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How heuristic pricing shapes the aggregate market: the "Cheap Twin Paradox"

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How do firms set prices when faced with an uncertain market? We study the pricing strategies of car dealers for used cars using online data and interviews. We find that 97% of 628 dealers employ an aspiration-level heuristic similar to a Dutch auction. Dealers adapt the parameters of the heuristic—initial price, duration, and change in price—to their local market conditions, such as number of competitors, population density, and GDP per capita. At the same time, the aggregate market is 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 classification: D22, D80, L81

1. 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% 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) 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 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 *et al.*, 2004; Einav *et al.*, 2018). Given such an uncertain environment, the major challenge for firms is to determine the best pricing strategy to use.

In his Nobel lecture, Vernon Smith (2002) pointed out that economists have a good understanding of the aggregate market; however, there is a dearth of research on how an individual

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agent successfully navigates the uncertain environment that markets frequently constitute. Specifically, markets can quickly converge to equilibrium even though agents operate under information conditions that are much weaker than specified in the theory as first shown by Vernon Smith (1962) (for a review see Vernon Smith, 2008). Addressing this gap, Vernon 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 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 are commonly used by experts such as managers (for a review see Artinger *et al*., 2015) and 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; Wübben and von Wangenheim, 2008; DeMiguel *et al*., 2009; Şimşek and Buckmann, 2015; Artinger *et al*., 2020, 2023; Katsikopoulos *et al*., 2022). The precise nature of the heuristics 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*., 2018).

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

[1] The principl distinction between two rational orders can already be found in the writings of Adam Smith (1776, 1759), Hume (1739), and, later, Hayek (e.g., Hayek, 1937, 1945), as well as in Savage (1954) 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.

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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 USA (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 2 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 3 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 4 and 5, respectively. Finally, the discussion in Section 6 centers on the role of adaptive heuristics in generating aggregate market phenomena.

2. Heuristic pricing

2.1 Aspiration adaptation

Aspiration levels are at the heart of a range of decision strategies and their use has been widely documented in empirical research (for a review see Artinger *et al*., 2022). 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) as well as modeling choice behavior (e.g., Manzini and Mariotti, 2007, 2012, 2014). 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:

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

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 β. 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

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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 β 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 on offer longer than time β but not the other, twins are priced differently. In general, price dispersion in the market among matching cars exists if dealers use a different α to set the initial price, a different β to set the duration of a given price, or a different γ that sets the amount by which a price changes.

2.2 Ecological rationality: when and why heuristics work

Heuristics, such as the aspiration-level strategy, are simple strategies that have often been assumed to generally 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 *et al*., 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 this balance, and has been widely applied in machine learning (Geman *et al*., 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 ε 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 1. 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.

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

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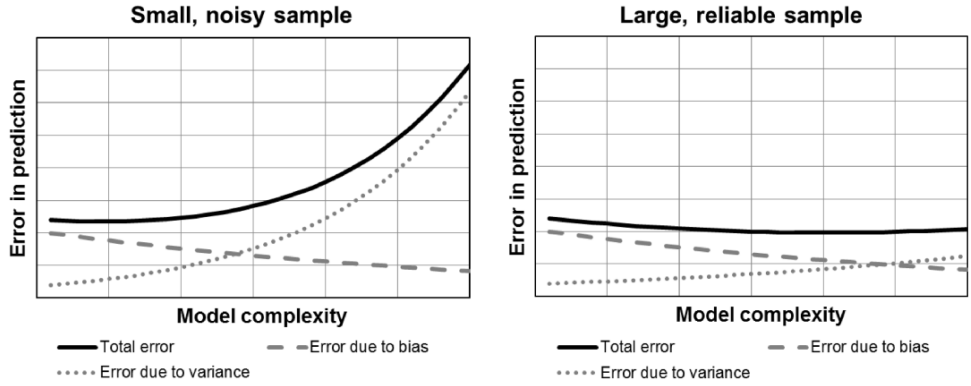


Figure 1. Illustration of the bias–variance dilemma. *Notes*: Total error in prediction results from bias and variance. Bias decreases with increasing complexity of the strategy, such as by adding more free parameters to a strategy, while variance increases. If estimates are necessarily based on small, 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.

samples (Figure 1, 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 β, the time that the price is kept constant, and how it changes with the environment. The choice of β is directly influenced by 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 β chosen.

