneman 1974). Although this assumption is correct in situations of certainty and risk, it does not hold in situations of uncertainty, where the decision maker lacks information such as about future states (Gigerenzer, Hertwig, and Pachur 2011). For instance, for the task of assessing whether or not customers will be active and buy from a given company, an aspiration level heuristic that managers apply predicted future purchases more accurately than a complex state-of-the-art optimization strategy (Wübben and von Wangenheim 2008). Note that optimization here refers to the procedure of estimating parameters and does not imply that this model is optimal in the sense that it performs best in making predictions. Key to understanding this result is that a decision strategy needs to balance model complexity with the characteristics of the data such as sample size or stability to avoid overfitting. Empirical research has long stressed the importance of overfitting when estimating the best-performing model using tools such as the Bayesian Information Criterion or cross validation. However, this insight has not been used in the development of constructivist theories when deriving how agents ought to behave. The need to balance model complexity with the characteristics of the data can directly explain when and why an optimization strategy can be outperformed by a simple heuristic.

The bias-variance dilemma provides a framework for analyzing the relation between expected performance of strategies and the characteristics of the data from the perspective of the individual agent, and has been widely applied in machine learning (Geman, Bienenstock, and Doursat 1992). Strategies that operate in an uncertain environment have to make predictions about future events, such as how likely a product will sell for a given price. The total error in prediction (i.e., sum of squared errors) can be decomposed as follows:

$$error = b^2 + v + \varepsilon$$

where $b$ refers to bias, $v$ to variance, and $\varepsilon$ is the irreducible error. Suppose the task is to predict the maximum willingness to pay for a given car in a population, generated from an underlying but unknown function $r$. Conventionally, the parameters of a strategy are estimated based on a single sample. However, the overall performance of a strategy can be determined solely by drawing $D$ independent samples and repeating calibration of the parameters of the strategy $D$ times. Bias is the difference between the mean of the $D$ predictions $\hat{r}$ and the unknown function $r$, that is, $b = r - \hat{r}$. Variance $v$ is the squared standard deviation of the $D$ predictions around the mean of all predictions, $\hat{r}$. Error from bias occurs if the strategy does not precisely match the unknown underlying function; error from variance reflects the sensitivity of the strategy to variation in the different samples.

Given a small and noisy sample, a simple strategy with few parameters can perform well because it is less exposed to error from variance, as shown in Figure I. A more complex, state-of-the-art optimization strategy might instead perform poorly because parameters cannot be estimated with sufficient reliability. Only with a large and reliable sample can greater complexity pay off in terms of accurate predictions. The degree of complexity of a strategy is not just a function of the number but also the functional form of the parameters, such as whether they are additive or multiplicative.

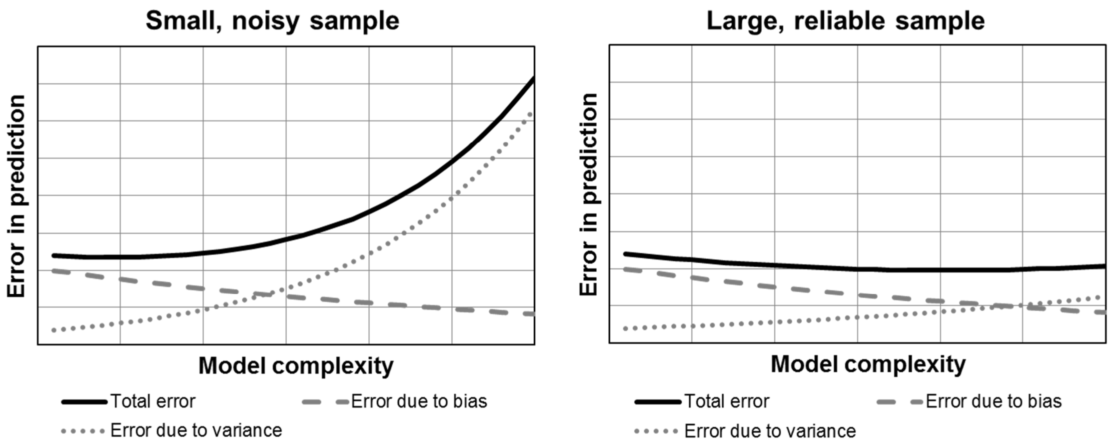


FIGURE I.

ILLUSTRATION OF THE BIAS-VARIANCE DILEMMA.

*Notes:* Total error in prediction results from bias and variance. Bias decreases with increasing complexity of the strategy, such as by adding more free parameters to a strategy, while variance increases. If estimates are necessarily based on small, noisy samples, as in a used car market with small groups of identical cars (left), variance increases quickly and, with it, the total error in prediction. If estimates can be based on large, reliable samples, variance is kept low and strategy complexity no longer reduces the quality of prediction.

A constructivist analysis typically assumes that the environment is known and hence that variance plays no role. That assumption holds approximately in situations with large and reliable samples (Figure I, right side). An ecological analysis, in contrast, does not make this assumption but instead studies how the performance of a given strategy depends on the characteristics of the environment, including, importantly, sample size and stability.

The used car market is dynamic, with a large set of differentiated products that provide only small and noisy samples, thereby generating a large degree of uncertainty for the individual dealer and making it difficult to learn the actual demand. Such an environment can provide a significant source of error due to variance. This kind of error can be countered by a simple strategy such as the aspiration level heuristic, which we expect to be prevalent among dealers.

Equation (1) defines a family of aspiration level heuristics from which a firm can choose. Given the use of the aspiration level heuristic, a first step in evaluating how well adapted it is can be achieved by inspecting $\beta$, the time that the price is kept constant, and how it changes with the environment. The choice of $\beta$ directly influences the sample size of potential buyers on which the dealer bases actions. For a given price, a monopolist in a sparsely populated area would need to keep the price constant longer than would a monopolist in a more densely populated area before inferring with sufficient confidence that the price is too high. If there are competitors, the dealer can observe others' posted prices in the clearing house, extending the information base. From this we expect that the more potential buyers and the more competitors a dealer can observe, the shorter the duration $\beta$ chosen.

### *II.C. Price stickiness*

A prominent feature of the aspiration level heuristic is that prices are adjusted in fixed time intervals $\beta$, that is, prices are sticky and do not respond instantaneously to changes in the market or cost structure. Fixed time intervals, also referred to as time-dependent pricing, can be used for a number of reasons (for a review see Klenow and Malin 2011). Conventional empirical testing of the different theories on price stickiness has been difficult because many of the most prominent rely on unobservable variables. At the same time, there is no agreed-upon metric to measure the degree of price stickiness as it has been proven futile to compute a benchmark measure of how quickly prices should change. By way of a solution, interviews with managers have been conducted to assess which theory describes actual pricing decisions well, taking on the perspective of the individual decision maker to understand the aggregate market (e.g., Blinder et al. 1998; Apel, Friberg, and Hallsten 2005). The studies show that either firms employ a purely time-dependent pricing rule where prices are adapted after a fixed time interval, or time-dependence is complemented by some degree of state-dependence, where changes in market or cost structure also influence the timing of price changes.

To evaluate the relevance of the most prominent theories for the used car market, we selected eight out of the twelve that Blinder et al. (1998) investigate (four theories were not used because they bear little relevance for the used car market; see the appendix): seven are classic theories of price stickiness focusing on direct or indirect costs associated with price changes, and the eighth theory focuses on consumers' perception of prices. All eight theories are modeled from a constructivist perspective and, unlike the aspiration level heuristic, none takes into account that dealers might need to learn which price best be set:

1. Menu costs. Changing prices is costly in itself, due to costs of advertising these anew, printing new price tags, etc. Therefore, prices do not adjust perfectly to changes in market conditions (Mankiw 1985).
2. Non-price competition. Prices are not necessarily the only element that facilitates market clearance. Firms can, for instance, also adjust service to keep the price constant (Carlton 1986).
3. Co-ordination failure. If there is no coordinating mechanism that allows all firms to move together in case of changes in the market or costs, prices remain constant (Cooper and John 1988).

4. Cost-based pricing. The costs of material and labor are essential for price calculations. Even in the face of a changing market, prices do not change instantly if costs remain constant (Bils 1987).
5. Judging quality by price. Firms do not reduce a price in a slack market out of fear that this will be interpreted as a reduction in product quality (Allen 1988).
6. Implicit contracts. Firms build long-term relationships with customers. One tool is to change prices as little as possible. Even if there are changes in the market or costs, firms do not respond immediately with a price change (Okun 1981).
7. Explicit contracts. Firms have contractual agreements with customers that determine prices in advance of a transaction (Fischer 1977). Breaking such contracts to adjust prices can be costly.
8. Price points. Levy et al. (2011) focus on consumers' perception of prices. They show that '9' is the most frequent price ending for a number of retail products. If prices change, most frequently these also end in '9'. If prices have to 'jump' to the next psychologically attractive digit, they are less sensitive to changes in the market or costs.

We add to this list the aspiration level pricing strategy adapted to situations where dealers face an uncertain environment, have difficulties in precisely estimating the willingness to pay of consumers, and need to learn the latter via a trial-and-error process:

9. Aspiration level strategy: Simon (1955) proposes that prices are set by using an aspiration level with the goal to search for the best price. Only when sufficient evidence has accumulated that this price cannot be achieved does it change.

Price points as described in proposition 8 can be combined with any other theory. We evaluate the relevance of these theories for pricing in the used car market on the basis of interviews with dealers along the lines of earlier studies on price stickiness.

## III. Constructivist Rationality

In 1962 V. L. Smith showed for the first time that agents need not possess perfect information in order for market equilibrium to emerge, as had been widely assumed until then. Instead, the actions of naïve, only privately informed agents can quickly converge to equilibrium. Since then, hundreds of papers have documented this phenomenon within a variety of institutions (e.g., Plott and Sunder 1982; V. L. Smith 1982; Plott and Sunder 1988; Huck, Normann, and Oechssler 2004; Isoni et al. 2016; for a review see V. L. Smith 2008). It is important to note that as theorists we need a fully specified environment to determine equilibrium conditions. Yet in the case of uninformed agents, market discipline can be sufficient for their behavior to reach equilibrium quickly (Sugden 1989; Sugden 1991). In line with this argument, Becker (1962) formally demonstrated that downward-sloping demand may not be the product of sophisticated individual strategies but of market structure. Gode and Sunder (1993) even showed that zero-intelligence traders, who randomize within their budget constraints, can produce allocative efficiency.

When analyzing markets with highly differentiated products such as real estate or the used car market, the literature has addressed two primary issues that possibly characterize the incentive structure to which decision makers respond. One stream focuses on how posted prices in clearing house markets are a function of difference in consumers' expertise (e.g., Rosenthal 1980; Varian 1980; Baye and Morgan 2001). Common to all models is that price dispersion emerges in equilibrium if informed and uninformed consumers coexist in a market. A second stream of literature starting with Akerlof (1970) focuses on the market for lemons, where adverse selection results in an unraveling of the market, with only the lowest quality and the cheapest price on offer. Empirical evidence, however, finds little support for such a market (e.g., Bond 1982; Genesove 1993). Given a clearing house, sellers can voluntarily disclose private information to buyers through photos and text. Using data from eBay, Lewis

(2011) shows that online disclosure is an important determinant of price as it allows buyers to at least partially contract on quality, reducing the possibility of adverse selection. Contrary to the assumption that only the cheapest offer sells, empirical evidence on used baseball cards shows that a price premium can be obtained from inexperienced but not from experienced consumers (Zhe and Kato 2006).

In his seminal paper on the economics of information, Stigler (1961) employs the used car market as an example. He points to informational costs leading to price dispersion—consumers' costs of acquiring information and producer's costs of transmitting information credibly. Building on Stigler, a large body of theoretical literature on equilibrium models investigates the clearing house market (for a review see Baye, Morgan, and Scholten 2006). The models employ two types of consumers: informed 'shoppers' consult the clearing house and pick the cheapest offer, while naïve or 'uninformed consumers' base their decision on other attributes such as their loyalty to a firm or its reputation. In response to such heterogeneity, models of price dispersion utilize a mixed strategy for price setting where prices are randomized between an upper and lower bound. Note that for complex products such as cars, differences between consumers can also be due to differences in expertise when evaluating a car and not necessarily to differences in external information.

Synthesizing the literature, Baye, Morgan, and Scholten (2004) develop a general clearing house model nesting three prominent models as special cases: Rosenthal (1980), Varian (1980), and Baye and Morgan (2001). In the general model, the market is characterized as follows: all consumers have unit demand and a maximum willingness to pay of $r$. There are two types of consumers. First there are $S$ informed shoppers who buy at the lowest price listed in the clearing house, provided their reservation price is equal to or exceeds the advertised price, $r \geq p$. There are also price-insensitive, uninformed consumers $U$ who buy from their preferred firm if $r \geq p$ or otherwise randomly select a firm as long as $r \geq p$. There are $n > 1$ firms, each with one offer, that simultaneously set linear prices $p$ for an identical good produced at constant marginal costs $c \in [0, r]$. The firm must decide on the price $p$ and whether or not to list it in the clearing house, at cost $\phi \geq 0$ per listing.

The three specific models differ as follows, where $M \geq 0$ denotes a constant:

- Rosenthal (1980): $\phi = 0$ and $U > 0$.
- Varian (1980): $\phi = 0$ and $U = \frac{M}{n}$, assuming that a proportion of customers is loyal to a specific firm.
- Baye and Morgan (2001): $\phi > 0$ assuming costs for advertising and $U = \frac{M}{n}$.

