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Abstract

In this article we propose a two stage procedure to model demand decisions by customers who are balancing several dimensions of a product. We then test our procedure by analyzing the behavior of buyers from an Austrian price comparison site. Although in such a market a consumer will typically search for the cheapest price for a given product, reliability and service of the supplier are other important characteristics of a retailer. In our data, consumers follow such a two stage procedure: they select a shortlist of suppliers by using the price variable only; finally, they trade off reliability and price among these shortlisted suppliers.

JEL Classifications: L81, D83.

Keywords: e-commerce, price comparison, decision theory, heuristics, seller reputation.

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1 Introduction

Consumers' decision making in realistic purchasing situations is often more complex than a standard utility maximization model can cope for. Due to time constraints, high search costs, lack of computational power or simply lack of cognitive knowledge in such situations, psychologists and decision theorists in marketing often refer to heuristical procedures (Gigerenzer et al., 1999) which are often able to perform better than more complicated algorithms suggested by economists.

In many cases, two-stage procedures are suggested, where the decision process is structured with different governing rules in the different stages. Assume you are buying a car: as cars have dozens of quality dimensions and there is a lot of different varieties available on the market a rational decision balancing all these dimensions seems almost impossible. Typically, a consumer makes a shortlist of potential varieties where only a limited number of features of the cars are taken into account. This is the first stage of the decision process. Once this shortlist is given, the consumer inspects the cars in more detail, arranges for a test drive, etc in order to come to a final decision("consider-then-choose model" by Gaskin et al. (2008), Yee et al. (2007)). Similar shortlist ideas are often used for literature prizes, recruitment decisions or investment projects [1].

Two-stage decision procedures are related to Herbert Simon's satisficing behavior (Simon, 1957): individuals fix a satisfactory aspiration level and then take the first object which satisfies this criterium. Theories of elimination by aspects (Tversky, 1972) or "fast and frugal heuristics" (Gigerenzer and Goldstein, 1996) evoke lexicographic preferences [2]. In simple cases, where binary decisions on product characteristics are possible, individuals decide first which characteristics are the most important ones and then they eliminate products step by step if required characteristics are missing. These heuristics are non-compensatory: bad features of one model cannot be compensated by good performance in another one. While they do describe many decision situations quite well, they suffer from some problems: How do individuals decide about the ranking of features in the lexicographic ordering? How can the non-compensatory principle be upheld if the varieties differ

[1] Academics are familiar with these procedures from conference paper evaluations: referees are often asked to mark papers with A(definite accept), B(possible accept), C(definite reject), where only B papers will additionally be checked by the program committee - the committee decisions follow different rules.

[2] See also Kohli and Jedidi (2007) for experiments on computer buyers and Payne (1976) for an early application on apartment choice.

widely in some features, like quality and price? [3]

In the following we will look at consumer decisions of online buyers. Relative to brick-and-mortar retailing, in online markets information is much easier to get and search costs are much lower. An extreme case are so-called price comparison sites or shopbots. On these websites, shoppers can compare prices for thousands of products with one mouse-click: a comfortable list of suppliers with information about prices but also on the reliability of the seller - typically given by evaluations of past customers - is available at practically no cost.

Such markets are close to perfect competition, so we should expect all shoppers to buy at the cheapest price only. Despite of this, price dispersion on the internet is not much lower as in brick-and-mortar stores (Brynjolfsson and Smith, 2000) because buyers value accessability of the site and the shop, reliability of order fulfilment and the modalities of delivery (Betancourt and Gautschi (1993) and Pan et al. (2002)). As information is practically costless in such markets - shoppers can see all the relevant price and quality information on one screen - they have every incentive to make a well-informed rational decision: they should take all the specifics of the seller into account and trade off a higher price for higher reliability of the seller. In other words, such markets are the least ones to expect heuristical procedures.

In this paper we will present a theoretical model capable to explain that consumers make shortcuts in their consumer decisions. Typically, shoppers decide on a shortlist of suppliers; a decision where the price is the most important determinant. Reliability considerations of the supplier don't play a big role here. In the second stage quality, reliability, and other supplier-specific characteristics are much more important aspects of the decision of the consumers. Supporting empirical evidence of consumer behavior for our decision model in a price search engine where the low information cost should represent the best prerequisites for completely rational behavior shows the importance of alternative concepts for the model for the standard utility maximizing decision model.

[3] Researchers in Marketing (Gensch, 1987) have developed two-stage decision models as well, but most of them have to assume the decision in the first stage as unobservable and latent. See Moe (2006) for a model where customers decide between different meal replacement products of one online retailer, where the costumers have to decide first which product they should take and second whether to buy it or not.