2.3 Price stickiness

A prominent feature of the aspiration-level heuristic is that prices are adjusted in fixed time intervals β, 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 (Blinder *et al.*, 1998; Apel *et al.*, 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.

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To evaluate the relevance of the most prominent theories for the used car market, we selected 8 out of the 12 that Blinder *et al.* (1998) investigate (four theories were not used because they bear little relevance for the used car market; see the Supplementary 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 best price 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:

9. Aspiration-level strategy: Prices are set by using an aspiration level with the goal to search for the best price (equation (1)). 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.

3. Constructivist rationality

In 1962, Vernon 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; Vernon Smith, 1982; Plott and Sunder, 1988; Huck *et al.*, 2004; Vernon Smith, 2008; Isoni *et al.*, 2016). 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, 1991).

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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 *et al*., 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 *et al*. (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

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

where

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

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The probability to list the product in the clearing house is

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

Firms earn an expected profit of

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

Depending on the parameters, Baye *et al.* (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 *et al.*, 2004; Pan *et al.*, 2004; Venkatesan *et al.*, 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 *et al.*, 2005).

The online data in the present study allow 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.

4. Methods

4.1 Online data

We collected data from the online used car platform Autoscout.de, which listed about 78% 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 from December 2010. We searched Autoscout.de bi-weekly for all BMW 320s and 730s on offer from professional sellers. The downloaded result 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 Supplementary 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 27 attributes to specify groups of matching cars. This includes the odometer values that are rounded to the next 10,000 km, in line with the evidence reported by Busse *et al.* (2013)

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that consumers tend to focus on the left-most digits 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 Supplementary Appendix Table A1; attributes with an asterisk were used). Such a procedure of relying on matching items was introduced by Elfenbein *et al.* (2012) to study charity auctions and employed by Einav *et al.* (2015, 2018) 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 seven of the eight primary car attributes. This check provided the same qualitative evidence as reported in the following.

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 1). 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 1). 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 1 of 82 regions in Germany. A region has a mean radius of 38 km and constitutes the local market we analyze. Table 1 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% 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.

4.2 Interviews

The interview contained three parts (see Supplementary 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 nine theories of price stickiness and how these relate to the practice of the dealers. The order of the nine 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 min, were recorded on audiotape, and were later transcribed. These transcriptions were given to two independent raters to categorize answers. They coded 96% of the transcriptions in the same way; where differences existed, the raters discussed these and agreed on a common rating.

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Table 1. Summary statistics per posting and car, and summary statistics per dealer

	Observations	Mean	Median	SD	Min.	Max.
Posting statistics: 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
Car statistics: 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
Car statistics: 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
Dealer statistics: local market						
Dealers	745	9.9	10	4.0	1	19
Population density (people per square km)	714	623	398	600	66	4340
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
Dealer statistics: 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

5. 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.

5.1 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. 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

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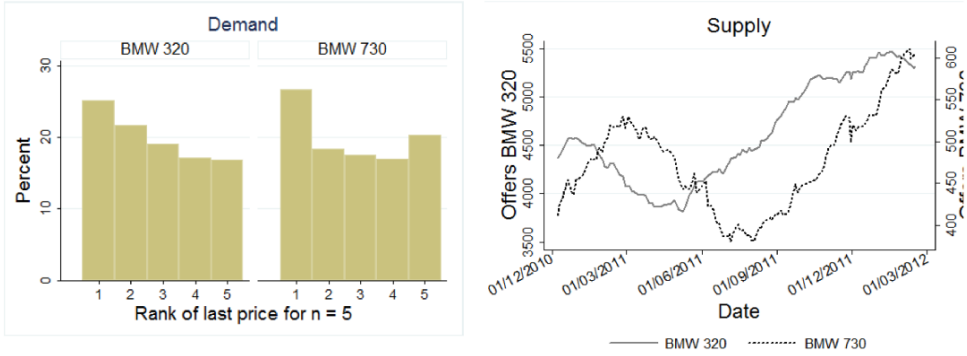


Figure 2. Demand for matching cars and supply.

group of matching cars, both are assigned a rank of 1. The left panel of Figure 2 illustrates the principle finding for a group size of five 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 2 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% 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.

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.

5.1.1 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 α, duration until price changes β, and magnitude of a price change γ.

