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Different strategies for evaluating consumer products: Attribute- and exemplar-based approaches compared

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ABSTRACT

Consumers' purchase decisions depend on whether a product is perceived as a bargain or as overpriced. But how do consumers evaluate sales prices? The standard approach in economics, psychology, and marketing suggests that consumers' estimates are best described by a attribute-based or piecemeal strategy that integrates information about products in a linear additive fashion. Here, we outline and test an alternative theoretical approach from the categorization literature suggesting that consumers sometimes follow an exemplar-based strategy that relies on similarity to previously encountered products. We hypothesize that people switch between these two estimation strategies depending on the context they face. To test this hypothesis, we conducted an experiment in which 64 participants repeatedly estimated the market price of different consumer products (bottles of wine). In one condition, the product prices could be well approximated with an attribute-based strategy whereas in the other condition an exemplar-based strategy worked best. Results of a subsequent testing phase indicated that participants switched between strategies depending on the structure of the presented sets. These results show that people rely on different strategies to estimate market prices, which should influence people's consumption behavior. The results suggest that theories on categorization learning can provide a deeper insight into behavior in an economic context and allow predicting consumer behavior more accurately.

I suppose it is tempting, if the only tool you have is a hammer, to treat everything as if it were a nail.

[Abraham Maslow, 1966, p. 15]

1. Introduction

Perceptions of product prices have an important influence on purchase decisions (Sitzia & Zizzo, 2012). Accordingly, price promotions are a popular tool to increase sales (e.g. Alba, Mela, Shimp, & Urbany, 1999; Blattberg, Briesch, & Fox, 1995). Price estimates are commonly considered to be a function of the information a consumer has about the product (e.g. Lancaster, 1966; Thrane, 2004). In the present work, our goal is to illustrate that consumers may use qualitatively different strategies to evaluate the acceptability of a product's price and that considering the selection of these strategies can increase the ability to predict consumers' price estimates and ultimately purchase decisions.

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Imagine a wine connoisseur who comes across a bottle of 1997 Chardonnay from the winery "Cantina di Terlano" in Northern Italy that is on sale for 80 USD. To decide whether this bottle is a good deal, she might try to estimate its market value by relying on what she knows about North Italian wines, the vintage, or perhaps even her knowledge about the particular winery itself. Alternatively, she could judge the bottle's worth by comparing it to similar offers she encountered in the past and how good or expensive they were. Importantly, depending on what judgment strategy she employs, she might come to different estimates of the bottle's value and consequently she might buy the bottle or refuse the offer.

Gaining a better understanding of the judgment processes underlying product evaluations and the conditions that influence these processes is an important step to better explain and predict consumer behavior. According to the standard approach in psychology, economics, and marketing, consumers evaluate products by integrating information about their attributes in a linear additive fashion (e.g. Combris, Lecocq, & Visser, 2000; Feenstra, 1995; Green & Wind, 1973; Shocker & Srinivasan, 1979). In contrast to this, it has been suggested that consumers do not always use the same strategy but rather evaluate options differently depending on the structure of the environment they face (Gigerenzer, Todd, & The ABC Research Group, 1999; Brocas & Carrillo, 2014). Here, one prominent alternative approach are so-called exemplar or instance-based models predicting that consumers evaluate products in comparison to similar options they encountered in the past (Cohen & Basu, 1987; Smith & Medin, 1981; Sujan, 1985). In the remainder of the manuscript, we outline these two theoretical accounts of how consumers evaluate prices in more detail and we report an empirical study showing the benefits of considering the strategy consumers use to evaluate products.

1.1. The standard attribute-based approach to modeling consumer judgments

The predominant approach to how people evaluate a continuous criterion such as the price of a product relies on the idea that the available attribute information is multiplied by its importance and then additively integrated to form an overall judgment (e.g. Keeney & Raiffa, 1993; Shocker & Srinivasan, 1979). The idea that the market price of a product can be described by a linear function of the product's attributes has also gained popularity as the price hedonic model in the economic literature (e.g. Feenstra, 1995; Thrane, 2004). These weighted-additive strategies are similar to linear regression approaches and they have been labeled as attribute-based, piecemeal, rule-based, feature-based, or cue abstraction approaches (Juslin, Olsson, & Olsson, 2003; Lynch, 1985; Sujan, 1985; Troutman & Shanteau, 1976; for a review on consumer inference processes see Kardes, Posavac, & Cronley, 2004). For instance, when deciding to buy a bottle of wine, one may evaluate whether the wine's attributes, such as its origin, age, or maturity, justify its price. Indeed, attribute-based models have been shown to accurately predict the observable outcomes of many judgment and decision tasks ranging from personnel evaluation (e.g. Rotundo & Sackett, 2002) to medical decisions (e.g. Agha, Arora, & Sevdalis, 2011) and they naturally lend themselves to estimations of continuous criteria such as the price or the quality of newly encountered products, as in the wine example above (e.g. Sujan, 1985). In general, attribute-based cognitive processes are thought to be of a reflective and deliberate nature and constrained by cognitive resources such as working memory capacity (Ashby & Maddox, 2005; Hoffmann, von Helversen, & Rieskamp, 2014; Juslin, Karlsson, & Olsson, 2008).