2 A Decision Procedure

In this section we introduce a simplified model of a decision process. The process is a shortlist method (SM) (Manzini and Mariotti, 2007). We assume that a buyer knows which good he wants to buy. Retailers of this good are plenty and they differ in the additional service they offer. These services may be availability of the good, pre and post sales services, payment options, etc. Without loss of generality we assume that the good in it's inert characteristics is homogeneous. For a given product let $X = \{x_1, .., x_n\} \subset \mathbb{R}^2_+$ denote the set of available offers, with $n > 2$ denoting the number of retailers offering this product. Each option represents the offer of one seller. We model the offer of a seller as having two components, the price and the service characteristic of the seller: $x_i = (p_i, s_i)$ where p_i is the price seller i charges for the product and s_i is the seller's service characteristic. For simplicity we assume that each seller's characteristics can be represented by a single number. One can easily extend the model to allow for product differentiation (i.e. consumers compare several differentiated products) or several dimensions of sellers' characteristics. Given our focus on buyers' decision procedure and for reasons of simplicity, we model X is exogenously given.

To model the decision of a buyer we assume each buyer has a complete binary preference relation $P \subseteq X \times X$ over all elements in X and we denote by $x \succeq y$, $x, y \in X$, that the customer likes option x at least as much as option y, i.e. $(x, y) \in P$. Hence, we assume that a buyer in principle has complete preferences when asked to choose between any sets of options. Our method is based on the assumption that a buyer first reduces his or her choice set before making a final decision. We need the following notation to identify utility maximizing choices from a set $Y \subseteq X$:

$$\max(Y; P) = \{x_i \in X \,|\nexists z \in Y \text{ such that } z \succ x_i\}.$$

Even though our decision process will model boundedly rational choice, we assume that the preference relation is complete. A SM is characterized as a process that the preference relation is applied only to a shortlist, a set $S(v, X) \subset X$. The procedure, we want to study, generates a shortlist S which is based on a consumer's individual cut-off price v. This cut-off price may be determined by a maximum willingness to pay for the good. We assume v is independent of service characteristics of a retailer. Given that it is a characteristic of a consumer, we assume it to be exogenous. The second stage of the decision procedure is to apply the complete preference relation P to $S(v, X)$. Let $C(v, X)$ denote the choice based on this procedure.[4] Hence our procedure consists of two steps:

[4]Mandler et al. (2008) propose a checklist method that can provide a choice method to

1. The customer generates a shortlist $S(v, X) := \{x_i \in X \,|p_i < v\}$.
2. Customers choose according to their preferences from $S(v, X)$: $C(v, X) := \max(S(v, X); P)$.

To compare this procedure to the standard rational choice procedure we define the rational choice $R(X)$ as $R(X) := \max(X; P)$. If one interprets the service characteristic of a seller as a characteristic of the good, then the otherwise homogeneous product differentiates itself according to the retailers' service characteristic. To compare our decision process to the literature, the standard approach in the literature is to follow Rosen (1974). His hedonic pricing approach would in our case state that among all the offers one can derive a hedonic price function $p(s) = \min_{\{x_i | s_i \geq s\}} p_i$ which gives the best price for the product given a certain minimum characteristic of the seller. The hedonic pricing approach is another way to simplify the decision by eliminating all options which have a higher price given a certain level of service. A decision is then made among all elements of a restricted set. This yields the same result as $R(X)$. For our process this is not necessarily the case: $\exists (X, v)\ C(v, X) \neq R(X)$. In contrast to this, our process allows customers to consider all offers; if they do so then their choice will be the same as in a rational choice decision, i.e. $C(\max p_i, X) = R(X)$.

In the following, we state some of the characteristics of $C(v, X)$. Proofs are generally omitted, as they are straightforward. For notational purposes denote by $p(C(v, X))$ and $s(C(v, X))$ the respective element of $C(v, X)$:

- If for $\forall x_i \in X \quad p_i = p$, i.e. all sellers charge the same price then $C(v, X) = R(X)$.
- $C(v, X)$ does not fulfill the weak axiom of revealed preferences (WARP): $\exists X, Y$ with $Y \subseteq X$ such that $C(v, X) \neq C(v, Y)$ and $p(C(v, X)) < p(C(v, Y))$.[5]
- For $v_1 < v_2$, iff $s(C(v_2, X)) \geq s(C(v_1, X))$ then $p(C(v_2, X)) \geq p(C(v_1, X))$.

mirror complete preferences. We do not specify how consumers make their choice among the items on the shortlist. The checklist method is a good candidate to model this decision, in this case our method just prescribes a first item on the checklist, i.e. the price.