We first consider the parameter for the initial price α 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 $\{p_{g,min}, \ldots, p_{g,max}\}$ 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 3A shows, only about 12% of dealers start with a price close to or on 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%, start with a price that is above the median of the price range. The mean dealer posts an initial price that is 0.46 (SD = 0.26) 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 0.50 (SD = 0.44) and of a BMW 730 is 0.49 (SD = 0.43) 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 β 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 $m = 1, \ldots, l$. The duration until the

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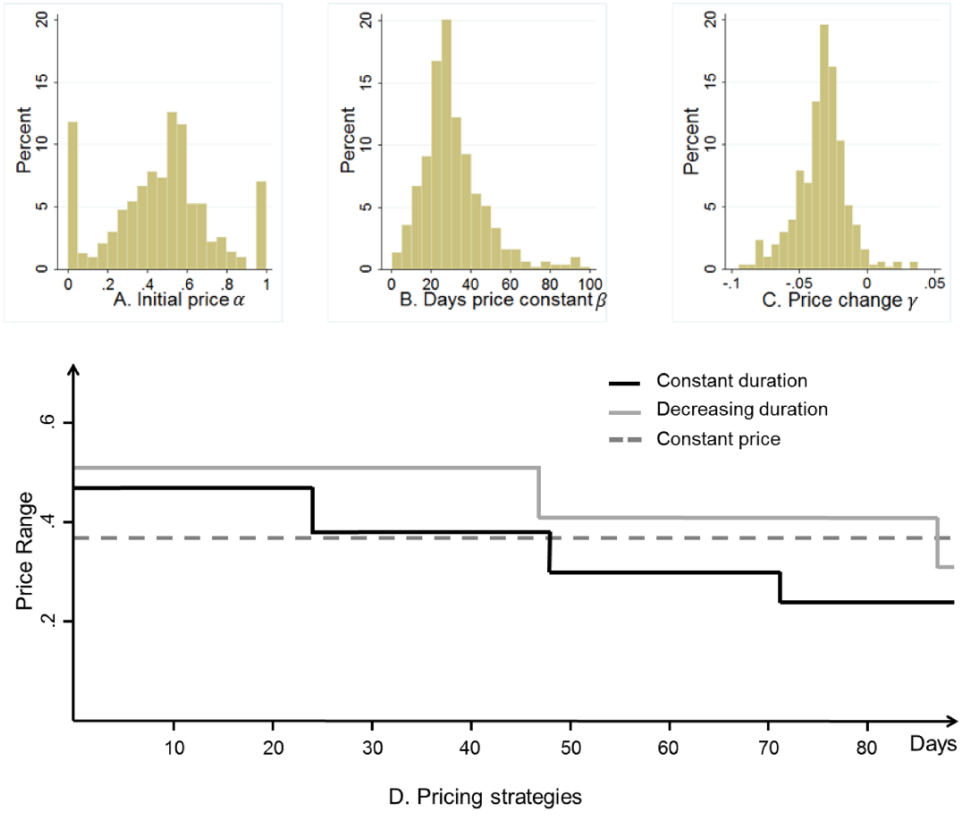


Figure 3. Pricing parameters and strategies. *Notes*: Mean value per dealer: (A) Initial price in price range. (B) Days until a price changes, excluding the last period when a car stops being on offer. (C) Relative price change. (D) Three main pricing strategies observed. Figure (D) shows the price percentile 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. Supplementary Table A2 in the Appendix shows the values of price percentile change and the relative price change γ.

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 3B 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% 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 γ. We compare the current price of a car $p_{i,m}$ to its previous price $p_{i,m-1}$.

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

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Figure 3C 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% (SD = 0.022) in the mean. At the car level, prices for the BMW 320 are reduced in the mean by 3.3% (SD = 0.031) and for the BMW 730 by 3.5% (SD = 0.035), 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% of the times that prices change, they are reduced.

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.

5.1.2 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 3D (see Supplementary Appendix Table A2 for a detailed presentation of the values). The most prominent strategy, "constant duration," used by 320 out of 628 dealers (51%), is to keep the price constant for a fixed interval and then lower it until the car is sold. This strategy accounts for 64% of all cars. These dealers start in the mean with an initial price of 0.47 (SD = 0.22) 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 rate.