1.2. Exemplar-based judgments

Exemplar or instance-based theories assume that people's judgments, choices, and decisions are influenced by similarity to previously encountered instances (Bröder, Newell, & Platzer, 2010; Gilboa & Schmeidler, 2001; Juslin et al., 2008; Nosofsky & Johansen, 2000; von Helversen, Herzog, & Rieskamp, 2014). Specifically, exemplar models suggested in the categorization literature assume that people evaluate options based on their similarity to previously encountered exemplars that are stored in memory (e.g. Nosofsky, 1984). When judging a new object, similar instances are retrieved from memory and used to evaluate the object under consideration. For instance, when evaluating the worth of a bottle of wine one may think back to the price of a similar wine encountered in the past, for instance from the same vineyard, region or year. In contrast to attribute- or rule-based processes, exemplar-based processes are assumed to be implicit and automatic processes that rely on episodic memory and only require relatively little working memory capacity (Ashby & Maddox, 2005; Hoffmann et al., 2014; Juslin et al., 2008).

In a consumer context, similarity-based processes have been mainly considered when trying to predict how people categorize products. For instance, it has been shown that similarity to well-known and successful brands can increase the choice share of the copycat product (van Horen & Pieters, 2012; Warlop & Alba, 2004). Furthermore, similarity influences how people categorize new products and how these categorizations influence brand attitudes (Basu, 1993; Cohen & Basu, 1987; Fiske, 1982; Lajos, Katona, Chattopadhyay, & Sarvary, 2009). Research in cognitive science and psychology suggests that people also frequently use similarity-based strategies to make quantitative judgments (Juslin et al., 2008; von Helversen & Rieskamp, 2009). Paying attention to similarity information has also been shown to increase models' accuracy in predicting market prices (Huang, Shih, Chiu, Hu, & Chiu, 2009). This suggests that similarity- or exemplar-based judgment strategies provide an alternative theoretical approach to understand the cognitive processes underlying consumer judgments such as price estimates.

1.3. Adaptive strategy selection

There is good evidence to suggest that people select strategies adaptively depending on the situation they face (Payne, Bettman, & Johnson, 1993; Rieskamp & Otto, 2006; Samson & Voyer, 2014; Scheibehenne, Rieskamp, & Wagenmakers, 2013; Scheibehenne, & von Helversen, 2015). The notion of adaptive behavior can be traced back to the early theorizing in economics, psychology, and cognitive sciences that considered the capacity to flexibly adjust to the demands of the environment to be a defining feature of rationality (Simon, 1990). In particular, it is often assumed that strategy selection is an adaptive trade-off between the performance and the effort involved in employing the respective strategies (Beach & Mitchell, 1978). In a similar vein, the idea that people adaptively shift between attribute (rule)-based and exemplar-based cognitive processes in response to the characteristics of the tasks they face and the cognitive abilities and resources they have at their disposal is widespread (e.g. Ashby & Maddox, 2005; Bröder et al., 2010; Erickson & Kruschke, 1998; Juslin et al., 2003, 2008). In line with this, it has been shown that people switch to exemplar-based judgment strategies in tasks in which exemplar-based strategies lead to more accurate judgments than attribute-based strategies (Juslin et al., 2008), when exemplars are easy to remember (Rouder & Ratcliff, 2004), or attribute-based strategies are difficult to employ because the attributes are difficult to verbalize (Ashby & Maddox, 2005). In addition, people seem to prefer exemplar-based strategies when the cognitive resources required to employ an attribute-based strategy are limited (Hoffmann, von Helversen, & Rieskamp, 2013) or if people lack the knowledge necessary to employ an attribute-based strategy (Platzer & Bröder, 2013; von Helversen, Karlsson, Mata, & Wilke, 2013). These findings correspond with consumer research suggesting that people change their categorization strategies depending on the task context and also on how the category knowledge was acquired in the first place (Basu, 1993). For example, experts who evaluate new consumer products are more likely to rely on similarity judgments if the new information matches their knowledge base but revert to attribute-based (i.e. piecemeal) strategies if they cannot align the new information with their past experience (Sujan, 1985).

1.4. Hypotheses

Based on this research, we hypothesize that attitude formation about new consumer products, in particular the estimation of sales prices, does not always result from attribute-based processes but can sometimes be better described by an exemplar-based strategy. Following the idea that people select strategies depending on how successful they were applied in the past (Rieskamp & Otto, 2006), we further hypothesize that decision makers adaptively switch between attribute-based and exemplar-based strategies in a predictable way. If a person learnt about a product category in an environment in which an attribute-based strategy was successful, this person will probably also apply this strategy when evaluating a new product from that category. In contrast, if the same person learnt about a product category in an environment where similarity to previous products was a good predictor, this person will rely on an exemplar-based strategy for judgments about newly encountered products. Thus, to the extent that judgment strategies depend on people's prior experiences, using only one single model to explain people's judgment process will decrease predictive accuracy.

In sum, we predict that consumers will make qualitatively different judgments for the same set of products depending on the structure of the environment they face and their previous experience with that product category. If so, we further expect that taking into account these qualitative differences in strategy use will increase accuracy when predicting consumer choices. To test these predictions, we conducted an experiment in which participants were incentivized to accurately estimate the market price of different bottles of wine, similar to the introductory example above, which we outline next.