[5]Proof: Given that we have unit demand, a choice process $W(X)$ fullfills WARP iff $Y \subseteq X \Rightarrow$if $W(X) \neq W(Y)$ then $p(W(X)) > p(W(Y))$. See Varian (2006) for a recent survey. A counter example proofs that our two stage decision process do not fulfils the WARP: Let $P = \{(x, y)\,|p(x) - s(x) < p(y) - s(y)\}$ i.e. a higher value of s denotes a preferable quality and price and quality are perfectly substitutable. If $X = \{(1, 7), (2, 5), (3, 3)\}$ and $Y = \{(1, 7), (3, 3)\}$ then with $v = 2.1$ $C(2.1, X) = (2, 5)$ and $C(2.1, Y) = (1, 7)$ contradicting WARP.

- For $X, Y \subset \mathbb{R}^2_+$, $C(v, X)$ fulfills the expansion property, i.e. $C(v, X \cup Y) \in \{C(v, X), C(v, Y)\}$.

Note that we differ from the rational shortlist methods by allowing for complete preferences over X. Manzini and Mariotti (2007) as well as Kfir and Ok (2006) assume that preferences are not complete, i.e. there exist options where neither $\preceq$ nor $\succeq$ applies. By allowing only two dimensions and having a natural ordering at least on the price, our choice method shares some features with these methods but it comes up with not conventional choices for a different reason. While in the cited procedures WARP is contradicted because the procedures determine which options are eliminated from the choice set given incomplete preferences, in our case the short list depends just on one characteristic, namely the price. The main difference to the cited procedures is that our sequential selection process is not affected by irrelevant alternatives.

Our two-stage procedure shares the dependence on irrelevant alternatives with the models suggested by Manzini and Mariotti (2007) or Kfir and Ok (2006) if v is determined endogenously, i.e. v is a function of X. Why? If $v(X)$ is such a function and $X_0 = X \cap \{x_0\}$ then consumers short list $S(v(X), X) \neq S(v(X_0), X_0)$ and thus the choice may change, even though $x_0 \notin S(v(X_0), X_0)$.

To see the similarity of the procedures, we can translate our first step, i.e. $S(v, X) := \{x_i \, |p_i < v\}$ into notation of Manzini and Mariotti (2007): $\{x_i, x_j\} \in P_1$ iff $p_i \leq v$ and $p_j > v$.[6]

Compared to the mentioned choice methods, our choice procedure - independent of whether v is exogenous or a function $v(X)$ - always generates a unique decision of a buyer given a set of alternatives X.

In the following empirical section we will take two views on shortlists. The first view is to exogeneously enforce a shortlist, i.e. assuming that customers really consider only the 5, 10 or 20 cheapest offers. Our second view is that the decision to put an offer on the shortlist - i.e. to consider an offer further - and the purchase decision are two separate steps. Given that we can observe clicks and can distinguish them from purchases, we consider all offers having been clicked at least once as those on the shortlist. With our simple theory in mind, the following states hypotheses resulting from the proposed procedure.

Hypothesis 1 *If clicks determine the shortlist then prices strongly determine the selection of shops that are visited at least once.*

[6]If v is a function X, for example $v(X) = \frac{1}{|X|} \sum p_i$, then, indeed, irrelevant alternatives can affect the choice because they change $v(X)$, namely if $p(x_0) > \frac{1}{|X|} \sum p_i$.

Hypothesis 2 *Service will be more important among the sellers that are visited / are on the shortlist.*

3 Data and Estimation Strategy

For our empirical analysis we use the database of www.geizhals.at[7]. This web-site offers a 'price search engine' which collects the price offers via standardized protocols from a predefined group of sellers and presents them electronically via its web-platform. Typically the quality and reliability of price offers in price search engines are higher and more serious in contrast to 'shopbots' which do an arbitrary price search for products on the whole web and offer the results of this web search online.

Geizhals.at has contracts with about 3,000 sellers which can list their price offerings for a total of 280,000 products on the Geizhals.at website[8].

Since Geizhals.at is by far the dominating firm in providing price comparisons in Austria, this price search engine is well-known and widely used by webshoppers. Hence, all e-tailers have an incentive to get their prices listed and we observe practically the complete Austrian market for online-traded goods on Geizhals.at. Due to computational limitations we have to restrict our data to an arbitrary week in the year 2006. The data in our analysis includes price offers for 38,374 products from a total of 449 sellers. From sellers' price offers we know the exact name of the product and the producer together with the products' mapping into a hierarchical classification system for the products (categories, subcategories, and subsubcategories). Furthermore, sellers' price offers include information on availability and shipping charges. Customers have the possibility to evaluate the (service)quality of the firms: 32,626 customers did so. Geizhals.at offers the possibility to evaluate the retailers' service quality on a 5-point scale between 1(=very satisfying) and 5 (=very unsatisfying)[9]. To a certain extent, these firm evaluations can be interpreted as a form of vertical firm differentiation. Furthermore, the data comprise detailed information on about 556,311 customer clicks requesting the referral to retail shops during this week.