In equilibrium, the distribution of prices listed at the clearing house is

(2) $$F(p) = \frac{1}{\tau}\left(1 - \left(\frac{\left(\frac{n}{n-1}\right)\phi + (r-p)U}{(p-c)S}\right)^{\frac{1}{n-1}}\right) \text{ on } [p_0, r]$$

where

(3) $$p_0 = \frac{\frac{n}{n-1}\phi + Ur + Sc}{U+S}.$$

The probability to list the product in the clearing house is

(4) $$\tau = 1 - \left(\frac{n\phi}{(n-1)(r-c)S}\right)^{\frac{1}{n-1}}.$$

Firms earn an expected profit of

(5) $$E\pi(p) = (r-c)U + \frac{\phi}{n-1}.$$

Depending on the parameters, Baye, Morgan, and Scholten (2004) find that the predictions of the three models differ for small to intermediate numbers of offers ($n < 40$) due to order statistics and strategic effects: as the number of competitors and therefore of offers grows, Rosenthal (1980) predicts an increase in average price but a decline in price dispersion, Varian (1980) predicts an increase in average price and price dispersion, and Baye and Morgan (2001) predict a decline in average price and price dispersion. Data from new consumer products posted on online platforms and in online markets show that prices and price dispersion on average decline as competition increases (Baye, Morgan, and Scholten 2004; Pan, Ratchford, and Shankar 2004; Venkatesan, Mehta, and Bapna 2007; Ghose and Yao 2011). Yet how the specifics of a market can affect observed prices is illustrated by a laboratory experiment with automated consumers that finds that price dispersion can also increase as the number of competitors increases (Morgan, Orzen, and Sefton 2005).

The online data in the present study allows two aspects to be assessed: (i) at the aggregate level, which equilibrium model best describes the used car market; (ii) at the individual level, how the pricing strategy that car dealers use compares to the mixed strategy underlying the equilibrium model. Lach (2002) finds evidence that supermarkets actually use a mixed strategy that generates price dispersion in the aggregate. The environment that Lach investigates is characterized by a large sample size and relatively stable environment. This facilitates learning about demand and ensures stable parameters of a model such as the one outlined in equations 2 to 5 insofar as the rich information reduces the role of error from variance. Yet the information environment is very different for used car dealers facing a dynamic market with noisy information and small samples of matching cars.

## IV. METHODS

### *IV.A. Online data*

We collected data from the online used car platform Autoscout.de, which listed about 78 percent of all used cars sold in Germany at the start of the data collection period in 2010 (Dudenhöffer and Schadowski 2011). Autoscout is the largest such platform in Europe, with more than 300 million visits per month. Nearly all consumers consult the online platform for used cars before visiting a dealership, and many visit only one dealership to make a purchase (Mohr et al. 2015). Posting an offer is costly: this includes costs per posting, costs a car generates each day it sits on the lot, and opportunity costs. We focus on two types of cars, the

BMW 320 and 730. In 2010, the BMW 320 was the most frequently sold BMW (BMW Group 2011). The BMW 730 addresses the premium market segment and serves our investigation whether the pricing strategies differ depending on the market segment.

The online data were collected for 15 months starting December 2010. We searched Autoscout.de bi-weekly for all BMW 320s and 730s on offer from professional sellers. The downloaded results pages contained per car posting 8 primary attributes and 30 further attributes from which the dealers could freely select to indicate properties of the car (see appendix Table A1 for a full list of attributes). In addition, each posting indicates the price of a car, the ZIP code and city of the dealership, the number of pictures that show the car, whether the car posting was highlighted in the search results page, and whether an additional warranty is available for the car.

Out of the total of 38 car attributes, analyses show that a number are strongly autocorrelated. We identify 26 attributes to specify groups of matching cars. This includes the odometer values that are rounded to the next 10,000 km, in line with evidence reported by Busse et al. (2013) that consumers tend to focus on the left-most digit of the odometer value. The possibility of obtaining a warranty can be a crucial feature in the used car market, which we therefore include as well. Cars that are identical with respect to all of their values on these 27 attributes on a given day constitute a group of matching cars (see appendix Table A1; attributes with an asterisk were used). Such a procedure of relying on matching items was introduced by Elfenbein, Fisman, and Mcmanus (2012) to study charity auctions and employed by Einav et al. (2015, in press) to study offers on eBay. Because used cars are a complex product with many dimensions, judgments about the similarity of cars also depend for instance on the degree of consumers' expertise. To check our conclusions, we conducted the analysis again but considered just 7 of the 8 primary car attributes. This check provided the same qualitative evidence as reported in the following.

TABLE I.A.

SUMMARY STATISTICS PER POSTING AND CAR

| | Observations | Mean | Median | SD | Min. | Max. |
|---|---|---|---|---|---|---|
| **Price (€)** | | | | | | |
| All | 623,709 | 27,152 | 24,990 | 12,596 | 400 | 114,900 |
| BMW 320 | 565,379 | 24,645 | 23,900 | 8,724 | 400 | 65,339 |
| BMW 730 | 58,330 | 51,456 | 54,740 | 17,531 | 1,490 | 114,900 |
| **Group size of matching cars > 1 on a given day** | | | | | | |
| All | 328,832 | 4.4 | 3 | 3.2 | 2 | 27 |
| BMW 320 | 291,741 | 4.3 | 3 | 2.9 | 2 | 21 |
| BMW 730 | 37,091 | 5.6 | 4 | 4.6 | 2 | 27 |
| **Duration until car sells (days) with group size > 1 and uniquely identifiable dealer** | | | | | | |
| All | 16,356 | 37 | 21 | 45 | 0 | 374 |
| BMW 320 | 14,848 | 36 | 20 | 44 | 0 | 374 |
| BMW 730 | 1,508 | 46 | 29 | 49 | 0 | 305 |

TABLE I.B.

SUMMARY STATISTICS PER DEALER

| | Observations | Mean | Median | SD | Min. | Max. |
|---|---|---|---|---|---|---|
| **Local market** | | | | | | |
| Dealers | 745 | 9.9 | 10 | 4.0 | 1 | 19 |
| Population density (people per sq. km) | 714 | 623 | 398 | 600 | 66 | 4,340 |
| GDP per capita (€) | 714 | 31,047 | 30,580 | 7,424 | 20,230 | 79,500 |
| **Dealership characteristics** | | | | | | |
| Share of dealers that are official BMW partner | 745 | 0.47 | 0.00 | 0.50 | 0.00 | 1.00 |
| Observed BMW 320s and 730s during 15 months | 722 | 44 | 18 | 83 | 1 | 1,279 |
| Share of BMW 320s out of 320 and 730s | 716 | 0.94 | 1.00 | 0.10 | 0.25 | 1.00 |
| Share of dealers part of larger dealer network | 745 | 0.19 | 0.00 | 0.39 | 0.00 | 1.00 |
| **Properties of cars at a dealership** | | | | | | |
| Mean km | 722 | 69,399 | 60,289 | 36,113 | 990 | 229,000 |
| Share of cars where extra warranty available | 722 | 0.25 | 0.00 | 0.34 | 0.00 | 1.00 |
| Mean number of pictures in ad | 722 | 8.5 | 8 | 3.2 | 1 | 15 |
| Share of cars with extra advertisement | 722 | 0.16 | 0.00 | 0.34 | 0.00 | 1.00 |

In its analysis the paper relies on those cars for which we could find at least one other matching car. With the given constraints of 27 attributes, we found at least one other matching car for 328,832 out of a total of 623,709 posts (see Table I.A). Because some dealerships share ZIP code and city, 745 out of 871 dealers we observed during the period of investigation could be uniquely identified. In order to pin down the pricing strategy of a dealer we used those cars whose entire price development could be traced from the first to the last day the car was posted. These restrictions (uniquely identifiable dealer, observing at least one car that matches another car, observing the car from the first to the last date of posting) yielded a sample of 628 dealers with 16,356 cars and 182,296 postings.

Furthermore, we obtained data from the Statistical National Office in Germany (Statistische Ämter des Bundes und der Länder 2013) to analyze the local market in which dealers operate. There are a few missing values due to regional changes the Statistical National Office undertook (Table I.B). The local market can be captured via the ZIP code of each dealer. The ZIP code consists of five digits, of which the first two refer to one of 82 regions in Germany. A region has a mean radius of 38km and constitutes the local market we analyze. Table I.B provides data on the local market, the characteristics of the dealership, and properties of the cars that dealers offer.

We used the online data to determine how often a dealer offers two or more matching cars at different prices at the same time, the cheap twin paradox. We found that it occurs quite frequently: for 14 percent of all cars there is at least one other matching car offered by the very same dealership on the same day for a different price.

*IV.B. Interviews*

The interview contained 3 parts (see appendix for the complete manuscript). In the first part, questions were asked concerning the characteristics of a dealership and the background of the interviewee. In the second part, pricing strategies were investigated. In the third part, we inquired about the relevance of 9 theories of price stickiness and how these relate to the practice of the dealers. The order of the 9 theories was randomized to prevent order effects.

The interviewees were recruited from a list of 902 car dealers listed on Autoscout.de as selling used BMWs in Germany in December 2010. During the online data collection period 871 of them were active. We focused on dealerships that operate in a more competitive environment. Using the city and ZIP code of dealerships we calculated the total number of dealers in a given combination of city and ZIP code and ranked dealers accordingly. Dealers up to rank 450 were sent an invitation by mail to participate in the interview, which 55 dealerships accepted; 30 interviews were conducted in person and a further 25 by telephone. Interviewees were randomly allocated to these two conditions, and their responses did not differ depending on the method (for pricing strategies $\chi^2(6) = 7.95, p = .21$, the same holds for theories $\chi^2(9) = 2.38, p = .98$).

All interviews were conducted in May 2011, lasted about 20 minutes, were recorded on audiotape, and were later transcribed. These transcriptions were given to two independent raters to categorize answers. They coded 96 percent of the transcriptions in the same way; where differences existed, the raters discussed these and agreed on a common rating.

## V. RESULTS

We first analyze the data from the online platform from an individual level perspective, tracing the specific decision strategies that dealers employ and how this matches the respective local market. The strategies are then compared to the results of the interviews, including an analysis of the reasons for price stickiness. Next, we turn to the aggregate level and investigate how price dispersion and average price change with the degree of competition and whether any of the three constructivist models can capture the market. Finally, we examine how well the pricing strategies the dealers use perform compared to the strategy underlying the aggregate market.

### *V.A. Pricing at the individual level: the online data*

**Market uncertainty**. If all consumers chose the cheapest product from a set, there would be no uncertainty about demand. However, not all consumers seeking to buy the product might be shoppers. In order to provide a first insight into the heterogeneity of consumers, we use the last posted price of a car as an indication that this price likely was sufficiently attractive for a customer to visit the dealership and buy the car. Ranking a group of matching cars accordingly allows investigating to what extent consumers indeed deviate from pursuing the cheapest offer among the group. Cars are ranked in ascending order. If two cars have the same price and are the cheapest in a group of matching cars, both are assigned a rank of 1. The left panel of Figure II illustrates the principle finding for a group size of 5 matching cars. If all consumers sought the cheapest car, the probability masses in the two histograms would be entirely in the left-most bars. For both types of BMWs, however, most of the last observed prices are above the price of the cheapest car. This pattern can be found for any group size of matching cars and reflects part of the demand uncertainty that dealers face.

The supply side is depicted in the right panel of Figure II and shows the number of offers for the two types of cars on a given day of data collection. Uncertainty is introduced if supply quickly and unpredictably changes, making it difficult to predict future supply. Here, supply varies substantially over time, with the number of offers changing by more than 20 percent within a 3-month time window for both types of cars. From December 2010 to September 2011, the changes in supply for BMW 320s and 730s co-vary little.

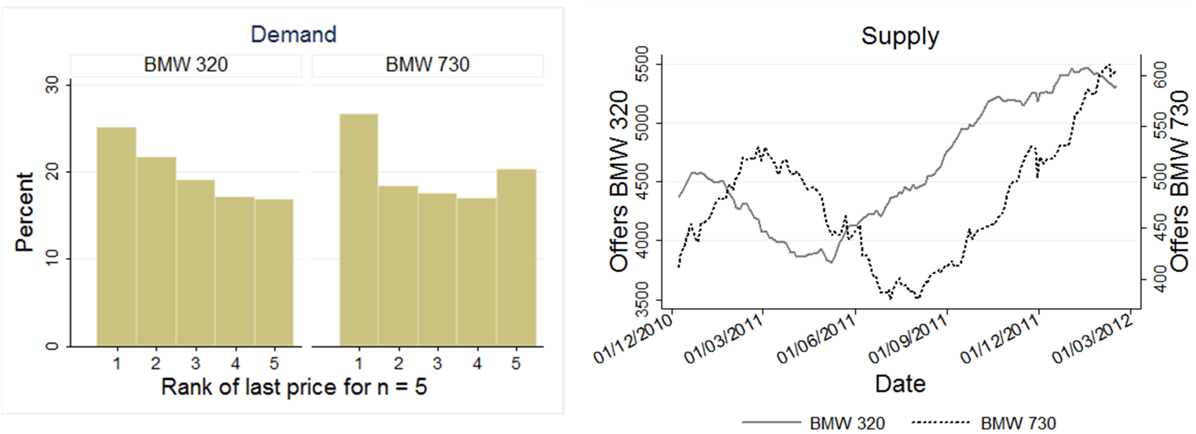


FIGURE II.

