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ADAPTIVE HEURISTIC PRICING

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INTRODUCTION: TWO LEVELS OF ANALYSES

Prices coordinate the actions of firms and allow for the efficient functioning of markets. Prices can be analyzed at two levels: the 'individual level' takes the perspective of the firm, investigating what strategies they use to set prices; the 'aggregate level' analyzes the incentive structure present in a market, that is, the operation of the invisible hand. It allows insights into aggregate patterns such as of how price dispersion changes in relation to the degree of competition. From an individual level perspective, an important 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' hardly ever holds and that "price dispersion is a manifestation—and, indeed, it is the measure—of ignorance in the market" (Stigler, 1961: 261). 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 (e.g., Brynjolfsson & Smith, 2000).

The 'ignorance' manifest in price dispersion is an indication for the level of uncertainty prevalent in a market. Simon (1972) proposes that under uncertainty, two strategies can be applied: sophisticated optimization techniques or simple satisficing strategies. Optimization strategies require a relatively stable, information-rich environment for robust calibration and, given complex environments, need to abstract or simplify. Aggregate level models of market equilibrium are commonly abstractions where optimization techniques are applied. Satisficing strategies, also referred to as heuristics, are simple decision strategies operating at the individual level that do not abstract but instead deal with the full complexity of the environment. Given relatively noisy, little, or unreliable information, a heuristic that is well-adapted to its environment can outperform sophisticated optimization strategies (e.g., Gigerenzer, Todd, & the ABC Research Group, 1999).

As a specific implementation of satisficing, Simon (1955) formally develops the aspiration level heuristic: 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. The aspiration level is adapted if, after a certain amount of search, no adequate object has been encountered. Aspiration adaptation closely resembles a Dutch auction where the price starts high and is sequentially lowered until the first customer has a willingness to pay that meets or exceeds the asking price. Simon (1955) suggests price setting in the real estate market as one relevant domain because the market is characterized by highly differentiated products with relatively few offers of the same good. A posted price serves as an aspiration level for evaluating whether there are customers with a sufficiently high willingness to pay.

Standard analyses at the aggregate level rely on equilibrium models that characterize market outcomes based on a rational choice agent (Muth, 1961). However, optimization

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techniques are not a necessary prerequisite for equilibrium to emerge but rather useful abstractions for the analyst that take an aggregate level perspective. Gode and Sunder (1993) show that equilibrium predictions emerge even with artificial zero intelligence traders that submit random bids and offers, subject only to a budget constraint. Classic experiments, often used in the classroom to illustrate basic economic concepts, demonstrate that equilibrium quickly emerges even in a market populated with novices (e.g., Smith, 1982).

METHODS

This paper is the first to use field data to examine the interaction between a heuristic strategy and the aggregate market. The data set comes from the online used car market in Germany, where we tracked the market for two types of car and the pricing of dealers that offer them for 15 months. Online platforms are of central importance to the used car market because they usually provide the primary point of information: 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). Central to the competition for consumers' attention are the advertised prices. Insights into the specific pricing process that dealers employ can be obtained from the 'twins'. On a given day, using only those cars that are identical on all of the advertised attributes except the price makes it possible to form groups of matching cars, which dealers commonly refer to as twins even if they are not offered by the same dealership.

We searched Autoscout.de bi-weekly for all BMW 320s and 730s on offer from professional sellers. We focus on two models of cars, BMW 320 and 730. In 2010, BMW 320 was the most frequently sold BMW (BMW Group, 2011). The BMW 730 addresses the premium market segment. Out of a total 623,709 posts, we find at least one other matching car for 328,832 cases. Because some dealerships share ZIP code and city, 745 out of 871 dealers we observe during the period of investigation can be uniquely identified. In order to pin down the pricing strategy of a dealer we use those cars whose entire price development can be traced from the first to the last day the car is posted. These restrictions yield 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 shed light onto the local market in which dealers operate.

RESULTS

Types of pricing strategies

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. In order to identify homogenous clusters of the specific combinations of the three parameters, we use a cluster analysis. This clusters 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.

Figure 1 about here

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The analysis points to three types of strategies that dealers employ, which are displayed in Figure 1. All three strategies are simple and correspond to the description of the aspiration level heuristic of Simon (1955). The most prominent strategy, 'constant duration', used by 320 out of 628 dealers (51.0 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. The second biggest cluster is the 'shortening duration' strategy, where dealers sequentially lower the price but shorten the duration for which consecutive prices are held constant. This cluster contains 171 of 628 dealers (27.2 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. This reveals a consistent pattern of keeping the initial price constant for a longer period than subsequent prices. The percentile price changes and the relative price change γ reveal a pattern of a slightly diminishing rate. A further 117 dealers (18.6 percent) form a separate cluster 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. There are 20 dealers offering 2 percent of all cars who cannot be assigned to any of the other clusters due to their idiosyncratic combination of the pricing parameters.