[7]Geizhals means stingy in German.

[8]For the time span April 23, 2006 till June 25, 2007 we have in total 2,917 sellers, 279,973 products, 106,289,817 price offers, 49,594,757 clicks, 78,369 retailer evaluations, 185,310 product evaluations in our database.

[9]Customers who want to evaluate a shop have to register at the Geizhals.at website which enhances the reliability of the evaluations. Besides the identification of the shopper which is deterring rude behavior, Geizhals.at has a firm policy to check these evaluations: strategic evaluations coming from suspect IPs or from competitors are removed.

For obvious reasons, it is not possible to verify the above presented two-stage decision strategy with our dataset in a direct way - a combination of mind protocols together with the detailed clickstream of consumers would be necessary to do that. However, our dataset is perfectly suitable to pursue an indirect approach: By estimating an indirect hedonic price function we will show that the price is the dominant variable in the first stage of the decision process; but the closer we are moving towards the actual purchase decision, the more important are other firm characteristics (e. g. firms' evaluation, country of origin, ...) relatively to the price. In particular, when we identify clicks with a higher purchase probability[10] we see that the importance of variables other than the price increases considerably. We will show that this is not an artefact of the way Geizhals.at presents their data on the website but rather a heuristic which is used irrespective of the way the information is presented.

We use the following indirect hedonic price function:

$$\#clicks_{ij} = f(relprice_{ij}, evaluation_j, ...) \tag{1}$$

In this equation $\#clicks_{ij}$ counts the consumers' referral requests on the Geizhals.at website (clicks) to retailer j for product i. The variable $relprice_{ij}$ measures the price of product i of retailer j divided by the average price of product i across all firms offering this product (hence $relprice_{ij} = \frac{p_{ij}}{\sum_{j=1}^{N} p_{ij}/N}$)[11]. Customers' average firm evaluations are depicted with the variable $evaluation_j$. Other control variables are included: *shipping cost*$_j$ for retailers were calculated from the information given at Geizhals.at. Since this variable was not available (or was not unambiguously constructible) for all retailers, we interpolated with the average shipping cost and included additionally a *missing shipping cost* dummy. $Germany_j$ is equal to 1 if the online shop is located in Germany - as opposed to Austria, $avail_j$ is equal to 1 if the product is deliverable at short notice, $pickup_j$ is equal to 1 if the retailer has a pick up store as well. Controlling for the general type of the e-tailer (discounter versus high-priced online-shop) the $pricelevel_j$ indicates the average of $relprice_{ij}$ for firm j for all offered products divided by the average over all firms and products. As we observe relative prices and demand for different products, we include also product fixed effects to control for different demand conditions across products. Table 1 shows descriptive statistics for these variables.

[10] For that purpose we use the known 'Last-Click-Through' concept discussed below.

[11] Since a retailer can change the prices up to 10 times a day we are using the retailers' average price over the observation period.

4 Empirical Results

The number of clicks to a retailer is highly skewed. 82.7 percent of the products across the retailers are never selected from the customers due to the large number of offers available to them; the mean offer attracts 0.62 clicks during the week of observation. As our dependent variable represents typical non negative count data, we are using negative binomial panel estimations including fixed effects for products to control for other unobservable characteristics of the respective markets[12].

Table 2 includes our main results. We show marginal effects of the relative price, the firm evaluation by the customers and some control variables. The first Column includes all product offers, whereas in Columns (2) to (4) we increasingly focus our analysis on top-listed firms, i.e. firms with the lowest prices among the shown list. Due to the large number of observations all variables are significantly estimated and almost all have the expected sign. If we concentrate first on all product offers we see that both the relative price as well as the firm evaluation (our service quality indicator) are important to explain demand for these products. Increasing the relative price by 10% would decrease demand by 0.13 clicks, which is considerable given a mean of 0.62 clicks per period. Likewise, increasing the numerical value of firm evaluation (which is coded as a decrease of firm quality) by one standard deviation (0.47) will decrease demand by 0.013 clicks.

Columns (2) to (4) restrict our sample step by step: if we look only among the 20 cheapest, the ten cheapest or the five cheapest shops, the coefficient of the relative price increases steadily – from -2.5 to -4.8. This is not surprising, because the offers with the highest prices - getting no clicks at all - are eliminated. More remarkable is the development of the firm evaluation coefficient. It increases by about tenfold and reaches the value -0.28. Among the five top-listed shops an increase of the firms' quality evaluation by half a grade will increase the number of clicks by 0.14. To show this realignment of coefficients more clearly, we calculate the "relative importance of price over service": while the marginal effect of relative price relative to firm evaluation is 47 in Column (1) with all firms this relation falls to only 17.1 in Column (4) using only the top five firms. While this comparison is somewhat arbitrary as we compare different measurement units, the development across Columns is instructive. Apparently these results support our suggested decision strategy, in which consumers select a short list of potential retailers according to the price in the first step and consider other variables more carefully only in the second step through which the relative importance of firm quality increases

[12]In all our models the likelihood ratio test for overdispersion rejects the poisson model.

if we restrict our dataset to the products with a higher purchase probability.