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%) offering 31% of the cars. The mean initial price is 0.51 (SD = 0.20) 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 six 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%) employing the strategy "constant price," where the initial price does not change. They account for 3% of all cars. These dealers use a comparatively low initial price with 0.38 (SD = 0.39) in the mean and 0.26 in the median of the price range. Finally, a very small group of 20 dealers (3%) offering 2% 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.

5.1.3 Adaptation of aspiration-level heuristics to the environment

Heuristics function well if they are adapted to the environment. Table 2 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 ordinary least squares (OLS) regressions reported in Table 2 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).

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Table 2. OLS regression on three pricing parameters of dealers

	(1) Initial price α	(2) Initial price α	(3) Duration (log days) β	(4) Duration (log days) β	(5) Price change γ	(6) Price change γ
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 square 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 × 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^2	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 β decreases by 3%, 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 kilometer, the duration a price is held constant decreases by about 3%, with the population density varying between 66 and 4340 people per square kilometer. At the same time, the higher the GDP per

Table 3. Pricing strategies and information use in interviews

		Initial price (α)			
		Higher than competition	**Same as competition**	**Lower than competition**	**Total**
Duration and price change (β, γ)	Fixed intervals and predetermined amounts	0.24	0.02	0.00	**0.26**
	Fixed intervals and information update	0.44	0.11	0.07	**0.62**
	Variable intervals and predetermined amounts	0.02	0.02	0.00	**0.04**
	Variable intervals and 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**	

capita in a region the longer the price is kept constant. For every 1000 euros in GDP per capita, the duration increases by 1%, with the GDP per capita varying across regions between 20,230 euros and 79,500 euros. The duration increases by 20% if the dealership is an official partner of BMW.

The finding on the duration the price is held constant β 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 α 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 γ 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.

5.2 Interviews

5.2.1 Pricing strategies

In the interviews, the dealers indicated which type of pricing strategy they use by selecting among a number of predefined options. Table 3 shows that only 11% reported that they price lower than the competition. This corresponds almost exactly with the online data, where we observe that only 12% 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 3 also shows that in sum, 88% of dealers reported that they use a fixed time interval after which they would consider changing the price, 6% of dealerships do not change the price at all, and only 6% 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 γ of change in price, 70% of dealers stated that they consult online platforms or market surveys. In contrast, the other 30% had already determined γ at the time of setting their initial price; they do not consult any further

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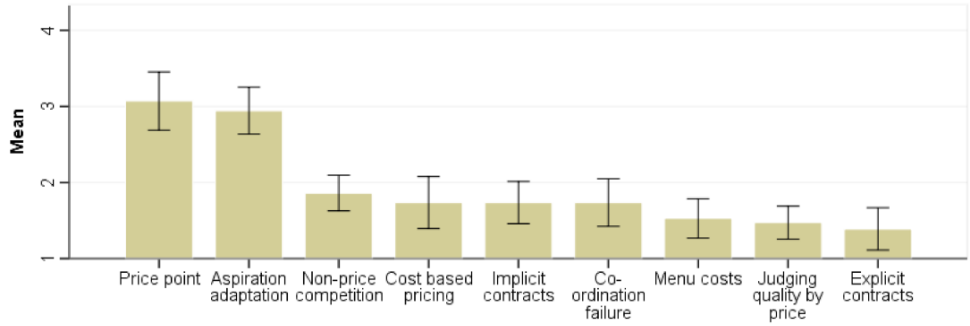


Figure 4. Mean ratings of relevance of pricing theories for car dealers. *Note*: Error bars show ±2 SE.

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% 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.

5.2.2 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 2.3). The theories were rated according to the following scale:

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

As can be seen in Figure 4, 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 = 0.9). 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.

5.3 Prices at the aggregate level

5.3.1 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 (CV), the standard measure for price dispersion. It is homogenous of degree zero, enabling comparison across different products, time, and different sample sizes. The CV is computed as

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

where σ_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

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Table 4. 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 square km)			0.001			−0.011
			(2.4)			(−5.8)
GDP per capita (per thousand €)			−0.000			0.000
			(−1.2)			(0.1)
Dealers × 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)
The table is truncated; complete table including 27 car attributes can be found in Supplementary Appendix, Table A3.						
Observations	266,105	266,105	259,747	266,105	266, 105	259,747
R^2	0.059	0.061	0.075	0.790	0.791	0.804
Number of dealers	678	678	638	678	678	638
Time Fixed Effects	Yes	Yes		Yes	Yes	
Random Effects			Yes			Yes

Coefficients and *t*-statistics (in parentheses). All *p*-values for the number (and log number) of offers <0.001.

the degree of price dispersion. With group size of matching cars larger than one the CV is in the mean 0.09 (SD = 0.07).