2. Material and methods

The experiment consisted of a training phase and a test phase (within-subject). In the initial training phase, participants received feedback about the true price of a set of bottles of wine (in Swiss Francs, CHF). The bottles in the training phase differed depending on the experimental condition (between-subjects). In the piecemeal condition, wines were selected such that true market prices could be accurately predicted with an attribute-based strategy but not with an exemplar-based strategy whereas in the exemplar condition it was the other way round.

In the crucial testing phase, all participants saw the same new set of bottles and had to (1) estimate the bottles' prices and (2) make decisions about which of two bottles of wine would be more expensive. This time, no feedback about the true price was given. As the main dependent variable, we tested whether the judgments of individual participants in the testing phase were better described by an attribute-based or an exemplar-based strategy.

Although this experimental procedure shares some features with an operant reinforcement paradigm, here the targeted response was a complex internal cognitive process. This intervening variable cannot be directly interpreted in terms of stimulus and response and thus goes beyond early behavioristic approaches that focus on overt behavior (Gureckis & Love, 2007). The details of how the wines for the training- and the test-set were selected and how the wines were presented to the participants are described in detail below.

2.1. Description of the bottles of wine

In both phases of the experiment, each bottle of wine was described by its name (e.g. "Cantina di Terlano Chardonnay"), country of origin (France, Italy, or USA), the type of grape (Chardonnay, Cabernet Sauvignon, or Pinot Noir), vintage year (ranging from 1960 to 2010), and maturation (mature or young). The description was presented next to a small picture of the actual bottle that was small enough so that no details on the label other than the name could be identified.

2.2. Learning phase

In the initial learning phase, 20 different bottles were repeatedly presented in 10 blocks, resulting in 200 trials. The order of items within each block was randomized for each individual. To incentivize learning, participants received points depending on the accuracy of their estimate in each trial. Here, a perfectly accurate estimate was rewarded with 100 points. From this maximum, the absolute difference between the true price and the estimate was subtracted up to a minimum of zero points. Points were summed across all trials and converted into an actual monetary reward at the end of the experiment based on a custom exchange rate that was provided in the instructions.

2.3. Test phase

In the crucial test phase, all participants saw the same set of 41 new wines that had not been previously presented. Each bottle was presented twice, resulting in a total of 82 test trials. The incentive scheme was similar to the training phase but this time, no immediate feedback was provided. In a second part of the test phase, participants were further presented with all possible 28 pair comparisons of a subset of 8 wines from the test set. For each pair of bottles, their task was to indicate which one they thought was more expensive.

2.4. Wine selection for the training sets

The wine descriptions for the experiment were sampled from a database maintained at the Robert Parker website (eRobertParker.com). Using actual wines and true sales prices allowed us to have a clearly defined criterion and thus control the importance of the attributes for the required evaluation. To identify suitable sets of wine for the two training sets, we ran a simulation study in which we randomly sampled 20 wines from the wine database and fitted a linear regression with country of origin, the type of grape, maturation (all dummy-coded) and vintage year as regressors and price as dependent variable. This procedure was repeated 10,000 times, each time keeping track of how much variance the predictors could explain. Out of all sets that had negative beta-weight on vintage and for which all attribute levels were present, we selected 100 sets for which the regression model performed best and 100 sets for which the regression performed worst. In a second step, we fitted an exemplar model with one free parameter (the details of the models are outlined below) to each of these sets. Finally, we selected two sets with a roughly comparable range of prices, one for the piecemeal condition where the regression but not the exemplar model performed well and one for the exemplar condition where the exemplar but not the regression model performed well.[1] In the final set for the piecemeal condition, a linear regression explained 89% of the price variance whereas an exemplar model only explained 27% of the variance. In the exemplar condition, it was the other way round. Here, an exemplar model explained 77% whereas a linear regression only explained 30% of the variance.

2.5. Wine selection for the test set

The test set was identical for both conditions. To select wines for the test set, we used the parameter values estimated for the exemplar model and the linear regression for the respective trainings sets and generated predictions for the remaining wines in the database that were not included in any of the training sets. We then selected 41 wines for the test set such that in each condition there were sufficient items for which the models made different price estimates. Finally, we also selected a subset of eight wines from the test set for which the predictions of both two models were as different as possible within each condition and as similar as possible between the two conditions. Thus, for a particular wine the exemplar model was expected to predict a low price whereas the linear regression was expected to predict a high price, or vice versa, irrespective of the experimental condition.

2.6. Mathematical implementation of the strategies

2.6.1. Piecemeal model

To implement the piecemeal or attribute-based strategy, we followed the implementation of Juslin et al. (2008) that assumes that attribute or rule-based strategies are best described by a serial, capacity-constrained cue abstraction process. This implies that people are able to abstract the importance of different attributes and combine them in a linear additive fashion (Juslin et al., 2008). Accordingly, the estimated criterion value $\hat{y}$ of an option p can be expressed as a weighted additive function of the objects' attributes $c_1, \ldots, c_j$:

$$\hat{y}_p = k + \sum_{1=j}^{J} w_j \cdot c_{pj}, \tag{1}$$

[1] See Appendix A for a description of all wines in the training and test sets.

where the weights w are free parameters reflecting the subjective importance weights given to each attribute, k is the intercept, and J is the total number of attributes. Mathematically, this implementation resembles a linear regression model.