Results from other product- or firm-specific characteristics corroborate this picture. We find other quality or service components of an online shop to have important effects on demand as well: these effects are in general several times larger if we look at the sub-sample of the cheapest shops. If the shop is located in Germany demand is considerably lower, presumably because customers fear warranty or delivery problems across borders. If the product in a shop is immediately available or if there is an additional pick up possibility, i.e. the online shop also has a brick-and-mortar store aside, these features are increasing the number of clicks: again, the importance of these effects increases with the focus to the cheapest price offers. The number of firm evaluations has a positive effect on demand, because customers might trust the reliability of the shop itself and also the evaluations of the shop to a larger extent.

As a control for the general type of the e-tailer we included the general price level in the shop, which has a negative effect on buying a particular product, given the relative price of this particular product. This not surprising result indicates consumers' preferences for discounters rather than high priced shops. This might reflect the psychological effect that on average consumers believe more strongly in a good bargain if they buy in a web-shop well-known for their cheap prices than in a high priced shop even if they ask for the same price. The effect of shipping costs is inconclusive: If all offers are included, relative shipping costs have a small positive effect on demand; this coefficient turns duly negative once we concentrate upon the selection among the 20 or even five cheapest firms. It seems that customers only start looking at shipping costs once they consider seriously about buying from the shop.There is no unambiguous expectation concerning the sign of the dummy variable for the missing shipping cost. The coefficient should be negative if consumers are not informed about this important variable in e-commerce business. It should be positive if the missing shipping cost are an indicator for special cheap rates. Shipping cost is the only variable which we have to parse from a text field. Obviously the parsing procedure requires some formal structure of the text field which will not be usable if the web-shop deviates from the default guideline because of special rates. Therefore we interpret the positive sign as an indicator for especially cheap shipping cost.

5 Robustness Checks

In the following subsections we will provide additional evidence for our result by using different subsamples and alternative interpretations of our dataset.

Bottom-Listed Firms

As a reverse check we look in Table 3 at firms which are bottom listed, i.e. whose prices are supposed to be above the unknown reservation price of the shoppers. If shoppers follow a two stage strategy - fixing the reservation price first and making a more elaborate evaluation among price and service quality later on - they should not care about firm evaluation in the case of offers above this reservation price. This is in fact, what we find: if we restrict firms to those ranked fortieth or above, firm evaluation turns minuscule and insignificant.

Few Suppliers

Another way to check the two stage procedure is to restrict the attention to products such that a heuristic is not necessary. If the number of shops is large, even the most meticulous shopper has to make shortcuts: she cannot check all details of the offers, a reservation price strategy might be a necessary first step in the decision process. However, if the number of shops is manageable, a full-fledged deliberation between price and service quality might be reasonable and possible. In Table 4 we restrict our analysis to products which are offered by a maximum of 20, 10 or only five firms. Column (1) shows again our baseline model from Table 2 using all products offered. Looking again horizontally across Columns we see that the impact of firm evaluation increases dramatically as we restrict the market size further and further: In markets with only 20, 10 or five firms, the coefficient for firm evaluation increases from -0.03 to -0.14, -0.29 up to -0.51. Comparing again this influence of relative price with the impact of service quality, we find the relative importance drop from 47 to 8.6 in the case of five firms. This is clear evidence for a different strategy in these markets: if many firms offer the good, the trade-off between price and service quality is less strong; the less firms there are, the more important quality dimensions get. The impact of other characteristics, like being a foreign (German) firm, having the product immediately available, having pickup possibilities and the number of evaluations for the firm, corroborates the conclusions: All these characteristics are much more important in small markets.

Last-Click-Through as indicators for actual purchases

A completely different view of the data offers additional support for our two stage decision process for the choice of the shortlist and the actual purchase. Looking at clicks to the website of an online shop - as we have done before - is the ideal way to define the shortlist of shops the customer is interested in. This should be contrasted with actual purchases. Unfortunately, the actual act of purchasing a product is unknown, because it happens at the e-tailer's own web site. In the literature, the concept of 'Last-Click-Through' (LCT) is often used as a proxy for the purchasing decision (e.g. Smith and Brynjolfsson (2001) or Bai (2004)). If a customer is searching for a product, she might meander around different web sites, comparing characteristics of the shops, but she will finally settle for the preferred shop and buy there online. The last click to a shop selling the product is usually identified as the click with the highest purchase probability.