The OLS regressions in Table 4 assess how the dependent variables price dispersion, as measured with the CV, and price 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.

Regressions 1 to 3 show that price dispersion increases with the number of offers. Increasing the number of matching cars by 1% raises the CV by 0.007; 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%, price increases by 0.024%. To illustrate, for a BMW 320 with an average price of

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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 are available, the more readily a consumer can at least partially contract on quality.

5.3.2 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.

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 2). 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%.[3] The result is similar to the finding of Brynjolfsson and Smith (2000), who report an estimate of 13%, 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% (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 0.1%. In the median it takes 21 days until a car sells, yielding total marginal costs of $c = 79.8\%$. The costs of advertising ϕ are 0.02% 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 4, 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 the market size. The reasoning Rosenthal provides is that these are loyal consumers whom each firm brings to the market. Our results, in 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 the 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 τ of listing a car is close to 100%.

5.3.3 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

[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, $x = S + \left(\frac{1-S}{n}\right)$. The proportion of shoppers S is then $S = \frac{xn-1}{n-1}$.

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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 $E\pi(p) = (r - c)\frac{1-S}{n}$. 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 three clusters—constant duration, decreasing duration, and constant price—we use those cars of dealers who can be uniquely identified. The estimated profit π_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 5 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% (SD =0.11) and the mixed strategy only 7% (SD = 0.3).

These results might seem puzzling, particularly given that the model by Varian (1980) fits the aggregate market well. It is known since Vernon 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

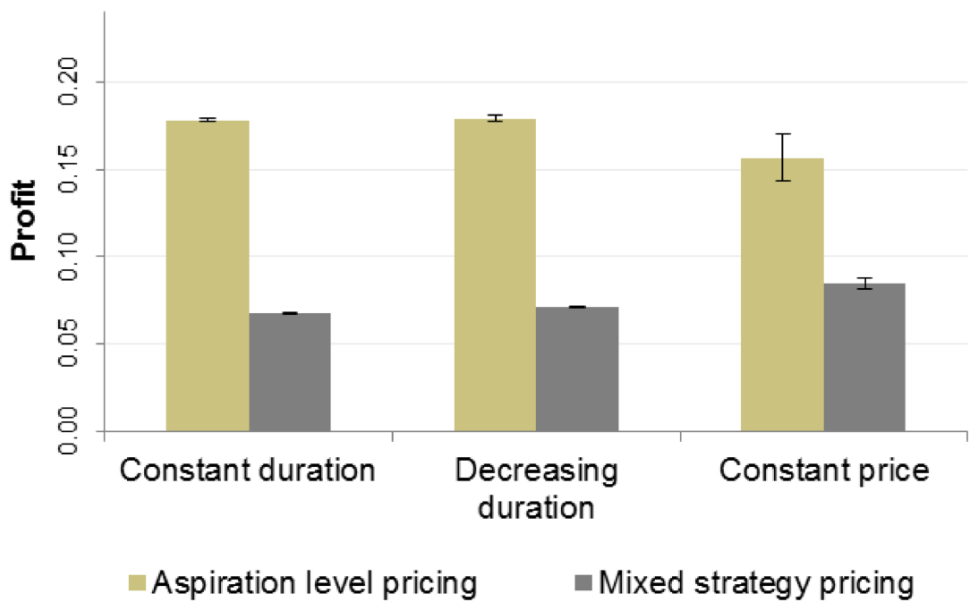


Figure 5. Mean estimated profit across cars for aspiration level and mixed strategy pricing. *Note*: Error bars show ±2 SE.

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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 2, 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 5. 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.

6. 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.*, 2018). 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 *et al.*, 2008; Şimşek, 2013; for a review see Gigerenzer (2016)), future research needs to further identify the conditions under which the aspiration-level heuristic performs well and also compare it to

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strategies such as dynamic pricing models that are computationally intensive and geared toward 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 Vernon 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 scientifc 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.

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Supplementary Data

Supplementary materials are available at *Industrial and Corporate Change* online.

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