2.6.2. Exemplar model

For the mathematical implementation of the exemplar-based strategy, we used Juslin's et al.'s (2008) extension of Nosofsky's (1984) generalized context model. The model assumes that judgments following an exemplar-based process are a function of the similarity of the previously encountered exemplars to the exemplar under consideration. Specifically, it is assumed that the estimate $\hat{y}$ of the criterion value of a new object p is based on the criterion value x_i of the retrieved exemplars i, weighted by their similarity to the object under consideration $S(p, i)$

$$\hat{y}_p = \frac{\sum_{i=1}^{I} S(p,i) \cdot x_i}{\sum_{i=1}^{I} S(p,i)}, \tag{2}$$

where I is the total number of exemplars stored in memory. The similarity $S(p, i)$ between an object and an exemplar is assumed to be a nonlinear function of the distance d between the two objects,

$$S(p,i) = e^{-d(p,i)}. \tag{3}$$

where d itself is assumed to be a function of the difference between the objects' values on each attribute dimension $c_1 \ldots, c_j$, the importance of each attribute dimension measured by an attention parameter s, and a sensitivity parameter h that reflects the discriminability in psychological space (cf. Nosofsky & Zaki, 1998):

$$d(p,i) = h\left[\sum_{j=1}^{J} s\left|c_{pj} - c_{ij}\right|\right]. \tag{4}$$

2.7. Participants

A total of 64 university students participated in the experiment, 32 in each condition. Participants, 49 female and 15 male, had a mean age of 24 years (SD = 6.8 years). As compensation for their participation, they received course credits and a variable bonus depending on their estimation accuracy. Across all participants, the mean bonus payment was 4.6 CHF (SD = 0.88).

3. Results

We first report participants' performance in the task before describing the strategies that were best in predicting their estimates.

3.1. Training performance

Fig. 1 plots the mean number of points earned across the ten training blocks. As can be seen from the Figure, estimation accuracy gradually increased over time in both experimental conditions, indicating that participants over time learned to estimate the prices of the bottles of wine accurately. Fig. 1 further shows that the accuracy was higher in the piecemeal condition than in the exemplar condition, indicating that it was more difficult to learn the prices in the exemplar condition. The difference diminished over time, however, and in the last training round, estimates in the exemplar condition were almost as accurate as in the piecemeal condition, $t(62) = 1.7$, $p = 0.092$; BF = 1.15[2].

3.2. Strategy classification

To determine whether participants' price estimates in the test set were better described by an attribute-based strategy or by an exemplar-based strategy, we fitted both models on the participants' price estimates for each wine in the test set, averaged across the two presentations within each participant. Specifically, we estimated the best fitting weights for the piecemeal strategy as specified in Eq. (1)with country of origin, the type of grape, maturation (all dummy-coded) and vintage year of the wines in the test set as regressors and the individual price estimates as dependent variable. To fit the exemplar model we used a nonlinear least square algorithm (implemented in Matlab) assuming that participants had stored the wines from the training set in memory. We relied on an exemplar model with one free parameter (the sensitivity parameter) thus assuming equal attention weights for all attributes. This implementation has been shown to be more robust than a model with separate attention parameters for each attribute (e.g. Hoffmann et al., 2013). As a goodness-of-fit measure, we relied on the Bayesian Information Criterion (BIC, Schwartz, 1978). The BIC is a common measure to compare model fit that takes model complexity into account by penalizing for the number of free parameters. We calculated the BIC using Raftery's (1995) approximation, which is based on the amount of variance explained by the model (cf. Raftery, p. 135):

[2] Bayes factors are expressed as the odds of the null over the alternative hypothesis and were estimated based on the recommendations by Rouder, Speckman, Sun, Morey, and Iverson (2009).

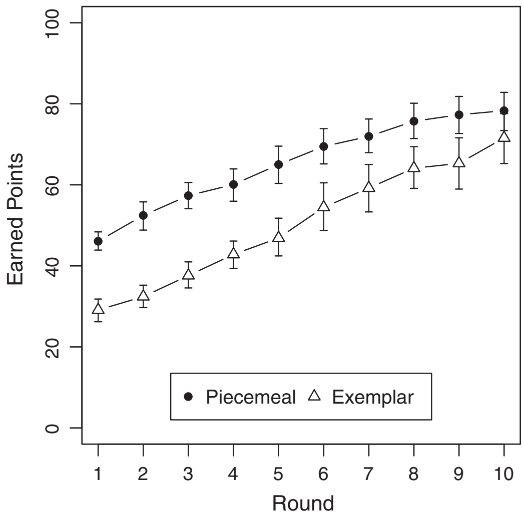

Fig. 1. Mean number of points earned in each experimental condition, plotted across the ten training blocks. Error bars indicate 95% confidence intervals (bootstrapped).