DEMAND FOR MATCHING CARS AND SUPPLY

Given uncertainty of supply and demand along with a small, unreliable, and noisy set of information, the bias-variance dilemma suggests that a simple decision strategy that reduces estimation error might perform better than a more complex strategy.

**Parameters of aspiration level pricing**. There are three parameters that characterize the pricing strategy of a dealer as laid out in equation 1: initial price $\alpha$, duration until price changes $\beta$, and magnitude of a price change $\gamma$.

We first consider the parameter for the initial price $\alpha$ where $p_{g,i,m=1}$ is the first price posted for a given car $i$ and $g$ refers to the group of matching cars on a given day. The total number of cars offered by a dealer is $j$. Does a dealer $d$ engage in price competition by starting with the minimum price $p_{g,min}$ of a group of matching cars $g$? Alternatively, how far up the price range $\{p_{g,min}, \dots, p_{g,max}\}$ does the dealer set the initial price? The average initial price of a dealer is computed as follows:

$$\widehat{\alpha_d} = \frac{1}{j}\sum_{i=1}^{j}\frac{p_{g,i,m=1} - p_{g,min}}{p_{g,max} - p_{g,min}}$$

As Figure III.A shows, only about 12 percent of dealers start with a price close to or at a par with the minimum price of a group of matching cars (the left-most bin of the histogram). In contrast, 307 out of 628 dealers, that is, 49 percent, start with a price that is above the median of the price range. The mean dealer posts an initial price that is .46 (SD = .26) of the price range. Considering the two types of cars, there is no difference in initial price: in the mean, the initial price of a BMW 320 is .50 (SD = .44) and of a BMW 730 is .49 (SD = .43) of the price range. The difference in mean values between dealers and cars is due to the fact that larger dealerships with a larger turnover tend to start with a higher initial price than smaller dealerships with fewer cars.

The second parameter of a pricing strategy is the duration $\beta$ until a price changes. Out of the 628 dealers, 117 dealers set only one price per car and keep it constant, whereas 511 change the price regularly. For a car $i$ a dealer posts in total $l$ prices with $m = 1, \dots, l$. The duration until the price of a car changes is $t(p_{i,m}) - t(p_{i,m-1})$. The final period in which a car stops being on offer is excluded. The average duration until a dealer changes a price is:

$$\widehat{\beta_d} = \frac{1}{j}\sum_{i=1}^{j}\frac{1}{l-2}\sum_{m=2}^{l-1} t(p_{i,m}) - t(p_{i,m-1})$$

Figure III.B shows the histogram of the mean days before a dealer changes the price. The data are binned in time spans of 5 days. Only 4.9 percent of dealers fall into one of the first two bins and change the price at least every 10 days. In the mean, a dealer changes the price of a car after 33 (SD= 20) days. Moving from the dealers to the types of cars, in the mean the price of the BMW 320 changes after 29 (SD = 21) days and the price of the BMW 730 after 27 (SD = 18) days. This suggests that there is little difference between the two types of cars in terms of the duration that a price is held constant.

The final parameter is the price change $\gamma$. We compare the current price of a car $p_{i,m}$ to its previous price $p_{i,m-1}$.

$$\widehat{\gamma_d} = \frac{1}{j}\sum_{i=1}^{j}\frac{1}{l-2}\sum_{m=2}^{l-1}\frac{p_{i,m} - p_{i,m-1}}{p_{i,m}}$$

Figure III.C shows a histogram with the mean price per dealer for those dealers who undertake price changes (N = 511). The dealer-level data exhibit a price reduction of 3.4 percent (SD = .022) in the mean. At the car level, prices for the BMW 320 are reduced in the mean by 3.3 percent (SD = .031) and for the BMW 730 by 3.5 percent (SD = .035), again suggesting that there is little difference between the two types of cars. A necessary indicator for the use of a mixed strategy is that dealers randomize prices, which would entail about the same number of increases and decreases in prices. However, this is not the case: 97 percent of the times that prices change, they are reduced.

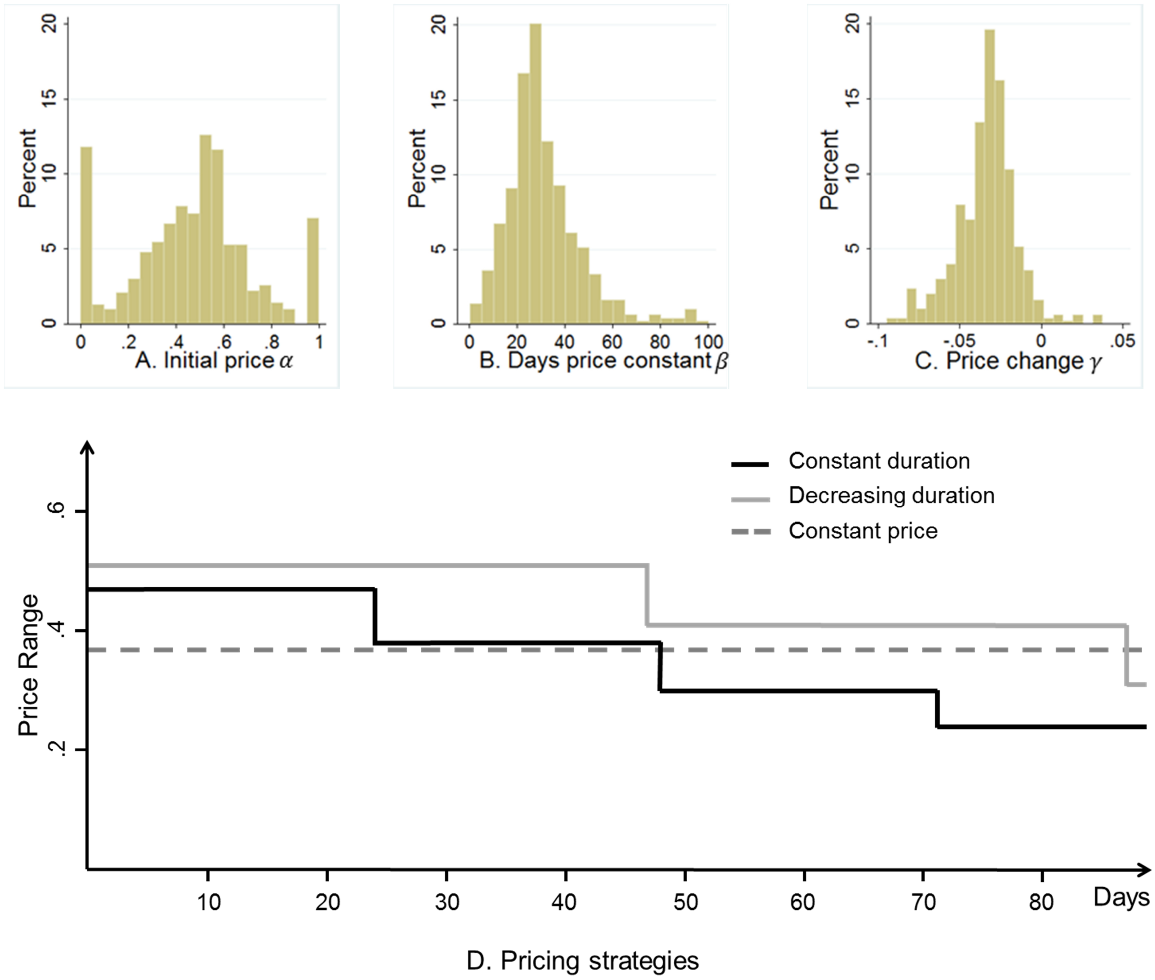


FIGURE III.

PRICING PARAMETERS AND STRATEGIES

*Notes*: Mean value per dealer: III.A. Initial price in price range. III.B. Days until a price changes, excluding the last period when a car stops being on offer. III.C. Relative price change. III.D. Three main pricing strategies observed. Figure III.D shows the price percentile adjustment, that is, to what extent the price changes relative to maximum and minimum prices in the group of matching cars. The price percentile adjustment is used for illustrative purposes because it maps onto the same scale as the initial price. However, a change in price percentile does not necessarily reflect a change in the price of a car; it can also be due to changes in the minimum and maximum price. Table A2 in the appendix shows the values of price percentile change and the relative price change $\gamma$.

The emerging pattern is that dealers start with a price well above the minimum price of matching cars. Most dealers do not change the price all too quickly but wait for a certain time before adjusting it. If dealers change the price, they do not randomize but instead generally lower it. These characteristics are applied irrespective of the car type. At the same time, there is considerable variation in each of the three pricing parameters. In the following we take a closer look at this in order to more precisely pin down the pricing strategies that are employed.

**Types of pricing strategies.** In order to identify homogenous clusters of the specific combinations of the three parameters, we use a cluster analysis. This clusters together those dealers who are similar in their parameter values using the Ward method with squared Euclidian distance as a measure for proximity, minimizing the variance within a cluster.

The analysis points to three types of strategies that dealers employ, which are displayed in Figure III.D (see appendix Table A2 for a detailed presentation of the values). The most prominent strategy, 'constant duration', used by 320 out of 628 dealers (51 percent), is to keep the price constant for a fixed interval and then lower it until the car is sold. This strategy accounts for 64 percent of all cars. These dealers start in the mean with an initial price of .47 (SD = .22) of the price range and keep it constant for 24 days. Conducting the same analysis but with six clusters provides insights into the variation still contained in this cluster: the two relevant sub-clusters reveal that all dealers wait for a fixed period before they lower the price, but some employ a 12-day period (N = 66), whereas others rely on intervals of 26 days (N = 254). Prices are reduced at a constant or slightly diminishing.

The second largest cluster is the 'decreasing duration' strategy, where dealers sequentially lower the price but decrease the duration for which consecutive prices are held constant. This cluster contains 171 of 628 dealers (27 percent) offering 31 percent of the cars. The mean initial price is .51 (SD = .20) of the price range. For the first period the price remains constant for 47 days, then 40, followed by 37 days. Running an analysis with 6 clusters shows that the two relevant sub-clusters lower the price after 42, 38, and 37 days (N = 129) or after 62, 46, and 37 days (N= 42). This reveals a consistent pattern of keeping the initial price constant for a longer period than subsequent prices. Prices are reduced at a slightly diminishing rate.

The third cluster consists of 117 dealers (19 percent) employing the strategy ‘constant price’, where the initial price does not change. They account for 3 percent of all cars. These dealers use a comparatively low initial price with .38 (SD = .39) in the mean and .26 in the median of the price range. Finally, a very small group of 20 dealers (3 percent) offering 2 percent of all cars could not be assigned to the three clusters due to their idiosyncratic combination of the pricing parameters.

Identifying the three main pricing strategies provides a clearer picture of how dealers actually set prices. At the same time the question arises, why do dealers price so differently? In the following, we address whether this heterogeneity can be attributed to dealers' systematically adapting their strategy to their environment. The answer sheds further light onto the ecological rationality of the strategies.

**Pricing and the environment.** Heuristics function well if they are adapted to the environment. Table II shows three sets of variables that define a dealer’s environment: variables pertaining to the characteristics of the local market, variables pertaining to characteristics of the dealership, and variables pertaining to characteristics of the cars the dealership offers. The OLS regressions reported in Table II examine how the three pricing parameters depend on these variables, starting with market level variables (1, 3, 5) and adding dealership and car characteristics (2, 4, 6).

TABLE II.

OLS REGRESSION ON THREE PRICING PARAMETERS OF DEALERS

| | (1) Initial price $\alpha$ | (2) Initial price $\alpha$ | (3) Duration (log days) $\beta$ | (4) Duration (log days) $\beta$ | (5) Price change $\gamma$ | (6) Price change $\gamma$ |
|---|---|---|---|---|---|---|
| Dealers in region | 0.001 | 0.001 | **-0.031** | **-0.031** | 0.000 | -0.000 |
| | (0.004) | (0.004) | (0.010) | (0.010) | (0.000) | (0.000) |
| | 0.875 | 0.754 | 0.001 | 0.002 | 0.964 | 0.967 |
| Population density (per 100 inhabitants per sq.km) | -0.001 | -0.003 | **-0.030** | **-0.031** | -0.000 | -0.000 |
| | (0.005) | (0.005) | (0.011) | (0.012) | (0.000) | (0.000) |
| | 0.795 | 0.625 | 0.008 | 0.009 | 0.374 | 0.324 |
| GDP per capita (per thousand €) | -0.000 | 0.000 | **0.012** | **0.012** | -0.000 | -0.000 |
| | (0.002) | (0.002) | (0.004) | (0.004) | (0.000) | (0.000) |
| | 0.926 | 0.799 | 0.009 | 0.006 | 0.581 | 0.544 |
| Dealers x population density | -0.000 | 0.000 | **0.002** | **0.003** | 0.000 | 0.000 |
| | (0.000) | (0.000) | (0.001) | (0.001) | (0.000) | (0.000) |
| | 0.942 | 0.938 | 0.024 | 0.015 | 0.464 | 0.462 |
| Official BMW partner | | 0.033 | | **0.198** | | **-0.007** |
| | | (0.024) | | (0.056) | | (0.002) |
| | | 0.160 | | 0.000 | | 0.004 |
| Observed BMW 320s and 730s per dealer (per 10 cars) | | 0.000 | | 0.000 | | -0.000 |
| | | (0.000) | | (0.000) | | (0.000) |
| | | 0.111 | | 0.423 | | 0.816 |
| Share of BMW 320s | | 0.006 | | 0.062 | | -0.017 |
| | | (0.110) | | (0.275) | | (0.011) |
| | | 0.960 | | 0.822 | | 0.133 |
| Part of larger dealer network | | -0.042 | | -0.033 | | -0.002 |
| | | (0.028) | | (0.064) | | (0.003) |
| | | 0.132 | | 0.609 | | 0.544 |
| Average mileage (mean km log) | | **-0.065** | | 0.040 | | -0.003 |
| | | (0.019) | | (0.049) | | (0.002) |
| | | 0.001 | | 0.423 | | 0.136 |
| Share of cars where extra warranty available | | -0.047 | | 0.040 | | -0.001 |
| | | (0.034) | | (0.080) | | (0.003) |
| | | 0.166 | | 0.615 | | 0.784 |
| Mean number of pictures in ad | | -0.000 | | -0.017 | | 0.000 |
| | | (0.004) | | (0.009) | | (0.000) |
| | | 0.999 | | 0.070 | | 0.721 |
| Share of cars with extra advertisement | | 0.049 | | -0.068 | | 0.003 |
| | | (0.032) | | (0.074) | | (0.003) |
| | | 0.129 | | 0.359 | | 0.282 |
| Constant | 0.474 | 1.127 | 3.333 | 2.843 | -0.031 | 0.021 |
| | (0.058) | (0.236) | (0.138) | (0.592) | (0.006) | (0.024) |
| | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.391 |
| Observations | 606 | 603 | 496 | 495 | 496 | 495 |
| R-squared | 0.001 | 0.041 | 0.029 | 0.077 | 0.006 | 0.036 |

Coefficients, standard errors in parentheses, and exact p-values are reported. Coefficients are in bold if $p \leq .05$.