In practice, it is not so simple to determine the 'Last-Click-Through' because buyers can shop for a specific product several times in a particular time interval. Analyzing the click behavior of a customer over time we have to define a 'searching period' which is finished with an actual purchase. If the customer searches for several days, say, then interrupts the search for a month or so, and reappears again, we might have the situation that a consumer buys more than one specific good at different points in time. Two approaches can be chosen for identification of such different search periods. By hierarchical clustering which sequentially adds the clicks with respect to their minimal temporal distance we get a dendrogramm in which the fixing of a hierarchical level results in a certain amount of search intervals. Choosing a low level results in many search spells, choosing a high level gives us fewer intervals. Since the definition of the hierarchical level is arbitrary we decided to find the different search intervals with the Grubbs' Test for Outlier Detection. By choosing a significance level of 95% those especially long time differences can be found out which are distinguishing different search intervals[13]. Since by definition a search requires the comparison of several alternatives even a search period of one hour would have outliers. Hence, we have to introduce additionally some minimal requirements - in one version a maximal time span has to be one week with at least 3 clicks, in a second version a maximal time span has to be one month with a least 5 clicks.

To complicate matters even more, customers might not only search for one specific product, they might look at substitutes during their search as well. The hierarchical mapping of the products into subsubcategories, subcategories and categories in the Geizhals.at data allows to cope with this issue since this classification scheme just describes the degree of substitutional relationship between the products (products in a subsubcategory are close substitutes, products in categories reflect a looser substitutional re-

[13]It can be shown that for each level in the hierarchical clustering a certain significance level for the Grubbs' Test for Outlier Detection can be found which results in identical search spells.

lationship between products). Hence, the consumers' different search spells can be analyzed at the level of products, subsubcategories, and subcategories (categories seem to be a too general classification)[14].

Given these possibilities we come up with three different measures for the identification of actual purchase clicks indicating the length of the presumed search period[15], and the substitutional relationship of search products: 'LCT prod-week', 'LCT subsubc-week', 'LCT subc-week'.

In Table 5 we report estimates using these three alternative measures to check for robustness. For comparison reasons we also show our benchmark results from Table 2 using all clicks (Column 1). Comparing all three LCT-variants with the benchmark results we see that in all cases the impact of firm evaluation increases considerably up to nearly twofold. Hence, for all of our three different measures of "purchase clicks" we can show that the firm evaluation has a much stronger relativ impact on the final selection of a product/firm compared to the situation where each referral request (click) is interpreted as final product decision. This again confirms our two stage selection model: The closer we come to the actual purchasing decision the more important other decision variables than the price get - this relies both to firm evaluation as such as well as other quality indicators, like availability, pick up possibility, etc.

Censored Dataset

To display the relevance of our two stage procedure from an other point of view we restrict our data to only those shops, where the potential buyer has already checked the firm-specific web-site due to the referral request to the respective online shops. Hence, all product offers with no clicks at all are dropped from the dataset. This corresponds to the idea, that making an actual purchasing decision requires that the shop was shortlisted before (censored purchase clicks). Table 6 shows these results again using the Last-Click-Through for counting the clicks with higher purchase probability. The results are very similar, the additional importance of firm evaluation is even higher as compared to Table 5. These results corroborate our previous findings: shoppers use different strategies when deciding about a shortlist of shops and when making a final buying decision: i) if a shopper clicks to an e-tailer's web-site this shop is part of the short-list, ii) among those on the

[14]In total 358 subsubcategories and 40 subcategories are given. As an example the category 'Video/Foto/TV' contains the subcategory 'TV-Sets' and the subsubcategory 'LCD TV sets with 30-39 inches'.

[15]We do not report the estimates for the search period of one month as they are very similar to our main results.

short-list, the shopper is making a rational decision balancing quality and price.

Substitutional Relationship between Offered Products

As Geizhals.at is typically ordering the offers increasing in prices, the price search engine is anticipating the natural way to think about the attention and cognitive reasoning of potential shoppers. The question arises if our empirical results are driven by the way the data are presented by the price search engine.

We can use information about the search behavior of shoppers by explicitly taking into account the substitutional relationship between the products. If someone is interested not in a specific product but rather in a specific type of product (eg. LCD TV sets with 30-39 inches) Geizhals.at allows to search for such a type, but the results are not ordered according to price[16]. This variation of product viewing at Geizhals.at, thus, gives a way to check the importance of ordering according to price for the two-stage decision process. If we can show in this new setting with no explicit price-ordering that the importance of quality vs. relative price increases as well if we concentrate on final purchases, this result would reinforce our suggested heuristic. In doing so we take advantage of the different firm specific product assortment within the subsubcategories resulting in different firm performances measured by the click frequency. Table 7 presents the results for this strategy.