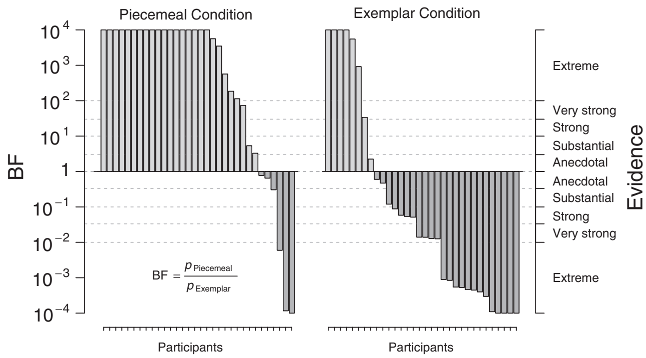

Fig. 2. Bayes factor (BF) of the piecemeal model over the exemplar model for each individual participant in the piecemeal condition (left plot) and the exemplar condition (right plot), ordered by BF (logarithmic scale). Positive values indicate stronger evidence in favor of the piecemeal model whereas negative values indicate stronger evidence for the exemplar model. BFs are truncated at 10^{-4} and 10^4 respectively.

$$\mathrm{BIC}_i = n \times \log(1 - R_i^2) + k_i \times \log(n), \tag{5}$$

where n denotes the number of observations, R^2 the amount of variance explained and k the number of free parameters of model i. Thus, the smaller the BIC the better the model captures a participant's judgment. Based on this criterion, 26 of 32 participants in the piecemeal condition were better described by a piecemeal model whereas in the exemplar condition, 24 of 32 participants were better described by an exemplar model, $\chi^2(1) = 18.1$, $p < .001$. Assuming uninformative priors, this difference translates to a Bayes Factor of 14,992 of the alternative hypothesis over the null hypothesis of no difference (Albert, 2007). This indicates that the different training sets led to a systematic and predictable difference in participants' strategy use.

Fig. 2 visualizes these results in more detail by plotting the evidence in favor of the piecemeal model over the exemplar model for each individual participant in both experimental conditions expressed as the Bayes factor (BF), which was approximated from the BIC differences between both models (Raftery, 1995). The Bayes factor provides an intuitive and easily interpretable model comparison metric: BFs above 10 or below 1/10 can be considered as strong evidence and BFs above 100 or below 1/100 can be considered as extreme or decisive evidence for the respective models (Jeffreys, 1961). In contrast, a BF of 1 provides equal evidence for both models under consideration. As can be seen from Fig. 2, most participants in the piecemeal condition were better described by the piecemeal model (as indicated by the predominantly positive BF-values) whereas most participants in the exemplar condition were better described by the exemplar model (as indicated by the predominantly negative BF-values). Fig. 2 further shows that BFs were mostly above 10 or below 1/10, indicating that participants could be distinctively categorized.

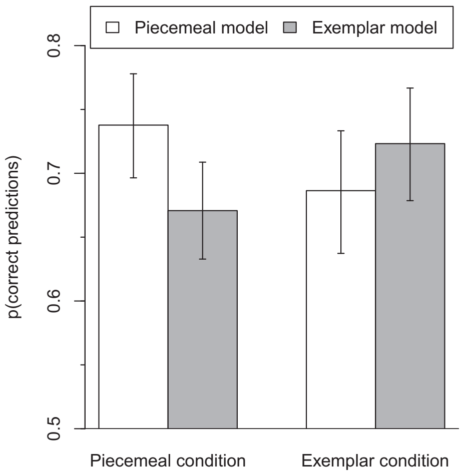

Fig. 3. Mean proportion of correctly predicted choices by the individually-fitted piecemeal and the exemplar models across both experimental conditions. Error bars are bootstrapped 95% confidence intervals.

3.3. Qualitative choice prediction

The pairwise choice task that followed the estimation task in the test phase represents a qualitative test of whether people apply a different strategy for making their judgments. The pairwise choice task was identical in both experimental conditions, so that if people made different choices in this task, this could be traced back to the different experience they had and to different cognitive processes underlying their choices.

A mixed ANOVA with condition as between-subject factor and gamble id as within factor shows that participants' choices differed between the two conditions as indicated by an interaction between condition and gamble id, $F(1,62) = 20.8$, $p < .001$. Subsequent Bayesian analyses indicate that a model that includes the interaction is much more probable than a baseline model with no interaction (BF > 10,000; Rouder, Morey, Speckman, & Province, 2012). To test whether these systematic differences could be explained by the use of qualitatively different strategies, we compared the observed choices against the predictions of the exemplar and the regression model, separately for each individual participant.

Towards this goal, predictions for both models were derived based on the estimated parameters of each individual in the previous test phase, assuming that the wine with the higher price prediction would be chosen. Because the qualitative choice data were not used to estimate the parameters, these out-of-sample predictions provide a rigorous criterion to compare both models (Busemeyer & Wang, 2000).

As displayed in Fig. 3, all predictions were clearly more accurate than random choice (i.e. 50% accuracy). In line with the theoretical predictions, Fig. 3 further shows that in the piecemeal condition, the piecemeal model was able to predict on average 73.8% ($SD = 11.9\%$) of the choices correctly as compared to the exemplar model with on average 67.1% ($SD = 11.2\%$) correctly predicted choices. In the exemplar condition, it was the other way around. Here the exemplar model was more accurate ($M = 72.4\%$, $SD = 13\%$) than the piecemeal model ($M = 68.6\%$, $SD = 14\%$). A mixed ANOVA with proportion of correct choice predictions as the dependent variable, the choice model as a within-factor, and the experimental condition as between-factor confirms this interaction between the experimental condition and the choice model, $F(1,62) = 12.6$, $p < .001$, and indicates no main effects. A subsequent Bayesian analysis yields a Bayes Factor of 40 for a model including interaction over a model with only main effects (Rouder et al., 2012). Contrasting the accuracy of both models within each experimental condition indicates a significant difference in the piecemeal condition, $t(31) = 2.8$, $p = .009$, BF = 4.9 and a somewhat weaker difference in the exemplar condition, $t(31) = 2.2$, $p = .036$, BF = 1.5.