Pricing in context

Heuristics can function well if they are adapted to an uncertain environment. The OLS regressions reported in Table 1 examine how the three pricing parameters depend on market level variables. The pricing parameter that adapts most to environmental characteristics is the duration a price is held constant β. For every additional competitor in the region, the duration the price is held constant decreases by about 3 percent, with the number of dealers varying per region between 1 and 19. A similar impact has the population density: as the population density increases by 100 inhabitants per sq. 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 sq. km. In contrast, 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.

Table 1 about here

The results suggest that dealers use the aspiration level heuristic to sample the environment and discover the maximum willingness to pay for a given car. The duration a price is kept constant is an instrument that enables dealers to adjust the sample size and adapt to the specific environment they operate in, thereby reflecting the adaptiveness of the pricing strategies. In areas with a higher number of dealerships but also of people per dealership, a dealer can more quickly infer that a car is unlikely to sell for a given price and therefore can reduce it more quickly, whereas in areas with less competition and in less densely populated areas the price

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needs to be held constant for a longer time before such an inference can be made with sufficient confidence.

Prices at the aggregate level

The evidence on the individual level indicates that dealers use different aspiration level pricing strategies. But how does the aggregate market look, specifically, how do price dispersion and average price change in relation to the degree of competition? Investigating the impact of competition on price dispersion and average market price in the context of a clearing house, Baye, Morgan, and Scholten (2004) develop a general clearing house model which rests on the assumption that there are two types of consumers: a number S of consumers are informed shoppers who buy at the lowest price listed in the clearing house, provided their reservation price r is equal to or exceeds the advertised price p, $r \geq p$. There are also price-insensitive, uninformed consumers U per firm who buy from their preferred firm if $r \geq p$ or otherwise randomly select a firm as long as $r \geq p$. The general clearing house model nests three prominent models as special cases: Varian (1980) who assumes simply that there exist uninformed consumers, Rosenthal (1980) who assumes that 'uninformed' consumers are those loyal to a specific firm, and Baye and Morgan (2001) who assume that uninformed consumers are due the costs of advertising a product which results in that only some products are posted in the clearinghouse. Baye, Morgan, and Scholten (2004) show that as the number of competitors grows for relatively small markets with up to 40 competitors, Varian (1980) predicts an increase in average price and price dispersion, Rosenthal (1980) predicts an increase in average price but a decline in price dispersion, and Baye and Morgan (2001) predict a decline in average price and price dispersion. For full model and the proofs see the appendix in Baye, Morgan, and Scholten (2004).

OLS regressions shed light on which of the models best describes the market. Price dispersion increases in offers. Increasing the number of matching cars by 1 percent raises the coefficient of variation (CV), a widely used measure of price dispersion, by .007. The number of matching cars is as large as 21 for BMW 320 and 27 for BMW 730. 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. Hedonic regressions show that the average price also increases in offers. Specifically, as offers increase by about 1 percent, price increases by .024 percent. To illustrate, for a BMW 320 with an average price of 24,645€ each additional offer increases the price by more than 250€. These results suggest that the model by Varian (1980), who predicts an increase in price dispersion and average price as competition increases, best describes the aggregate market.

The equilibrium model of Varian (1980) is based on that firms use a mixed strategy to set prices. As the model describes the market well, the question arises how well dealers would have done if they would have used the mixed strategy instead of the aspiration level heuristic. Figure 2 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. The difference is considerable: in the mean across all cars, aspiration level pricing achieves a profit of 18 percent (SD =.11, M = .19), the mixed strategy 7 percent (SD = .3, M = .07).

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Figure 2 about here

The fact that the heuristic outperforms the rational choice benchmark used in modeling the market might be puzzling at first sight, particularly since the model by Varian (1980) predicts the aggregate market well. We suggest two reasons for this phenomenon: First, Varian's model abstract and does not regard the specific conditions of a local market. Using the aspiration level heuristic, dealers can vary the parameters, specifically the duration a price is held constant, as an effective tool to evaluate conditions in a local market. Second, an underlying assumption of Varian and other models of price dispersion is that prices need to be randomized as a best response to consumer behavior. Rather than employing such a randomization, however, the dealers in the used car market skim the market and thereby achieve on average a higher price. Dealers have developed an adaptive strategy that performs rather well in the specific context in which they operate.