*Notes*: Different interaction effects were tested for the market level variables; however, only number of dealers interacting with population density was significant.

In areas with a higher population density and a corresponding number of dealerships, a dealer can more quickly infer that a car is unlikely to sell for a given price, whereas in less densely populated areas with less competition the price needs to be held constant for a longer time before such an inference can be made with sufficient confidence. Consistent with this hypothesis, for every additional competitor in the region, the duration the price is held constant $\beta$ decreases by 3 percent, with the number of dealers varying per region between 1 and 19. Population density has a similar impact: as the population density increases by 100 inhabitants per square km, the duration a price is held constant decreases by about 3 percent, with the population density varying between 66 and 4,340 people per square km. At the same time, the higher the GDP per capita in a region the longer the price is kept constant. For every 1,000 euros in GDP per capita, the duration increases by 1 percent, with the GDP per capita varying across regions between 20,230 euros and 79,500 euros. The duration increases by 20 percent if the dealership is an official partner of BMW.

The finding on the duration the price is held constant $\beta$ is consistent with the hypothesis that dealers adapt the aspiration level pricing strategy to the sample size their local market provides. One effect of this adaptation to the local environment is less error from bias. Similarly, in regions with a higher GDP per capita, the willingness to pay should be higher, warranting a longer duration in which a price is held constant. Dealers who are an official partner of BMW are also willing to wait longer, possibly because they attract more customers on the basis of their status.

The initial price $\alpha$ is affected only by the average mileage of the fleet of a dealership, which means that dealers initially price a BMW lower if their other cars have on average higher mileage. None of the other variables—most notably the number of dealers in a region, which captures how competitive a local market is—had a significant effect. Changes in price $\gamma$ were affected solely by whether or not the dealership is an official partner of BMW; official partners apply smaller price changes.

The interviews will provide further insights into whether the reason for the use of such sticky prices adheres to any of the classical theories or whether it is instead due to a learning process that reflects the aspiration level heuristic and the search for the highest willingness to pay for a given car.

*V.B. Interviews*

**Pricing strategies.** In the interviews, the dealers indicated which type of pricing strategy they use by selecting among a number of predefined options. Table III shows that only 11 percent reported that they price lower than the competition. This corresponds almost exactly with the online data, where we observe that only 12 percent of dealers start with a price close to or at the minimum price of a group of matching cars, whereas the majority of dealers begin with a substantially higher price. Table III also shows that in sum, 88 percent of dealers reported that they use a fixed time interval after which they would consider changing the price, 6 percent of dealerships do not change the price at all, and only 6 percent change the price if they observe shifts in the market or in cost structure. These reports correspond closely to the pattern in the online data. Overall, the statements made by dealers in the interviews provide an independent validation of the conclusions drawn from the online platform.

In addition, the interviews provide specific details about the pricing strategies that cannot be obtained from the online data. When deciding about the size $\gamma$ of change in price, 70 percent of dealers stated that they consult online platforms or market surveys. In contrast, the other 30 percent had already determined $\gamma$ at the time of setting their initial price; they do not consult any further information when changing prices. The interviews also provided a clear answer to the question of whether dealers employ multiple pricing strategies. All dealers stated that in the consumer market they use only one strategy. In a business-to-business context 29 percent said that they use different strategies. The online data captured only cars sold to consumers, and, consistent with the dealer statements, we did not observe any differences in pricing strategies between the BMW 320 and 730 models. All interviewees said that they advertise cars immediately online once a car is on the lot. This confirms that the online platform is a representative source of information about the current market.

TABLE III.

PRICING STRATEGIES AND INFORMATION USE IN INTERVIEWS

| | | **Initial price ($\alpha$)** | | | |
|---|---|---|---|---|---|
| | | **Higher than competition** | **Same as competition** | **Lower than competition** | **Total** |
| **Duration and price change ($\boldsymbol{\beta}, \gamma$)** | **fixed** intervals & **predetermined** amounts | 0.24 | 0.02 | 0.00 | **0.26** |
| | **fixed** intervals & information **update** | 0.44 | 0.11 | 0.07 | **0.62** |
| | **variable** intervals & **predetermined** amounts | 0.02 | 0.02 | 0.00 | **0.04** |
| | **variable** intervals & information **update** | 0.02 | 0.00 | 0.00 | **0.02** |
| | no price change | 0.00 | 0.02 | 0.04 | **0.06** |
| | **Total** | **0.72** | **0.17** | **0.11** | |

**Pricing theories.** An important question that cannot be answered solely by the online data is why dealers change their prices. Interviewees responded to nine statements, each of which reflects a particular pricing theory (Section II.C). The theories were rated according to the following scale:

| | |
|---|---|
| 1 = totally unimportant | 2 = of minor importance |
| 3 = moderately important | 4 = very important |

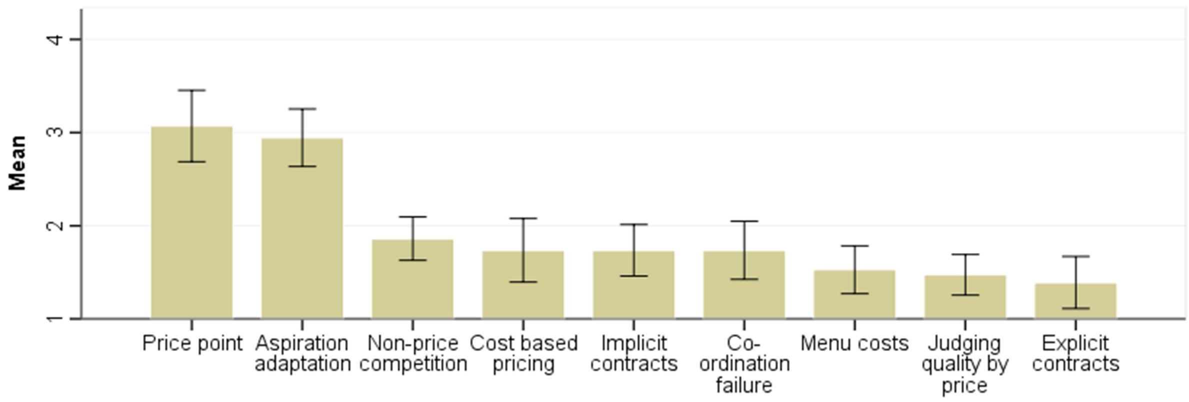


FIGURE IV.

MEAN RATINGS OF RELEVANCE OF PRICING THEORIES FOR CAR DEALERS

*Notes*: Error bars show +-2 SE

As can be seen in Figure IV, only two theories receive on average more than 2 points, which Blinder et al. (1998) regard as a critical mark, below which a theory bears little relevance for actual pricing. Aspiration level received a mean rating of 2.9 (SD = .9). The highest-ranking statement refers to price points as an important element when setting prices with a mean rating of 3.0 (SD = 1.2). It suggests that prices ‘jump’ to psychologically attractive numbers. Classical theories of price stickiness are not considered to be important by the interviewees. This result provides further independent evidence for the conclusion from the online-analysis that dealers use aspiration-level heuristics in combination with psychologically attractive numbers to price used cars.

*V.C. Prices at the aggregate level*

**Changes in price dispersion and average price.** The evidence on the individual level indicates that dealers use the aspiration level heuristic. How does this relate to the aggregate market, that is, how do price dispersion and average price change in relation to the degree of competition?

In order to compute the degree of price dispersion we use the coefficient of variation, the standard measure for price dispersion. It is homogenous of degree zero, enabling comparison across different products, time, and different sample sizes. The coefficient of variation is computed as

$$\widehat{CV} = \frac{\sigma_g}{\frac{1}{n}\sum_{i=1}^{n} p_{g,i}}$$

where $\sigma_g$ denotes the standard deviation in a group $g$ with $n$ offers of matching cars on a given day. The matching cars in a group on a given day constitute the number of offers used to compute the degree of price dispersion. With group size of matching cars larger than one the CV is in the mean .09 (SD = .07).

The OLS regressions in Table IV assess how the dependent variables price dispersion, as measured with the CV, and price changes vary with the number of offers, controlling for 27 attributes used to identify groups of matching cars, properties of the local market, and dealership characteristics. Regressions 1, 2 and 4, 5 include fixed effects for the time when the car was listed. Regressions 3 and 6 use random effects to check the robustness of the results. All regressions were run with group size of matching cars larger than one and dealers who can be uniquely identified and included all prices posted on a given day, irrespective of whether the car was completely observed for the entire duration it was posted.

## TABLE IV.

### PRICE DISPERSION AND HEDONIC REGRESSION

| | (1) Price dispersion (CV) | (2) Price dispersion (CV) | (3) Price dispersion (CV) | (4) Price (log) | (5) Price (log) | (6) Price (log) |
|---|---|---|---|---|---|---|
| Number of offers | 0.001 | | | 0.004 | | |
| | (22.0) | | | (35.5) | | |
| Number of offers (log) | | 0.007 | 0.007 | | 0.024 | 0.024 |
| | | (31.1) | (30.6) | | (40.2) | (39.7) |
| Kilometers (log) | 0.000 | 0.001 | 0.001 | -0.189 | -0.188 | -0.191 |
| | (3.2) | (5.0) | (4.1) | (-490.8) | (-489.2) | (-478.2) |
| Extra warranty available | -0.022 | -0.022 | -0.022 | 0.102 | 0.102 | 0.104 |
| | (-51.6) | (-52.1) | (-52.0) | (97.2) | (97.2) | (98.7) |
| Number of photos | -0.000 | -0.000 | -0.000 | 0.001 | 0.001 | 0.001 |
| | (-3.7) | (-3.7) | (-4.0) | (9.0) | (9.0) | (9.3) |
| Extra advertisement | -0.004 | -0.004 | -0.004 | -0.001 | -0.001 | -0.003 |
| | (-3.5) | (-3.3) | (-3.9) | (-0.3) | (-0.2) | (-0.9) |
| Dealers in region | | | 0.001 | | | -0.004 |
| | | | (1.4) | | | (-2.4) |
| Population density (per 100 inhabitants per sq.km) | | | 0.001 | | | -0.011 |
| | | | (2.4) | | | (-5.8) |
| GDP per capita (per thousand €) | | | -0.000 | | | 0.000 |
| | | | (-1.2) | | | (0.1) |
| Dealers x population density | | | -0.000 | | | 0.001 |
| | | | (-2.0) | | | (3.9) |
| Official BMW partner | | | -0.006 | | | 0.054 |
| | | | (-1.9) | | | (5.4) |
| Observed BMW 320s and 730s per dealer (per 10 cars) | | | -0.000 | | | 0.000 |
| | | | (-2.4) | | | (6.0) |
| Share of BMW 320s | | | 0.028 | | | -0.277 |
| | | | (1.9) | | | (-5.8) |
| Part of larger dealer network | | | -0.005 | | | 0.010 |
| | | | (-1.3) | | | (0.8) |
| *Table is truncated; complete table including 27 car attributes can be found in Appendix, Table A3.* | | | | | | |
| Observations | 266,105 | 266,105 | 259,747 | 266,105 | 266,105 | 259,747 |
| R-squared | 0.059 | 0.061 | 0.075 | 0.790 | 0.791 | 0.804 |
| Number of dealers | 678 | 678 | 638 | 678 | 678 | 638 |
| Time FE | Yes | Yes | | Yes | Yes | |
| RE | | | Yes | | | Yes |

Coefficients and t-statistics (in parentheses). All p-values for the number (and log number) of offers <.001.