In absolute terms, the proportion of correctly predicted choices by the models was quite close to the theoretical predictions based on participants' price estimates in the previous testing round: Deterministically choosing the more expensive wine according to the participants' individual estimates in the test round would yield 78.8% ($SD = 13.5\%$) correctly predicted choices in the piecemeal condition and 72.1% ($SD = 11.6\%$) correctly predicted choices in the exemplar condition. These percentages indicate the upper bound of what both choice models (that were fitted to the individual estimates) could possibly explain.

4. Discussion

The evaluations of sales prices are an important determinant of purchase decisions because they determine whether a product will be perceived as a bargain or as overpriced (Blattberg et al., 1995; Zeithaml, 1988). If a person evaluates an item as overpriced, purchase intentions will decrease and the person will be motivated to search for a better deal. On the other hand, perceiving an offer as a bargain will increase sales (Monroe, 1990). Thus, modeling the cognitive processes that govern this estimation process is an important step to a better understanding of consumer decision making. Towards that goal, the standard approach in psychology, economics, and consumer research is based on the assumption that people weight and sum up different attribute values and that they can be best predicted based on a piecemeal or attribute-based approach (Fiske, 1982; Keeney & Raiffa, 1993; Shocker & Srinivasan, 1979; Sujan, 1985).

In contrast to this, past research in psychology suggests that people have a repertoire of qualitatively different strategies from which they choose adaptively depending on the situation they face (Gigerenzer & Selten, 2002; Rieskamp & Hoffrage, 1999). Based on this assumption of "ecological rationality" (Todd & Gigerenzer, 2012), we tested the hypothesis that consumers sometimes rely on a similarity- or exemplar-based approach such that they determine the price of a given product by comparing it to similar items encountered in the past. In line with this prediction, our results show that there are situations where consumers apply qualitatively different estimation strategies depending on the structure of the environment they face. When an exemplar-based strategy allowed accurate price estimates in the learning phase, in the test phase the majority of participants were best described by an exemplar model. In contrast, if the task could be solved with a piecemeal strategy, participants' estimates were best predicted by a piecemeal strategy. These results highlight the importance of considering the cognitive strategy that consumers rely on when evaluating products and they suggest that exemplar models that take similarity judgments into account should be considered as feasible candidates to complement current toolbox approaches. In the case on hand, this approach clearly increased the accuracy in predicting behavior.

4.1. Implications for economic research

In economic research, similarity-based processes have been mostly considered to explain how people categorize consumer products and how these categorizations can influence the formation of impressions (Basu, 1993; Cohen & Basu, 1987; Sujan, 1985). Our results indicate that similarity-based strategies such as exemplar models can guide consumer behavior beyond categorization tasks and that this class of models can be fruitfully applied to judgment tasks where the goal is to estimate continuous criteria such as sales prices. As the evaluation of a product is an important determinant of purchasing behavior, these processes are also expected to affect choices.

Under which conditions will people rely on stored exemplars when evaluating options in an economic context? Our results suggest that the accuracy of the strategy plays an important role, hence strengthening the general idea that people adapt their behavior depending on the structure of the environment they face (Payne et al., 1993; Pizzi, Scarpi, & Marzocchi, 2014; Rieskamp & Otto, 2006). Following up on this general idea, past research identified a number of environmental, task, and person characteristics that influence whether people rely on exemplar- or attribute-based strategies and that have important implications for research on consumer behavior. Specifically, it has been shown that exemplar-based processes are more likely to occur in environments where the criterion is a non-linear function of the cues (Juslin et al., 2008; Karlsson, Juslin, & Olsson, 2007), if there are few and distinct exemplars (Rouder & Ratcliff, 2004), or if the cue dimensions are difficult to verbalize (Ashby & Maddox, 2005). Presumably, in these environments, instance-based strategies are more prevalent because exemplars can be formed more easily (Sujan, 1985). With respect to task characteristics, people are more likely to rely on exemplar strategies evaluating each option sequentially rather than choosing between options (Pachur & Olsson, 2012) when they are distracted by other tasks (Hoffmann et al., 2013), and when they learn about the task in an unsupervised context (Henriksson, 2012).

In a consumer context this suggests, for instance, that exemplar-based processes may be more frequent when the relevant product dimensions are difficult to verbalize such as with books, music, or art, and in domains where the market is dominated by few distinct exemplars as, for instance, with sports cars. In contrast, rule-based processes may be more frequent when products can be evaluated based on clearly defined and communicable dimensions such as electronic equipment or investment products, and in domains where the market offers a large number of similar products as, for instance, with compact cars. Precise predictions of which model is best to predict behavior in a specific domain, however, would involve an analysis of the underlying characteristics of the decision environment, which is an important topic for ongoing and future research (e.g. Todd & Gigerenzer, 2012).