DISCUSSION

How do firms set prices in an uncertain market? In line with Simon's (1955) proposition, online data and interviews show that aspiration level pricing together with targeting certain price points is commonly used in the used car market. Dealers use the duration a price is constant as a central tool to adapt to local market conditions. Even though dealers rely on a fairly simple heuristic in setting prices, the aggregate market patterns are 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 presented in the market well and that individual agents have developed an adaptive response despite their limited information. The success and adaptiveness of the dealers' strategy is reflected in that the estimated profits earned through the aspiration level pricing are higher than those for the mixed strategy that underlies the aggregate model.

REFERENCES AVAILABLE FROM THE AUTHORS

Figure 1. Pricing strategies.

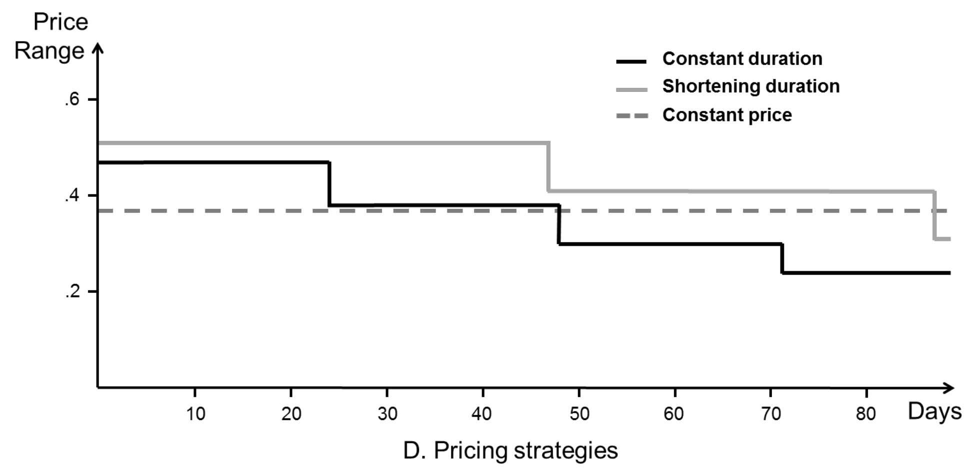

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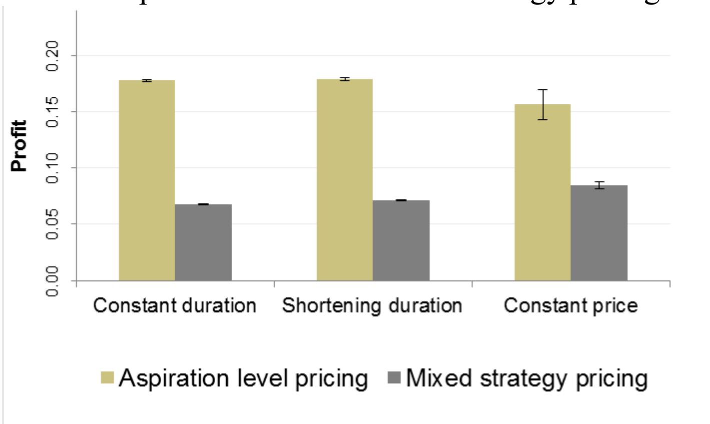
Figure 2. Mean profit for aspiration level and mixed strategy pricing.



Error bars show +-2 SE

Table 1: OLS regressions of the three pricing parameters

	(1) Initial price (α)	(2) Duration (log days) (β)	(3) Price change (γ)
Dealers in region	0.001	**-0.031**	0.000
	(0.004)	(0.010)	(0.000)
	0.875	0.001	0.964
Population density (per 100 inhabitants per sq. km)	-0.001	**-0.030**	-0.000
	(0.005)	(0.011)	(0.000)
	0.795	0.008	0.374
GDP per capita (per thousand €)	-0.000	**0.012**	-0.000
	(0.002)	(0.004)	(0.000)
	0.926	0.009	0.581
Dealers x population density	-0.000	**0.002**	0.000
	(0.000)	(0.001)	(0.000)
	0.942	0.024	0.464
Constant	**0.474**	**3.333**	**-0.031**
	(0.058)	(0.138)	(0.006)
	0.000	0.000	0.000
Observations	606	496	496
R-squared	0.001	0.029	0.006

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