In order to control for the substitutional relationship between the products on the subsubcategorial level we have collapsed the dataset by averaging the variables on the subsubcategorial level for each firm - some of these variables are firm specific constants anyway). In the resulting dataset the firm's success measured with the average purchase clicks in the subsubcategory can be regressed again on firm specific variables (eg. average price of substitutes in the subsubcategory, firm evaluation, ...). It should be noted that by averaging purchase clicks over the various products a firm offers changes the character of the dependent variable from a count to a continuous variable. We can therefore use Ordinary Least Squares estimations with a fixed effect on the subsubcategorial level. Whereas Column(1) includes the offers of all products, Columns (2) to (4) are reduced to the 120 cheapest, the 80 cheapest and the 40 cheapest shops[17].

[16]It should be mentioned that Geizhals.at has offered this feature at a later point in time.

[17]Due to averaging over different products and the fact that we only have 366 subsubcategories we have to increase the number of top-listed firms in order to get a meaningful dataset.

Although no price ranking is available on the website for the substitutes within a subcategory at this point in time we find our two stage decision strategy confirmed. Whereas the coefficient for the price variable declines considerably and turns into insignificance the coefficient for the firm evaluation increases over the different sub-samples. Again the relative importance of the price variable is decreasing in support of a much stronger influence of non price related variables if we focus on the set of firms with a higher purchase probability. This applies to firm evaluation, but also to other reliability-related characteristics, like the firm being located abroad, pick-up possibilities and availability. Consumers construct a short-list according to the price on the first stage, in the second stage other variables have a much stronger influence on the actual decision process.

6 Conclusions

We suggest a new sequential decision strategy for shoppers who have the choice between several different dimensions of a product. For the empirical validation of the procedure a new comprehensive data set from an Austrian price search engine is used. The dataset is unique because it covers a very large number of products and firms and allows to control for substitutional relationships between the various products.

Our two stage decisions model proposes that consumers fix a reservation price and winnow all product offers with higher prices on the first stage. Within the remaining shortlist of product offers consumers will carry out a comprehensive consideration of the different choice alternatives. We found convincing evidence for this decision model in data from an Austrian price search engine www.geizhals.at: Although we could not test the two stage decision procedure directly we can show with indirect hedonic price functions that the price variable is the dominant variable in the first stage of the decision process - however, the more we restrict our dataset to the set of product offers with a higher purchase probability the more important become other variables like firms' service evaluation by customers, product availability, pick up facility of a web-shop etc. Identification of referral requests with higher purchase probability is being done by restricting our data to different subsamples as well as the usage of the so-called Last Click Through concept.

This result is quite remarkable and robust; in particular in light of our special market situation: buying online with a price comparison site is probably the decision making situation where a fully informed and rational decision is easiest to accomplish and still we find overwhelming evidence of a short-list behavior. While we cannot extrapolate our results to other markets, the suspicion remains that in other markets non-fully rational procedures might abound.

Table 1: Descriptives

	Min	Max	Median	Mean	Std. Dev.	Description
#Clicks	0	3434	0	0.60	6.68	Number of clicks (referral requests) from consumers for firms' product offers
Rel. price	0.0056	5	0.99	1	0.18	Firm's product price relative to the market's mean product price
Firm evaluation	1.05	3.55	1.68	1.74	0.47	Customers evaluations of the e-tailer (1 best and 5 worst)
Germany	0	1	1	0.69		Dummy: 1 if firms' country of origin is Germany, 0 if country of origin origin is Austria
Avail	0	1	0	0.29		Dummy: 1 if offered product is immediately available
Pick up	0	1	0	0.24		Dummy: 1 if e-tailer offers pick-up possibility
Pricelevel	0.24	1.47	0.991	1	0.068	General price level of the firm relativ to the average general price level
#evaluations	5	1076	48	113.48	161.54	Number of customers evaluations per firm
Rel. Shipping Cost	0.047	3.94	1.03	1	0.386	Firm's shipping cost (cash on delivery) relativ to the average (imputation with mean if not available)
Miss. ship. cost	0	1	0	0.10		Dummy: 1 if shipping cost are not available
LCT prod-week	0	158	0	0.044	0.46	Identification of Purchase Click with 'Last-Click Through' concept on product level
LCT subsubc-week	0	70	0	0.025	0.27	Identification of Purchase Click with 'Last-Click-Through' concept on subsubcategorial level
LCT subc-week	0	38	0	0.0087	0.128	Identification of Purchase Click with 'Last-Click-Through' concept on subcategorial level