Regressions 1 to 3 show that price dispersion increases with the the number of offers. Increasing the number of matching cars by 1 percent raises the CV by .007; the number of matching cars is as large as 21 for BMW 320s and 27 for BMW 730s. If price dispersion is a measure of the uncertainty in the market, as proposed by Stigler (1961), this suggests that increasing the number of offers does not reduce uncertainty. Making an extra warranty available to consumers or adding photos, in contrast, does reduce price dispersion and uncertainty.

The hedonic regressions 4 to 6 show that the average price also increases in offers. As offers increase by 1 percent, price increases by .024 percent. To illustrate, for a BMW 320 with an average price of 24,645 euros, each additional offer increases the price by more than 130 euros. The availability of an extra warranty and an increase in the number of pictures also have a positive effect on the price. The latter replicates the finding by Lewis (2011), who uses US data from used cars on eBay. He argues that the more photos available, the more readily a consumer can at least partially contract on quality.

**Aggregate level models.** In order to compare the empirical results to the price dispersion models, we need to calibrate the general clearing house model of Baye et al. (2004). Since the calibration can be done in a number of ways, we conducted robustness checks, which all yielded the same qualitative results as presented in the following.

In order to estimate the number of shoppers, we use the last posted price of a car as an indication that this price likely was sufficiently attractive for a customer to visit the dealership and buy the car (see also Figure II). For each group size we rank cars according to price, which allows estimating the relative frequency of how often the cheapest car is the one that dealers stop posting. Shoppers opt for the cheapest car on offer, whereas naïve or uninformed consumers pick the cheapest with probability $1/n$, where $n$ is the number of matching cars on a given day. This allows estimating the number of shoppers $S$, which is 10.4 percent.[3] The result is similar to the finding of Brynjolfsson and M. D. Smith (2000), who report an estimate of 13 percent, which Baye et al. (2004) use. Note that for the given models it is not necessary to estimate continuous demand function because they focus on two classes of consumers only, shoppers and uninformed consumers. For marginal costs $c$, industry estimates show that the share of fixed costs per car is 77.7 percent (Löhe 2010). Dealers vary in the time until they sell a car. Each additional day a car is on the lot reduces the revenue of that car by .1 percent. In the median it takes 21 days until a car sells, yielding total marginal costs of $c = 79.8$ percent. The costs of advertising $\phi$ are 0.02 percent per car.

When calibrating the models the major difficulty is to infer a reservation price $r$ for a group of matching cars. Given the dynamic market environment and the relatively small samples of matching cars, this exercise must be performed with caution. One conservative way is to set the maximum willingness to pay $r$ for a group of matching cars equal to the highest last price observed for this group across the entire period of 15 months. Limiting the period of observation does not change the general predictions that each of the three models makes. We obtain the same predictions as those of Baye et al. (2004), which also reflects the robustness of the results: as competition increases, the model by Rosenthal (1980) predicts an increase in average price but a decline in price dispersion, Varian (1980) predicts an increase in average price and price dispersion, and Baye and Morgan (2001) predict a decline in average price and price dispersion.

Comparing this to Table IV, the model by Varian (1980) provides the best description of the used car market. This fit suggests that differences between consumers are central to the emergence of price dispersion. Rosenthal's (1980) model differs from Varian's in assuming that there is constant fraction of naïve or uninformed consumers $U > 0$ per firm regardless of

[3] If $x$ is the proportion of the last observed price of the cheapest cars among all last observed prices in a group of matching cars, $x = S + (\frac{1-S}{n})$. The proportion of shoppers $S$ is then $S = \frac{xn-1}{n-1}$.

the market size. The reasoning Rosenthal provides is that these are loyal consumers whom each firm brings to the market. Our results, by contrast, suggest that loyal consumers do not play a major role in shaping the aggregate market outcome. The predictions of Baye and Morgan (2001) differ from Varian's in the event that only some offers are listed in the clearing house due to costs of advertising, $\phi > 0$. Dealers indeed incur these costs, however, Mohr et al. (2015) report that almost all customers use the internet in order to identify a car at a dealership; not advertising on the online platform is therefore no longer viable. The empirical probability $\tau$ of listing a car is close to 100 percent.

**Profitability.** The equilibrium model of Varian (1980) is based on the assumption that firms use a mixed strategy to set prices. Seeing as the model describes the market well, the question arises how well dealers would have done if they had used the mixed strategy instead of the aspiration level heuristic.

The expected theoretical profit derived from the Varian (1980) model is $\mathrm{E}\pi(\mathrm{p}) = (\mathrm{r} - \mathrm{c})\frac{1-\mathrm{S}}{\mathrm{n}}$. The calibration of the theoretical profit function for a given car follows the calibration of the aggregate model outlined above. Again, the most challenging parameter to derive is the maximum willingness to pay r for a group of matching cars. In line with the aggregate model, we use the highest last price observed for a group of matching cars across the entire period of 15 months. This provides the highest values for the Varian model in terms of profits in comparison to for instance using a smaller time window. In order to compare the theoretical profit function with the estimated profits obtained using the aspiration level heuristic across the 3 clusters—constant duration, decreasing duration, and constant price—we use those cars of dealers who can be uniquely identified. The estimated profit $\pi_i$ of a car $i$ is calculated as follows:

$$\pi_i = p_{g,i,l} - \left[\left(\frac{1}{I}\sum_{i=1}^{I} p_{g,i,l}\ h\right) + p_{g,i,l}\,Tb\right],$$

where $p_{g,i,l}$ denotes the last observed price of car $i$ and $I$ denotes the total number of cars observed in a group of matching cars during the 15 months the market was observed. To calculate the costs we compute the mean from the last observed prices of the cars in this group times the share of fixed costs of a car $h = .777$. The total time a car was on offer is denoted by $T$; each day a car is on the lot reduces the revenue of the car by $b = .01$.

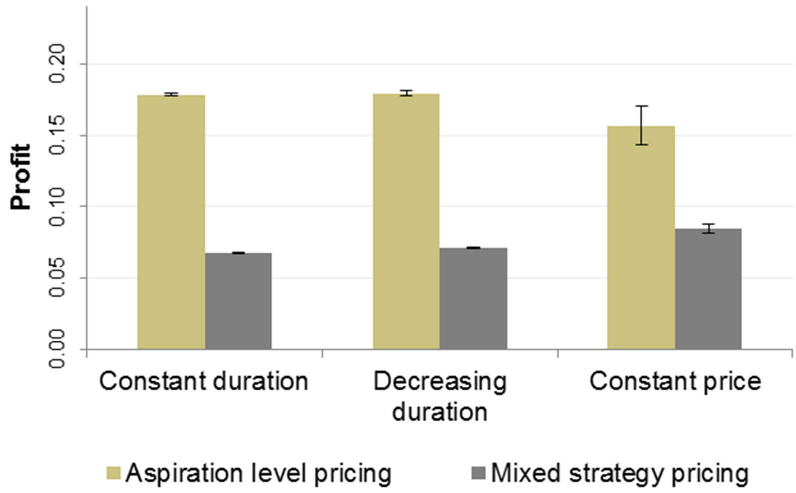


FIGURE V.

MEAN PROFIT ACROSS CARS FOR ASPIRATION LEVEL AND MIXED STRATEGY PRICING

*Notes*: Error bars show +-2 SE

Figure V shows the mean estimated profit per car for the three types of aspiration level pricing and compares it with the profits that would have been generated with a mixed strategy. Each of the three variants of the aspiration level heuristic performs better than mixed strategy pricing. The difference is substantial: in the mean across all cars, aspiration level pricing achieves a profit of 18 percent (SD =.11, M = .19), the mixed strategy only 7 percent (SD = .3).

These results might seem puzzling, particularly given that the model by Varian (1980) fits the aggregate market well. It is known since V. L. Smith (1962) that, despite the uncertainty that the individual agent faces, equilibrium can readily emerge. If the researcher correctly identifies the underlying incentive structure, making the appropriate abstractions, the steady state of the market can be readily identified. The mixed strategy is the equilibrium strategy in this well-specified, but static and abstract environment.

Used car dealers do not operate in such a steady state but rather in a highly dynamic market where they have developed an adaptive strategy that operates well under weak information conditions. This result is supported by the regression analysis in Table II, which shows that parameters of the aspiration level heuristic vary in a predictable way with the local environment of a dealer. Abstraction in a constructivist approach is necessary insofar as it allows generating a tractable model. However, this might also come at a cost. For instance, Varian (1980) assumes that there are only two types of consumers, informed and uninformed, where the best response is to randomize prices. He argues that absent randomization, even naïve or uninformed consumers would learn and pick the cheapest product on offer. Yet, such randomization yields on average a lower final price than the auction like mechanism of the aspiration level strategy. This suggests that the dealers have found an effective pricing strategy "creaming" a large portion of consumers and randomization seems unnecessary. The strategy is well adapted to the environment in the sense that it performs well and reduces error from bias.

The Varian model is also more likely than the heuristic to suffer from error due to variance, which reflects the sensitivity of the model to a specific sample. Estimating parameters in the Varian model for the environment of the dealers with sufficient reliability, crucially the value $r$ for the willingness to pay for a group of matching cars, is plagued by the unreliable information that small samples in a dynamic market provide, which increases the total error, as demonstrated in Figure V. Given these results for individual dealer's profits, one needs to keep in mind that Varian's (1980) model was designed to shed light on how price dispersion changes within a competitive environment. And it does this very well.

## VI. DISCUSSION

In this article, we asked, how do firms set prices given uncertain market conditions? In line with Simon's (1955) proposition, online data and interviews consistently show that virtually all dealers rely on an aspiration level heuristic together with targeting certain price points in the used car market. In addition, they use the three parameters of the heuristic, specifically the duration a price is held constant, as tools to adapt to local market conditions. The heuristic is similar to a 'slow' Dutch auction. Auctions rather than posted prices are efficient mechanisms for selling goods when the seller does not know demand precisely (Einav et al., in press). Despite the fact that firms consistently rely on aspiration level pricing, the aggregate market pattern that the heuristic gives rise to is well characterized by Varian's (1980) classic model. Its predictions that price dispersion and average prices increase with the number of offers are in line with the data. This consistency suggests that the model by Varian captures the incentives for an equilibrium analysis at the aggregate market level well. At the same time, individual agents have developed an adaptive response despite their limited information. The success and ecological rationality of the dealers' strategy is reflected in that pricing strategies systematically vary with the local conditions in which the dealers operate and the estimated profits earned through the aspiration level pricing are higher than those for the mixed strategy that underlies the aggregate model.

The results show that it is crucial to take into account the information condition under which the individual agent operates. Given sufficiently strong information conditions, that is, a stable world of regular purchases such as in a supermarket, agents can develop decision strategies in line with rational choice models. For instance, Lach (2002) reports that supermarkets randomize their prices, as prescribed by a mixed strategy, leading in the aggregate to price dispersion as predicted by Varian (1980). Here, constructivist and ecological rationality converge in their analyses of which strategy is best.

Given weak information conditions, that is, a dynamic environment with noisy information and small samples, a heuristic can perform strongly if it is well adapted to the structure of the environment. Although the ecological rationality of lexicographical heuristics has been analyzed mathematically and empirically (e.g., Martignon and Hoffrage 2002; Baucells, Carrasco, and Hogarth 2008; Şimşek 2013; for a review see Gigerenzer 2016), that of the aspiration level heuristic has not been studied before. Future research needs to further identify the conditions under which the aspiration level heuristic performs well and also compare it to strategies such as dynamic pricing models that are computationally intensive and geared towards the perspective of an individual agent (Elmaghraby and Keskinocak 2003).

Empirical studies have demonstrated that a constructivist analysis successfully predicts aggregate market outcomes even if the information conditions that agents face are surprisingly weak. As Plott notes in a personal letter to V. L. Smith (2008, 30): "Although this [insight] is a giant victory for the economic theory of markets it simultaneously demonstrates that the theory is incomplete. The unexpectedly weak conditions under which the results obtain are good news for market performance, but not such good news for the scientific community because it demonstrates that we do not understand why markets work as they do." The answer proposed in this article is that under weak information conditions agents develop—in a process akin to a Darwinian selection process—adaptive heuristics that effectively perform under conditions where optimization is out of reach. It is under weak information conditions that constructivist and ecological rationality can complement each other in a better understanding of the market and its agents.

## REFERENCES


Akerlof, George A. 1970. "The Market for 'Lemons': Quality Uncertainty and the Market Mechanism." *Quarterly Journal of Economics* 84 (3): 488–500. doi:10.2307/1879431.

Allen, Franklin. 1988. "A Theory of Price Rigidities When Quality Is Unobservable." *Review of Economic Studies* 55 (1): 139–51. doi:10.2307/2297534.

Apel, Mikael, Richard Friberg, and Kerstin Hallsten. 2005. "Microfoundations of Macroeconomic Price Adjustment: Survey Evidence from Swedish Firms." *Journal of Money, Credit and Banking* 37 (2): 313–38.

Argote, Linda, and Henrich R. Greve. 2007. "A Behavioral Theory of the Firm - 40 Years and Counting: Introduction and Impact." *Organization Science* 18 (3): 337–49. doi:10.1287/orsc.1070.0280.

Åstebro, Thomas, and Samir Elhedhli. 2006. "The Effectiveness of Simple Decision Heuristics: Forecasting Commercial Success for Early-Stage Ventures." *Management Science* 52 (3): 395–409. doi:10.1287/mnsc.1050.0468.

Baucells, Manel, Juan A. Carrasco, and Robin M. Hogarth. 2008. "Cumulative Dominance and Heuristic Performance in Binary Multiattribute Choice." *Operations Research* 56 (5): 1289–1304. doi:10.1287/opre.1070.0485.