Besides characteristics of the task or the environment, the preference for exemplar- and rule-based processes also depends on inter-individual differences such as age, memory capacity, or knowledge about the task. For instance, people with better episodic memory rely more frequently on exemplar-based processes (Hoffmann et al., 2014). In contrast, older participants or participants with more knowledge about the task and how cues relate to the criterion tend to rely on attribute-based processes (Mata, von Helversen, Karlsson, & Cüpper, 2012; von Helversen et al., 2013). This suggests that when designing products for a specific target group it could be worthwhile to consider the cognitive strategies the group members are likely to use.

4.2. Cognitive complexity

Whereas attribute-based strategies are usually assumed to require cognitive control, exemplar-based processes are frequently assumed to be of an implicit nature and can still be employed when distracted by another task (Hoffmann et al., 2013). Although from this perspective, exemplar strategies appear to be less cognitively demanding than piecemeal strategies; both models can probably be considered to be more complex and computationally demanding than simple choice heuristics as, for instance, proposed by Gigerenzer et al. (1999). However, in the context at hand, it is difficult to draw reliable conclusions regarding the actual cognitive complexity of a given decision strategy, because it eventually depends on the information-processing system in which the strategies are implemented (Marewski & Mehlhorn, 2011).

4.3. Summary

The goal of this study was to establish the importance of considering different strategies for the ability to predict consumer judgments. Towards this goal, we conducted a controlled laboratory experiment in which participants' price estimates for consumer products systematically depended on their experience within a previous learning task. The sample of products participants experienced in the learning task influenced their general impression of the products (Denrell, 2005; Fiedler, 2000; Fiedler & Juslin, 2006), but also shaped the strategies they relied on to make future judgments. Thus, when piecemeal or attribute-based strategies do not allow accurate evaluations, people may resort to relying on the similarity to exemplars that they encountered in the past. Considering these differences in strategies will help to better understand and predict behavior in an economic context.

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Appendix A

List of all wines in the training and in the test set.

Condition	Name	Vintage	Country	Grape	Maturation	Price (CHF)
exe	Domaine Anne et Francois Gros Clos de Vougeot le Grand Maupertuis	1990	France	Pinot noir	Mature	70
exe	Domaine Matibat Cabernet Sauvignon Vin de Pays	1991	France	Cabernet	Mature	5
exe	Marcassin Chardonnay Lorenzo Vineyard	1995	USA	Chardonnay	Mature	199
exe	Domaine Leflaive Chevalier Montrachet	1995	France	Chardonnay	Mature	800
exe	Domaine Etienne Sauzet Montrachet	1995	France	Chardonnay	Mature	882
exe	Boccadigabbia Cabernet Sauvignon Akronte	1997	Italy	Cabernet	Mature	32
exe	Santa Anastasia Litra Cabernet Sauvignon	1999	Italy	Cabernet	Mature	43
exe	Falchini Campora IGT	1999	Italy	Cabernet	Mature	75
exe	Az Agr Gini Chardonnay Sorai	2000	Italy	Chardonnay	Mature	24
exe	Vincent Girardin Puligny Montrachet Pucelles	2001	France	Chardonnay	Mature	62
exe	Domaine Leroy Corton Renardes	2002	France	Pinot noir	Mature	450
exe	Maison Lucien le Moine Bonnes Mares	2003	France	Pinot noir	Young	200
exe	Robert Arnoux Vosne Romanee les Suchots	2006	France	Pinot noir	Young	160
exe	Lis Neris Jurosa White	2007	Italy	Chardonnay	Mature	30
exe	Feudi della Medusa Alba Nora	2007	Italy	Chardonnay	Mature	56
exe	Montepeloso Gabbro IGT	2008	Italy	Cabernet	Young	150
exe	Alois Lageder Chardonnay Gaun	2009	Italy	Chardonnay	Mature	20
exe	Domaine Joseph Drouhin Meursault Perrieres	2009	France	Chardonnay	Young	90
exe	Remoissenet Pere et Fils Meursault les Genevrieres	2009	France	Chardonnay	Young	103
exe	Kongsgaard Chardonnay The Judge	2009	USA	Chardonnay	Young	200
reg	Bellavista Chardonnay Annunciata	1995	Italy	Chardonnay	Mature	40
reg	Domaine Leroy Chambertin	1999	France	Pinot noir	Mature	680
reg	Az Agr la Cadalora Chardonnay	2000	Italy	Chardonnay	Mature	12
reg	Az Agr Gini Chardonnay Sorai	2000	Italy	Chardonnay	Mature	24
reg	Marcassin Chardonnay Three Sisters Vineyard	2001	USA	Chardonnay	Mature	240
reg	Stroblhof Blauburgunder Riserva	2003	Italy	Pinot noir	Mature	64
reg	Ca del Bosco Chardonnay Terre di Franciacorta	2004	Italy	Chardonnay	Mature	70
reg	Tenuta di Nozzole Il Pareto Vino da Tavola	2004	Italy	Cabernet	Young	86
reg	Flavio Roddolo Langhe Rosso Bricco Appiani	2005	Italy	Cabernet	Young	70
reg	Aubert Chardonnay Reuling Vineyard	2005	USA	Chardonnay	Mature	250
reg	Peter Michael Winery Chardonnay Point Rouge	2005	USA	Chardonnay	Mature	300
reg	Abreu Cabernet Sauvignon Thorevilos	2005	USA	Cabernet	Young	500

(*continued on next page*)

Appendix A (*continued*)

Condition	Name	Vintage	Country	Grape	Maturation	Price (CHF)
reg	Lis Neris Jurosa White	2006	Italy	Chardonnay	Mature	30
reg	Coppo Chardonnay Monteriolo	2006	Italy	Chardonnay	Mature	55
reg	Landmark Chardonnay Bien Nacido	2007	Italy	Chardonnay	Mature	42
reg	Feudi della Medusa Alba Nora	2007	Italy	Chardonnay	Mature	56
reg	Alois Lageder Chardonnay Gaun	2009	Italy	Chardonnay	Mature	20
reg	Ronco del Gnemiz Chardonnay Sol	2009	Italy	Chardonnay	Mature	40
reg	Billaud-Simon Chablis Preuses	2009	France	Chardonnay	Young	70
reg	Vine Hill Ranch Cabernet Sauvignon	2009	USA	Cabernet	Young	150
test	Beaulieu Cabernet Sauvignon Private Reserve Georges de Latour	1960	USA	Cabernet	Mature	482
test	Domaine de l'Arjolle Cabernet Sauvignon	1986	France	Cabernet	Mature	10
test	Domaine de l'Arjolle Cabernet Sauvignon	1989	France	Cabernet	Mature	10
test	Domaine de l'Arjolle Cabernet Sauvignon	1990	France	Cabernet	Mature	10
test	Domaine de l'Arjolle Cabernet Sauvignon	1991	France	Cabernet	Mature	10
test	Domaine Richeaume Cabernet Cotes de Provence	1992	France	Cabernet	Mature	15
test	Domaine Maris VDP d'Oc Cabernet Sauvignon	1993	France	Cabernet	Mature	10
test	Chateau de Combebelle La Colline Cabernet Sauvignon	1994	France	Cabernet	Mature	13
test	Domaine des Moulins Cabernet Sauvignon VDP Herault	1995	France	Cabernet	Mature	9
test	Domaine de la Romanee Conti Montrachet	1995	France	Chardonnay	Young	900
test	Domaine D'Auvenay Chevalier Montrachet	1996	France	Chardonnay	Young	550
test	Domaine de Triennes Cabernet Sauvignon	1997	France	Cabernet	Mature	13
test	Cantina di Terlano Chardonnay	1997	Italy	Chardonnay	Young	120
test	Dom Ruinart Blanc de Blanc	1998	France	Chardonnay	Young	160
test	Jacques Selosse Extra Brut Blanc de Blancs	1999	France	Chardonnay	Young	240
test	Krug Blanc de Blancs Clos du Mesnil	2000	France	Chardonnay	Young	726
test	Domaine D'Auvenay Chevalier Montrachet	2002	France	Chardonnay	Young	730
test	Ca del Bosco Pinero	2003	Italy	Pinot noir	Young	88
test	Deutz Amour de Deutz Blanc de Blancs	2003	France	Chardonnay	Young	195
test	Castello di Pomino Pomino Casafonte	2004	Italy	Pinot noir	Young	42
test	Domaine William Fevre Chablis Bougros Cote Bouguerots	2004	France	Chardonnay	Mature	75
test	Scarecrow Cabernet Sauvignon	2004	USA	Cabernet	Young	550
test	Marchesi Pancrazi Pinot Noir Riserva Vigna Baragazza	2005	Italy	Pinot noir	Young	81
test	Comte Armand Pommard Clos des Epeneaux	2005	France	Pinot noir	Mature	200
test	Scarecrow Cabernet Sauvignon	2005	USA	Cabernet	Young	600
test	G D Vajra Pinot Nero Pn 497	2006	Italy	Pinot noir	Young	26
test	Marcassin Pinot Noir Marcassin Vineyard	2006	USA	Pinot noir	Young	300
test	Schrader Cellars Cabernet Sauvignon RBS To Kalon Vineyard	2006	USA	Cabernet	Young	600
test	Jean-Marc Pillot Chassagne Montrachet les Vergers Clos Saint Marc	2007	France	Chardonnay	Mature	100
test	Fontodi Pinot Nero	2008	Italy	Pinot noir	Young	68
test	Louis Jadot Batard Montrachet	2008	France	Chardonnay	Mature	200
test	Di Majo Norante Cabernet Terra Degli Osci	2009	Italy	Cabernet	Mature	12
test	Di Majo Norante Cabernet Terra Degli Osci	2010	Italy	Cabernet	Mature	12
test*	Comte de Vogue Musigny Vieilles Vignes	1990	France	Pinot noir	Young	675
test*	Domaine de la Cour d'Ardenay Anjou les Touches	1996	France	Cabernet	Mature	18
test*	Cantina di Terlano Chardonnay	1996	Italy	Chardonnay	Young	120
test*	Colgin Cabernet Sauvignon Tychson Hill Vineyard	2004	USA	Cabernet	Mature	500

Appendix A (*continued*)

Condition	Name	Vintage	Country	Grape	Maturation	Price (CHF)
test*	J Rochioli Pinot Noir West Block	2006	USA	Pinot noir	Mature	195
test*	Stroblhof Blauburgunder Pigeno	2007	Italy	Pinot noir	Young	34
test*	Castello di Volpaia Cabernet Sauvignon Prelius	2008	Italy	Cabernet	Mature	22
test*	Guy Roulot Meursault Tillets	2009	France	Chardonnay	Mature	100

Note: * denotes the wines that were used to construct the pair comparisons.

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