Baye, Michael R., and John Morgan. 2001. "Information Gatekeepers on the Internet and the Competitiveness of Homogeneous Product Markets." *American Economic Review* 91 (3): 454–74.

Baye, Michael R., John Morgan, and Patrick Scholten. 2004. "Price Dispersion in the Small and in the Large: Evidence from an Internet Price Comparison Site." *Journal of Industrial Economics* 18 (4): 463–96.

———. 2006. "Information, Search, and Price Dispersion." Edited by Terrence Hendershott. *Handbook on Economics and Information*. Amsterdam: Elsevier Press, 323–71.

Becker, Gary S. 1962. "Irrational Behavior and Economic Theory." *Journal of Political Economy* 70 (1): 1–13. http://www.jstor.org/stable/1827018.

Bils, Mark. 1987. "The Cyclical Behavior of Marginal Cost and Price." *American Economic Review* 77 (5): 838–55.

Blinder, Alan S., Eile R.D. Canetti, David E. Lebow, and Jeremy B. Rudd. 1998. *Asking about Prices - A New Approach to Understanding Price Stickiness*. New York: Russell Sage Foundation.

BMW Group. 2011. "BMW Group Annual Report 2010."

Bond, Eric W. 1982. "A Direct Test of the 'Lemons' Model: The Market for Used Pickup Trucks." *American Economic Review* 72 (4): 836–40. doi:10.4324/9780203878460.

Brynjolfsson, Erik, and Michael D. Smith. 2000. "Frictionless Commerce? A Comparison of Internet and Conventional Retailers." *Management Science* 46 (4): 563–85. doi:10.1287/mnsc.46.4.563.12061.

Busse, Meghan R., Nicola Lacetera, Devin G. Pope, Jorge Silva-Risso, and Justin R. Sydnor. 2013. "Estimating the Effect of Salience in Wholesale and Retail Car Markets." *American Economic Review: Paper & Proceedings* 103 (3): 575–79. doi:10.1257/aer.103.3.575.

Carlton, Dennis W. 1986. "The Rigidity of Prices." *American Economic Review* 76 (4): 637–58.

Chow, Gregory C. 1989. "Rational versus Adaptive Expectations in Present Value Models." *Review of Economics and Statistics* 71 (3): 376–84.

Conlisk, John. 2003. "A Note on Convergence of Adaptive Satisficing to Optimal Stopping." *Journal of Political Economy* 111 (6): 1353–60. doi:10.1086/378527.

Cooper, Russell, and Andrew John. 1988. "Coordinating Coordination Failures in Keynesian Models." *Quarterly Journal of Economics* 103 (3): 441–63. doi:10.2307/1885539.

Cyert, Richard M., and James G. March. 1963. *A Behavioral Theory of the Firm*. New Jersey: Prentice-Hall.

DeMiguel, Victor, Lorenzo Garlappi, and Raman Uppal. 2007. "Optimal Versus Naive Diversification: How Inefficient Is the 1/N Portfolio Strategy?" *Review of Financial Studies* 22 (5): 1915–53. doi:10.1093/rfs/hhm075.

Dudenhöffer, Ferdinand, and Alexander Schadowski. 2011. "Die Online-Gebrauchtwagen-Börsen in Europa." Universität Duisburg-Essen, CAR-Center Automotive Research.

Einav, Liran, Chiara Farronato, Jonathan Levin, and Neel Sundaresan. 2016. "Auctions versus Posted Prices in Online Markets." *Working Paper*.

Einav, Liran, Theresa Kuchler, Jonathan Levin, and Neel Sundaresan. 2015. "Assessing Sale Strategies in Online Markets Using Matched Listings." *American Economic Journal: Microeconomics* 7 (2): 215–47.

Elfenbein, Daniel W., Ray Fisman, and Brian Mcmanus. 2012. "Charity as a Substitute for Reputation: Evidence from an Online Market Place." *Review of Economic Studies* 79: 1441–68.

Elmaghraby, Wedad, and Pinar Keskinocak. 2003. "Dynamic Pricing in the Presence of Inventory Considerations: Research Overview, Current Practices, and Future

Directions." *Management Science* 49 (10): 1287–1309.

Erev, Ido, and Alvin E. Roth. 1998. "Predicting How People Play Games: Reinforcement Learning in Experimental Games with Unique, Mixed Strategy Equilibria." *American Economic Review* 88 (4): 848–81.

Fischer, Stanley. 1977. "Long-Term Contracts, Rational Expectations, and the Optimal Money Supply Rule." *Journal of Political Economy* 85 (1): 191–205.

Geman, Stuart, Elie Bienenstock, and René Doursat. 1992. "Neural Networks and the Bias/Variance Dilemma." *Neural Computation* 4 (1): 1–58. doi:10.1162/neco.1992.4.1.1.

Genesove, David. 1993. "Adverse Selection in the Wholesale Used Car Market." *Journal of Political Economy* 101 (4): 644–65. doi:10.1086/261891.

Ghose, Anindya, and Yuliang Yao. 2011. "Using Transaction Prices to Re-Examine Price Dispersion in Electronic Markets." *Information Systems Research* 22 (2): 269–88. doi:10.1287/isre.1090.0252.

Gigerenzer, Gerd. 2016. "Towards a Rational Theory of Heuristics." In *Minds, Model, and Milieu. Commemorating the Centenary of Herbert Simon's Birth*, edited by Roger Frantz and Leslie Marsh. Palgrave Macmillan.

Gigerenzer, Gerd, Ralph Hertwig, and Thorsten Pachur, eds. 2011. *Heuristics: The Foundations of Adaptive Behavior.* New York: Oxford University Press.

Gigerenzer, Gerd, Peter M. Todd, and the ABC Research Group. 1999. *Simple Heuristics That Make Us Smart*. New York, NY: Oxford University Press. doi:10.1002/mar.10060.

Gode, Dhananjay K., and Shyam Sunder. 1993. "Allocative Efficiency of Markets with Zero-Intelligence Traders: Market as a Partial Substitute for Individual Rationality." *Journal of Political Economy* 101 (1): 119–37. doi:10.1086/261868.

Hayek, Friedrich A. 1937. "Economics and Knowledge." *Economica*. http://www.jstor.org/stable/2548786.

———. 1945. "The Use of Knowledge in Society." *American Economic Review* 35 (4): 519–30. http://www.jstor.org/stable/1809376.

Huck, Steffen, Hans-Theo Normann, and Jörg Oechssler. 2004. "Two Are Few and Four Are Many: Number Effects in Experimental Oligopolies." *Journal of Economic Behavior & Organization* 53: 435–46. http://www.sciencedirect.com/science/article/pii/S0167268103001380.

Hume, David. 1739. *A Treatise of Human Nature*.

Isoni, Andrea, Peter Brooks, Graham Loomes, and Robert Sugden. 2016. "Do Markets Reveal Preferences or Shape Them?" *Journal of Economic Behavior & Organization* 122

(February): 1–16. doi:10.1016/j.jebo.2015.11.006.

Jacobs, Rodney L., and Robert A. Jones. 1980. “Price Expectations in the United States: 1947-75.” *American Economic Review* 70 (3): 269–77. http://www.jstor.org/stable/1805218.

Keynes, John Maynard. 1921. *Treatise on Probability*. London: Macmillan.

Klenow, Peter J., and Benjamin A. Malin. 2011. “Microeconomic Evidence on Price-Setting.” In *Handbook of Monetary Economics*, 3:231–84. Amsterdam: North-Holland. doi:10.1016/B978-0-444-53238-1.00006-5.

Knight, Frank H. 1921. *Risk, Uncertainty and Profit*. Boston: Houghton-Mifflin.

Lach, Saul. 2002. “Existence and Persistence of Price Dispersion: An Empirical Analysis.” *Review of Economics and Statistics* 84 (3): 433–44. doi:10.1162/003465302320259457.

Lant, Theresa K. 1992. “Aspiration Level Adaptation: An Empirical Exploration.” *Management Science* 38 (5): 623–44. doi:10.1287/mnsc.38.5.623.

Levy, Daniel, Dongwon Lee, Haipeng Allan Chen, Robert J. Kauffman, and Mark Bergen. 2011. “Price Points and Price Rigidity.” *Review of Economics and Statistics* 93 (4): 1417–31.

Lewis, Gregory. 2011. “Asymmetric Information , Adverse Selection and Online Disclosure: The Case of eBay Motors.” *American Economic Review* 101 (4): 1535–46.

Löhe, Jan. 2010. “Studie Zur Professionalisierung Im Gebrauchtwagengeschäft: Handlungsfelder Und Potentiale,” Working paper, European Business School, .

Lucas, Robert E. Jr. 1986. “Adaptive Behavior and Economic Theory.” *Journal of Business* 59 (4): 401–26. http://www.jstor.org/stable/2352771.

Mankiw, N. Gregory. 1985. “Small Menu Costs and Large Business Cycles: A Macroeconomic Model of Monopoly.” *Quarterly Journal of Economics* 100 (2): 529–37. doi:10.2307/1885395.

Martignon, Laura, and Ulrich Hoffrage. 2002. “Fast, Frugal, and Fit: Simple Heuristics for Paired Comparison.” *Theory and Decision* 52 (1): 29–71.

Mohr, Detlev, Hans-Werner Kaas, Paul Gao, Gianluca Camplone, Marcus Hohmann, Jan-Christoph Koestring, and Robert Mathis. 2015. “Innovating Automobile Retail: Journey towards Customer-Centric, Multiformat Sales and Service Network.” *McKinsey & Company*.

Morgan, John, Henrik Orzen, and Martin Sefton. 2005. “An Experimental Study of Price Dispersion.” *Games and Economic Behavior* 54 (1): 134–58. doi:10.1016/j.geb.2004.07.005.

Nelson, Richard R., and Sidney G. Winter. 1973. "Toward an Evolutionary Theory of Economic Capabilities." *American Economic Review* 63 (2): 440–49.

Okun, Arthur M. 1981. *Prices and Quantities: A Macroeconomic Analysis*. Brookings.

Pan, Xing, Brian T. Ratchford, and Venkatesh Shankar. 2004. "Price Dispersion on the-Internet: A Review and Directions for Future Research." *Journal of Interactive Marketing* 18 (4): 116–35. doi:10.1002/dir.20019.

Plott, Charles R., and Shyam Sunder. 1982. "Efficiency of Experimental Security Markets with Insider Information: An Application of Rational-Expectations Models." *Journal of Political Economy* 90 (4): 663–98. http://www.jstor.org/stable/1831348.

———. 1988. "Rational Expectations and the Aggregation of Diverse Information in Laboratory Security Markets." *Econometrica* 56 (5): 1085–1118. http://www.jstor.org/stable/1911360.

Rosenthal, Robert W. 1980. "A Model in Which an Increase in the Number of Sellers Leads to a Higher Price." *Econometrica* 48 (6): 1575–79. doi:10.2307/1912828.

Savage, Leonard J. 1951. *The Foundations of Statistics*. Wiley.

Simon, Herbert A. 1955. "A Behavioral Model of Rational Choice." *Quarterly Journal of Economics* 69 (1): 99–118.

———. 1956. "Rational Choice and the Structure of the Environment." *Psychological Review* 63 (2): 129–38.

Şimşek, Özgür. 2013. "Linear Decision Rule as Aspiration for Simple Decision Heuristics." *Advances in Neural Information Processing Systems* 26 (1): 2904–2912.

Smith, Adam. 1776. *An Inquiry into the Nature and Causes of the Wealth of Nations*. 1976thed. Oxford: Clarendon Press.

———. 1779. *The Theory of Moral Sentiments*. Edited by D. D. Raphael and A. L. Macfie. 1981sted. Indianapolis: Liberty Fund.

Smith, Vernon L. 1962. "An Experimental Study of Competitive Market Behavior." *Journal of Political Economy* 70: 111–37. http://www.jstor.org/stable/1861810.

———. 1982. "Microeconomic Systems as an Experimental Science." *American Economic Review* 72 (5): 923–55.

———. 2008. *Rationality in Economics: Constructivist and Ecological Forms*. Cambridge: Cambridge University Press.

Statistische Ämter des Bundes und der Länder. 2013. "Indikatoren Und Karten Zur Raum- Und Stadtentwicklung."

Stigler, George J. 1961. "The Economics of Information." *Journal of Political Economy* 69

(3): 213–25.

Sugden, Robert. 1989. “Spontaneous Order.” *The Journal of Economic Perspectives* 3 (4): 85–97. http://www.jstor.org/stable/1942911?seq=2#page_scan_tab_contents.

———. 1991. “Rational Choice: A Survey of Contributions from Economics and Philosophy.” *The Economic Journal* 101 (407): 751–85. http://www.jstor.org/stable/2233854?seq=2#page_scan_tab_contents.

Tversky, Amos, and Daniel Kahneman. 1974. “Judgment under Uncertainty: Heuristics and Biases.” *Science* 185 (4157): 1124–31. doi:10.1126/science.185.4157.1124.

Varian, Hal R. 1980. “A Model of Sales.” *American Economic Review* 70 (4): 651–59. doi:10.2307/1803562.

Venkatesan, Rajkumar, Kumar Mehta, and Ravi Bapna. 2007. “Do Market Characteristics Impact the Relationship between Retailer Characteristics and Online Prices?” *Journal of Retailing* 83 (3): 309–24. http://www.sciencedirect.com/science/article/pii/S0022435907000164.

Wübben, Markus, and Florian von Wangenheim. 2008. “Instant Customer Base Analysis: Managerial Heuristics Often ‘Get It Right.’” *Journal of Marketing* 72 (May): 82–93. doi:10.1509/jmkg.72.3.82.

Zhe, Ginger Jin, and Andrew Kato. 2006. “Price, Quality, and Reputation: Evidence from an Online Field Experiment.” *RAND Journal of Economics* 37 (4): 983–1004.

**For online publication.**

## ONLINE APPENDIX

A. Discussion on additional four theories on sticky prices used by Blinder et al. (1998)

Four theories are omitted on the basis of previous studies showing that they are not relevant to price setting and also do not relate to the used car market. A list of these theories follows, together with the particular question that Blinder et al. (1998) consider and an explanation for why each theory was not used here: 1. Procyclical elasticity of demand. “It has been suggested that when business turns down, a company loses its least loyal customer first and retains its most loyal ones. Since the remaining customers are not very sensitive to price, reducing markups will not stimulate sales very much” (Blinder et al. 1998). In the used cars business, we expect that a relatively small share of business is made with the same customers. Hence, there is only a small base of loyal customers. 2. Constant costs. “It has been suggested that many firms base prices on costs. Hence firms with constant variable costs per unit have no reason to change prices when production changes” (Blinder et al. 1998). This theory received very low scores in Blinder et al. (1998), and apparently interviewees had difficulties understanding the question. 3. Hierarchies. “Some people think that price changes are slowed down by the difficulty of getting a large, hierarchical organization to take action” (Blinder et al. 1998). Car dealers are frequently small in size; hence this theory is not relevant for the average dealer. 4. Inventories. “According to this idea, a firms’ initial response to fluctuations in demand is to let inventory stocks, rather than prices vary. That is, when demand rises, they first let inventories fall rather than raise prices. And when demand falls, they first let inventories build up rather than reduce prices” (Blinder et al. 1998). Generally, car dealers do not rely on storage facilities that they can use to build up an inventory.

## *B. Interview with car dealers*

- *Text in italics and underlined is intended solely for the interviewer.*
- *The interview is recorded on audio tape and transcribed.*
- *The interview lasts about 20 minutes.*
- *Each interview is given an ID. This ID is identical to the ID from the online data set in order to compare statements made in the interview to the actual pricing behavior.*
- *UC = used car*

Xxx is interviewing used car dealers for the Germany-wide study “Pricing behavior of used car dealers”. You will be asked to respond to questions regarding how you set prices for UCs in order to contribute to the success of your enterprise. The aim of the study is to document how UC dealers price. Anything you say is anonymized and analyzed on an aggregate level only. For this the audio recordings will be transcribed and destroyed afterwards. The final analysis is based on the interviews and data from the online market Autoscout.de.

### I. General Questions

1. What is your function in the dealership: ______________________
2. a) How many cars, old and new, are currently on offer in this dealership: _____

   b) How many of these are UCs: _____

   c) How many UCs are BMWs: ______
3. How large is the percentage of returning customers, i.e., those who bought at least their last car from the dealership: ________
4. a) Is the dealership part of a larger organization, and if so, how many branches does the latter have: _______

   b) *if a. > 1*: Are the prices for UCs

   ☐ done centrally ☐ done individually at each dealership

5. Since when have you been pricing UCs: ________

**II. Prices – specific questions**

6. Initial price:

   a) What do you do if you have to price a UC the first time:

   ______________________________________________________________

   __________________________________________

   b) Which information is important for determining the initial price:

   ____________________________________________________

   ____________________________________________________

7. You are faced with a situation where your competitors offer a similar UC. The initial price of your UC is

   ☐ i) lower than the price of the competitor

   ☐ ii) the same as the competitor's

   ☐ iii) higher than the competitor's

8. What is the geographical size of the market you are selling your product (*km in diameter*)

   ________________

9. a) Do you commonly change prices: *yes or no*

   b) *if a = yes:* How do you proceed if you have to change a price?

   ____________________________________________________

   ____________________________________________________

   c) When do you change a price: (*time interval, date, event*):_______________

   d) By how much do you change the price: (*in % or €*):___________

   e) If you change the price of a UC, do you collect information on a competitor's current price of a similar car each time you do this:

   ____________________________________________________

f) Is there a point of time when you offer the UC more cheaply than similar cars of your competitors so that your car is ranked first in the online platform:

_________________________________________________

g) *if f = no:* Why not:

_________________________________________________

10. a) Do you use the same pricing strategy for all (most) of your UCs:

    *yes or no*

    b1) *if a = no:* Which criteria do you apply to differentiate between UCs, which pricing strategy do you apply, and how often do you apply them?

    _________________________________________________

11. a) Are all UCs on the lot also advertised on the internet market? *yes or no*

    b) *if b = no:* Why not: __________________________

12. How large is the share of customers that focus ***only*** on price for their buying decision**:**________

**III. Economic Theories**

How important are any of the following theories with regards to the pricing of second hand cars in your daily business [the order of the questions was randomized for each interviewee].

1 = totally unimportant 2 = of minor importance

3 = moderately important 4 = very important

I. *(menu costs)* Another idea is that the act of changing prices entails special costs in themselves, so firms hesitate to change prices too frequently or buy too much. The costs we have in mind are not production costs but those such as printing a new catalogue, price lists, etc., or hidden costs such as loss of future sales by antagonizing customers, decision-making time of executives, problems with sales person, and so on (Blinder et al. 1998).

II. (*non-price competition*) The idea here is that firms don't cut prices when demand falls because price is just one of several elements that matter to buyers. More frequently, they shorten delivery lags, make greater selling efforts, improve service, or improve product quality (Blinder et al. 1998).

III. *(co-ordination failure)* The next idea is that firms would often like to change their prices, but are afraid to go out of line with what they expect competitors to charge. They do not want to be the first ones to raise prices. But when competing goods rise in price, firms raise their own prices promptly (Blinder et al. 1998).

IV. (*cost-based pricing*) A different idea holds that prices depend mainly on the costs of labor and of materials and supplies that companies buy from other companies. Firms are thought to delay price increases until their costs rise, which may take a while. But then they raise selling prices promptly (Blinder et al. 1998).

V. (*judging quality by price*) One idea is that firms hesitate to reduce their prices because they fear that customers will interpret a price cut as a signal that the quality of the product has been reduced (Blinder et al. 1998).

VI. (*implicit contracts*) Another idea has been suggested for cases in which price increases are not prohibited by explicit contracts. The idea is that firms have implicit understandings with their customers, who expect the firms not to take advantage of the situation by raising prices when the market is tight (Blinder et al. 1998).

VII. (*explicit contracts*) One idea is that many goods are sold under explicit contractual agreements that set prices in advance, meaning that firms are not free to raise prices as long as contracts remain in force (Blinder et al. 1998).

VIII. (*price points*) Another idea is that particular threshold prices are more attractive to customers than other prices. For instance, prices rather change from €10,500 to €9,999 than to €10,050.

IX. (*aspiration level*) A theory says that firms know only approximately the price that customers are willing to pay. Firms therefore search for the best possible price, adapting the posted price at regular time intervals until a customer is found with a sufficiently high willingness to pay.

## *C. Further statistics*

### *Attributes of online posting*

TABLE A1.

ATTRIBUTES OF ONLINE POSTING.

| | All | | | BMW 320 | | | BMW 730 | | |
|---|---|---|---|---|---|---|---|---|---|
| | **Obs.** | **Mean** | **SD** | **Obs.** | **Mean** | **SD** | **Obs.** | **Mean** | **SD** |
| Price | 623,709 | €27,152 | 12,596 | 565,379 | €24,645 | 8,724 | 58,330 | €51,456 | 17,531 |
| Extra warranty offered* | 623,709 | 0.41 | 0.49 | 565,379 | 0.40 | 0.49 | 58,330 | 0.44 | 0.50 |
| Extra advertisement - car highlighted in search results | 623,709 | 0.18 | 0.39 | 565,379 | 0.18 | 0.38 | 58,330 | 0.21 | 0.41 |
| Number of pictures in ad | 623,709 | 8.49 | 4.51 | 565,379 | 8.51 | 4.50 | 58,330 | 8.32 | 4.61 |
| **Primary attributes** | | | | | | | | | |
| Odometer value (km)* | 623,709 | 56,195 | 41,820 | 565,379 | 56,616 | 42,042 | 58,330 | 52,117 | 39,367 |
| Registration date* | 623,709 | | | 565,379 | | | 58,330 | | |
| Kilowatt of engine | 623,709 | 130 | 17 | 565,379 | 126 | 9 | 58,330 | 177 | 7 |
| Horsepower* | 623,709 | 178 | 23 | 565,379 | 171 | 12 | 58,330 | 240 | 9 |
| Fuel* | 619,290 | | | 561,196 | | | 58,094 | | |
| Gears* | 623,526 | | | 565,196 | | | 58,330 | | |
| Form of car body* | 615,874 | | | 557,788 | | | 58,086 | | |
| **Further attributes** | | | | | | | | | |
| ABS* | 623,709 | 0.95 | 0.21 | 565,379 | 0.95 | 0.21 | 58,330 | 0.95 | 0.22 |
| Airbag* | 623,709 | 0.90 | 0.30 | 565,379 | 0.90 | 0.30 | 58,330 | 0.90 | 0.29 |
| Alarm* | 623,709 | 0.14 | 0.35 | 565,379 | 0.11 | 0.31 | 58,330 | 0.41 | 0.49 |
| Four-wheel drive* | 623,709 | 0.03 | 0.18 | 565,379 | 0.04 | 0.19 | 58,330 | 0.00 | 0.02 |
| Aluminum rims* | 623,709 | 0.75 | 0.43 | 565,379 | 0.74 | 0.44 | 58,330 | 0.85 | 0.35 |
| Hitch* | 623,709 | 0.08 | 0.28 | 565,379 | 0.09 | 0.28 | 58,330 | 0.07 | 0.26 |
| Passenger airbag* | 623,709 | 0.70 | 0.46 | 565,379 | 0.71 | 0.45 | 58,330 | 0.58 | 0.49 |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Board computer* | 623,709 | 0.74 | 0.44 | 565,379 | 0.74 | 0.44 | 58,330 | 0.76 | 0.43 |
| Roof rack* | 623,709 | 0.04 | 0.19 | 565,379 | 0.04 | 0.20 | 58,330 | 0.00 | - |
| Parking assistant* | 623,709 | 0.71 | 0.45 | 565,379 | 0.71 | 0.45 | 58,330 | 0.72 | 0.45 |
| Electric windows* | 623,709 | 0.27 | 0.44 | 565,379 | 0.27 | 0.44 | 58,330 | 0.22 | 0.41 |
| Electric seats* | 623,709 | 0.02 | 0.12 | 565,379 | 0.01 | 0.10 | 58,330 | 0.06 | 0.25 |
| Electronic stability program (ESP)* | 623,709 | 0.04 | 0.20 | 565,379 | 0.04 | 0.20 | 58,330 | 0.03 | 0.18 |
| Air conditioning* | 623,709 | 0.07 | 0.25 | 565,379 | 0.07 | 0.25 | 58,330 | 0.04 | 0.19 |
| Leather seats* | 623,709 | 0.01 | 0.12 | 565,379 | 0.01 | 0.12 | 58,330 | 0.01 | 0.11 |
| GPS* | 623,709 | 0.01 | 0.12 | 565,379 | 0.02 | 0.12 | 58,330 | 0.00 | 0.06 |
| Fog lamps* | 623,709 | 0.01 | 0.09 | 565,379 | 0.01 | 0.09 | 58,330 | 0.00 | - |
| Sun roof* | 623,709 | 0.00 | 0.05 | 565,379 | 0.00 | 0.06 | 58,330 | 0.00 | 0.03 |
| Side airbag | 623,709 | 0.00 | 0.01 | 565,379 | 0.00 | 0.01 | 58,330 | 0.00 | - |
| Electronic steering wheel | 623,709 | 0.00 | 0.04 | 565,379 | 0.00 | 0.04 | 58,330 | 0.00 | 0.02 |
| Heated seats* | 623,709 | 0.00 | 0.04 | 565,379 | 0.00 | 0.05 | 58,330 | 0.00 | 0.01 |
| Cruise control | 623,709 | 0.00 | 0.02 | 565,379 | 0.00 | 0.02 | 58,330 | 0.00 | - |
| Engine immobilizer | 623,709 | 0.00 | 0.01 | 565,379 | 0.00 | 0.02 | 58,330 | 0.00 | 0.01 |
| Xenon head lamps | 623,709 | 0.00 | 0.02 | 565,379 | 0.00 | 0.02 | 58,330 | 0.00 | - |
| Radio + CD | 623,709 | 0.00 | 0.04 | 565,379 | 0.00 | 0.04 | 58,330 | 0.00 | - |
| Central lock | 623,709 | 0.00 | 0.02 | 565,379 | 0.00 | 0.02 | 58,330 | 0.00 | - |
| Pre-heating | 623,709 | 0.00 | 0.02 | 565,379 | 0.00 | 0.02 | 58,330 | 0.00 | - |
| Traction control | 623,709 | 0.00 | 0.01 | 565,379 | 0.00 | 0.01 | 58,330 | 0.00 | - |
| Suited for handicapped | 623,709 | 0.00 | 0.01 | 565,379 | 0.00 | 0.01 | 58,330 | 0.00 | 0.01 |
| Radio* | 623,709 | 0.00 | 0.05 | 565,379 | 0.00 | 0.05 | 58,330 | 0.00 | - |

* Attributes used for matching similar cars.

[1] Categorical variables. Fuel: 1 = diesel, 2 = petrol, 3 = gas, 4 = other. Gears: 1 = automatic, 2 = shift stick. Form of car body: 1 = 2/3 doors, 2 = 4/5 doors, 3 = cabrio, 4 = coupe, 5 = SUV, 6 = van, 7 = other.

## TABLE A2.

## CLUSTERS OF PRICING STRATEGIES

| | | Initial price | Duration | Rel. price change | Percentile change | Dur. 1 | Dur. 2 | Dur. 3 | Rel. p change 1 | Rel. p change 2 | Rel. p change 3 | Perc. change 1 | Perc. change 2 | Perc. change 3 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Constant duration** | Mean | 0.47 | 22 | -3.0% | -0.08 | 24 | 24 | 23 | -3.2% | -3.0% | -3.0% | -0.088 | -0.079 | -0.061 |
| | Median | 0.49 | 24 | -2.9% | -0.07 | 24 | 23 | 22 | -3.0% | -2.9% | -2.7% | -0.058 | -0.039 | -0.038 |
| | SD | 0.22 | 7 | 1.9% | 0.13 | 10 | 11 | 13 | 2.3% | 2.3% | 2.3% | 0.143 | 0.137 | 0.141 |
| | N | 320 | 320 | 320 | 315 | 320 | 255 | 203 | 320 | 255 | 203 | 315 | 254 | 203 |
| | F-test | 0.70 | 0.12 | 0.75 | 0.95 | 0.19 | 0.37 | 0.53 | 0.86 | 0.81 | 0.85 | 1.01 | 0.81 | 0.60 |
| **Shortening duration** | Mean | 0.51 | 44 | -3.8% | -0.10 | 47 | 40 | 37 | -4.1% | -3.8% | -3.4% | -0.104 | -0.107 | -0.075 |
| | Median | 0.52 | 42 | -0.04 | -0.08 | 46 | 37 | 36 | -3.9% | -3.5% | -3.1% | -0.075 | -0.043 | -0.040 |
| | SD | 0.20 | 9 | 2.0% | 0.11 | 14 | 17 | 18 | 0.02 | 0.03 | 0.03 | 0.123 | 0.176 | 0.253 |
| | N | 171 | 171 | 171 | 170 | 171 | 143 | 93 | 171 | 143 | 93 | 170 | 141 | 91 |
| | F-test | 0.61 | 0.19 | 0.77 | 0.77 | 0.43 | 0.85 | 0.92 | 0.76 | 1.02 | 1.32 | 0.74 | 1.34 | 1.93 |
| **Other** | Mean | 0.39 | 104 | -6.0% | -0.14 | 104 | 90 | 108 | -6.3% | -3.1% | -4.7% | -0.145 | -0.088 | -0.032 |
| | Median | 0.40 | 93 | -0.05 | -0.03 | 95 | 95 | 108 | -5.6% | -4.5% | -4.7% | 0.00 | 0.00 | -0.03 |
| | SD | 0.27 | 29 | 4.9% | 0.25 | 33 | 46 | 97 | 0.05 | 0.07 | 0.01 | 0.249 | 0.137 | 0.045 |
| | N | 20 | 20 | 20 | 20 | 20 | 7 | 2 | 20 | 7 | 2 | 20 | 7 | 2 |
| | F-test | 1.03 | 2.11 | 4.95 | 3.66 | 2.31 | 6.30 | 27.29 | 3.43 | 7.19 | 0.10 | 3.04 | 0.81 | 0.06 |
| **Fixed price** | Mean | 0.38 | | | | | | | | | | | | |
| | Median | 0.26 | | | | | | | | | | | | |
| | SD | 0.39 | | | | | | | | | | | | |
| | N | 117 | | | | | | | | | | | | |
| | F-test | 2.25 | | | | | | | | | | | | |
| **Total** | Mean | 0.46 | 33 | -3.4% | -0.09 | 34 | 31 | 28 | -3.6% | -3.3% | -3.1% | -0.096 | -0.089 | -0.065 |
| | Median | 0.49 | 28 | -0.03 | -0.07 | 30 | 28 | 25 | -3.3% | -3.1% | -2.8% | -0.06 | -0.04 | -0.04 |
| | SD | 0.26 | 20 | 2.2% | 0.13 | 22 | 18 | 19 | 0.03 | 0.03 | 0.02 | 0.143 | 0.152 | 0.182 |
| | N | 628 | 511 | 511 | 505 | 511 | 405 | 298 | 511 | 405 | 298 | 505 | 402 | 296 |

*Notes*: An F-value below 1 indicates a lower variance and hence larger degree of homogeneity for that cluster than in the complete data set. The relative price change is equal to $\gamma$. The price percentile change is used for illustrative purposes in Figure III.D because it maps onto the same scale as the initial price. The percentile change equals to what extent the price changes relative to maximum and minimum prices in the group of matching cars.

## TABLE A3.

## COMPLETE REGRESSION - PRICE DISPERSION AND HEDONIC REGRESSION

| | (1) Price dispersion CV | (2) Price dispersion CV | (3) Price dispersion CV | (4) Price (log) | (5) Price (log) | (6) Price (log) |
|---|---|---|---|---|---|---|
| Number of offers | 0.001 | | | 0.004 | | |
| | (22.0) | | | (35.5) | | |
| Number of offers (log) | | 0.007 | 0.007 | | 0.024 | 0.024 |
| | | (31.1) | (30.6) | | (40.2) | (39.7) |
| Kilometers (log) | 0.000 | 0.001 | 0.001 | -0.189 | -0.188 | -0.191 |
| | (3.2) | (5.0) | (4.1) | (-490.8) | (-489.2) | (-478.2) |
| Extra warranty available | -0.022 | -0.022 | -0.022 | 0.102 | 0.102 | 0.104 |
| | (-51.6) | (-52.1) | (-52.0) | (97.2) | (97.2) | (98.7) |
| Number of photos | -0.000 | -0.000 | -0.000 | 0.001 | 0.001 | 0.001 |
| | (-3.7) | (-3.7) | (-4.0) | (9.0) | (9.0) | (9.3) |
| Extra advertisement | -0.004 | -0.004 | -0.004 | -0.001 | -0.001 | -0.003 |
| | (-3.5) | (-3.3) | (-3.9) | (-0.3) | (-0.2) | (-0.9) |
| Dealers in region | | | 0.001 | | | -0.004 |
| | | | (1.4) | | | (-2.4) |
| Population density (per 100 | | | 0.001 | | | -0.011 |
| inhabitants per sq.km) | | | (2.4) | | | (-5.8) |
| GDP per capita (per thousand €) | | | -0.000 | | | 0.000 |
| | | | (-1.2) | | | (0.1) |
| Dealers x population density | | | -0.000 | | | 0.001 |
| | | | (-2.0) | | | (3.9) |
| Official BMW partner | | | -0.006 | | | 0.054 |
| | | | (-1.9) | | | (5.4) |
| Observed BMW 320s and 730s per | | | -0.000 | | | 0.000 |
| dealer (per 10 cars) | | | (-2.4) | | | (6.0) |
| Share of BMW 320 | | | 0.028 | | | -0.277 |
| | | | (1.9) | | | (-5.8) |
| Part of larger dealer network | | | -0.005 | | | 0.010 |
| | | | (-1.3) | | | (0.8) |
| Horsepower | -0.000 | -0.000 | -0.000 | 0.010 | 0.010 | 0.010 |
| | (-3.3) | (-4.5) | (-3.6) | (535.9) | (535.6) | (529.9) |
| Fuel type | -0.024 | -0.024 | -0.024 | -0.048 | -0.048 | -0.047 |
| | (-75.9) | (-75.9) | (-74.7) | (-60.8) | (-60.7) | (-59.6) |
| Gears type | -0.001 | -0.001 | -0.001 | -0.040 | -0.040 | -0.039 |
| | (-4.5) | (-5.3) | (-5.2) | (-55.9) | (-56.3) | (-54.9) |
| Car body | -0.002 | -0.002 | -0.002 | 0.006 | 0.006 | 0.006 |
| | (-22.7) | (-23.2) | (-23.5) | (30.3) | (29.7) | (30.1) |
| ABS | 0.037 | 0.036 | 0.036 | -0.016 | -0.017 | -0.016 |
| | (17.8) | (17.6) | (17.4) | (-3.1) | (-3.3) | (-3.0) |
| Airbag | 0.001 | 0.001 | 0.002 | -0.050 | -0.051 | -0.055 |
| | (0.7) | (0.4) | (0.9) | (-11.3) | (-11.6) | (-12.3) |
| Alarm | -0.009 | -0.008 | -0.009 | 0.068 | 0.069 | 0.071 |
| | (-12.6) | (-11.9) | (-12.5) | (39.5) | (40.2) | (40.7) |
| Four wheel drive | -0.013 | -0.013 | -0.012 | 0.123 | 0.123 | 0.121 |

| | | | | | | |
|---|---|---|---|---|---|---|
| | (-13.2) | (-13.0) | (-12.3) | (49.5) | (49.4) | (48.1) |
| Aluminum rims | 0.014 | 0.014 | 0.014 | 0.015 | 0.014 | 0.015 |
| | (39.5) | (38.7) | (38.8) | (16.9) | (16.1) | (16.6) |
| Hitch | -0.010 | -0.009 | -0.009 | -0.003 | -0.002 | 0.001 |
| | (-10.8) | (-9.7) | (-9.5) | (-1.5) | (-0.7) | (0.3) |
| Passenger airbag | -0.004 | -0.004 | -0.004 | -0.060 | -0.061 | -0.058 |
| | (-3.1) | (-3.2) | (-2.9) | (-17.4) | (-17.5) | (-16.8) |
| Board computer | -0.003 | -0.004 | -0.004 | -0.007 | -0.008 | -0.005 |
| | (-5.3) | (-6.4) | (-6.2) | (-4.5) | (-5.4) | (-3.2) |
| Roof Rack | 0.002 | 0.003 | 0.005 | 0.019 | 0.020 | 0.018 |
| | (2.2) | (2.7) | (4.9) | (7.5) | (7.8) | (6.9) |
| Parking Assistant | -0.001 | -0.002 | -0.002 | 0.030 | 0.027 | 0.027 |
| | (-1.9) | (-2.8) | (-2.9) | (16.2) | (15.1) | (14.8) |
| Electric windows | -0.014 | -0.013 | -0.013 | -0.046 | -0.045 | -0.044 |
| | (-18.0) | (-17.5) | (-17.5) | (-24.4) | (-23.9) | (-22.8) |
| Electric seats | -0.028 | -0.027 | -0.028 | 0.047 | 0.050 | 0.057 |
| | (-16.2) | (-15.4) | (-16.2) | (10.8) | (11.4) | (12.9) |
| ESP | 0.004 | 0.004 | 0.006 | -0.016 | -0.016 | -0.019 |
| | (2.3) | (2.4) | (3.2) | (-3.7) | (-3.6) | (-4.2) |
| Air condition | -0.008 | -0.008 | -0.008 | -0.014 | -0.014 | -0.010 |
| | (-4.2) | (-4.1) | (-4.0) | (-2.9) | (-2.9) | (-2.0) |
| Leather interior | -0.019 | -0.019 | -0.019 | -0.028 | -0.029 | -0.030 |
| | (-8.2) | (-8.3) | (-8.5) | (-5.0) | (-5.1) | (-5.2) |
| GPS | -0.006 | -0.006 | -0.002 | -0.110 | -0.112 | -0.123 |
| | (-2.3) | (-2.6) | (-0.8) | (-17.5) | (-17.7) | (-18.3) |
| Fog lamps | -0.020 | -0.020 | -0.019 | -0.321 | -0.320 | -0.324 |
| | (-4.3) | (-4.2) | (-4.0) | (-27.0) | (-27.0) | (-27.3) |
| Sun roof | -0.029 | -0.029 | -0.030 | 0.126 | 0.125 | 0.134 |
| | (-5.1) | (-5.2) | (-5.4) | (9.0) | (8.9) | (9.5) |
| Heated Seats | 0.021 | 0.020 | 0.018 | -0.163 | -0.165 | -0.158 |
| | (2.7) | (2.6) | (2.3) | (-8.3) | (-8.4) | (-8.0) |
| Radio | -0.031 | -0.031 | -0.032 | -0.002 | -0.000 | 0.003 |
| | (-1.6) | (-1.6) | (-1.7) | (-0.0) | (-0.0) | (0.1) |
| Constant | 0.103 | 0.099 | 0.085 | 10.541 | 10.531 | 10.776 |
| | (26.9) | (25.9) | (5.1) | (1,103.0) | (1,101.5) | (201.7) |
| | *Coefficients on time effects are suppressed.* | | | | | |
| Observations | 266,105 | 266,105 | 259,747 | 266,105 | 266,105 | 259,747 |
| R-squared | 0.059 | 0.061 | 0.075 | 0.790 | 0.791 | 0.804 |
| Number of dealers | 678 | 678 | 638 | 678 | 678 | 638 |
| Time FE | Yes | Yes | | Yes | Yes | |
| RE | | | Yes | | | Yes |

Coefficients and t-statistics in parentheses are reported.