Table 2: Demand for Top-listed Firms

Data Sample	all product offers	top-listed 20 firms	top-listed 10 firms	top-listed 5 firms
Rel. Price	-1.3210***	-2.4633***	-3.3768***	-4.8273***
	(0.0098)	(0.0257)	(0.0455)	(0.0918)
Firm evaluation	-0.0281***	-0.0800***	-0.1508***	-0.2831***
	(0.0014)	(0.0033)	(0.0056)	(0.0108)
Rel. Shipping costs	0.0127***	-0.0011	-0.0136***	-0.0234**
	(0.0014)	(0.0032)	(0.0052)	(0.0095)
Germany	-0.2202***	-0.5148***	-0.6374***	-0.6996***
	(0.0024)	(0.0072)	(0.0122)	(0.0214)
Availability	0.0990***	0.1674***	0.2313***	0.3357***
	(0.0016)	(0.0036)	(0.006)	(0.0113)
Pick Up	0.0495***	0.1008***	0.1640***	0.2758***
	(0.0016)	(0.0039)	(0.0069)	(0.0135)
Pricelevel	-0.3773***	-0.4238***	-0.4752***	-0.5431***
	(0.0121)	(0.0278)	(0.0455)	(0.0833)
Miss. ship. cost	0.1256***	0.1989***	0.2394***	0.3014***
	(0.0025)	(0.0052)	(0.0082)	(0.0148)
#evaluations	0.0003***	0.0005***	0.0006***	0.0007***
	(0.00001)	(0.00002)	(0.00003)	(0.00008)
Observations	847641	416623	247697	135250
Products	34139	33500	32296	30408
χ^2	89682	44299	24564	11354
LL	-422771	-284898	-197681	-118157
rel. Importance of price over service	47.0	30.8	22.4	17.1

Method of Estimation: Negative Binomial with product fixed effects - marginal effects with respective standard errors are shown. *, ** and *** indicate statistical significance at the 10-percent, 5-percent and 1-percent level. Constant is not shown in Table. Marginal effects for dummy variables represent discrete change from 0 to 1.

Table 3: Demand for Bottom-listed Firms

Data Sample	all product offers	offers with firm rank >20	offers with firm rank >40	offers with firm rank >60
Rel. Price	-1.3210***	-0.3281***	-0.1023***	-0.0096
	(0.0098)	(0.0088)	(0.0091)	(0.0099)
Firm evaluation	-0.0281***	-0.0121***	-0.0050*	-0.0001
	(0.0014)	(0.002)	(0.0029)	(0.0046)
Rel. Shipping costs	0.0127***	0.0143***	0.0175***	0.0180***
	(0.0014)	(0.0019)	(0.0027)	(0.0042)
Germany	-0.2202***	-0.2066***	-0.1617***	-0.1304***
	(0.0024)	(0.0035)	(0.0044)	(0.0061)
Availability	0.0990***	0.0831***	0.0866***	0.0840***
	(0.0016)	(0.0023)	(0.0036)	(0.0058)
Pick Up	0.0495***	0.0319***	0.0368***	0.0452***
	(0.0016)	(0.0019)	(0.0028)	(0.0046)
Pricelevel	-0.3773***	-0.1689***	-0.1946***	-0.1695***
	(0.0121)	(0.0165)	(0.0229)	(0.0344)
Miss. ship. cost	0.1256***	0.0874***	0.0864***	0.0819***
	(0.0025)	(0.0037)	(0.0057)	(0.0092)
#evaluations	0.0003***	0.0003***	0.0002***	0.0002***
	(0.00001)	(0.00001)	(0.00001)	(0.00001)
Observations	847641	289784	118970	46094
Products	34139	7350	3182	1339
χ^2	89682	30854	11511	3683
LL	-422771	-99553	-37619	-13688
rel. Importance of price over service	47.0	27.1	20.5	-

Method of Estimation: Negative Binomial with product fixed effects - marginal effects with respective standard errors are shown. *, ** and *** indicate statistical significance at the 10-percent, 5-percent and 1-percent level. Constant is not shown in Table. Marginal effects for dummy variables represent discrete change from 0 to 1.

Table 4: Demand for Products with Few Suppliers

Data Sample	all product offers	products with max. 20 firms	products with max. 10 firms	products with max. 5 firms
Rel. Price	-1.3210***	-2.7662***	-3.6066***	-4.3609***
	(0.0098)	(0.0457)	(0.0904)	(0.1815)
Firm evaluation	-0.0281***	-0.1422***	-0.2860***	-0.5061***
	(0.0014)	(0.0081)	(0.0182)	(0.0414)
Rel. Shipping costs	0.0127***	0.0362***	0.0343**	0.0043
	(0.0014)	(0.0081)	(0.0172)	(0.0372)
Germany	-0.2202***	-0.5133***	-0.6470***	-0.5792***
	(0.0024)	(0.0122)	(0.0235)	(0.0409)
Availability	0.0990***	0.2447***	0.3452***	0.4666***
	(0.0016)	(0.0089)	(0.0184)	(0.0405)
Pick Up	0.0495***	0.0985***	0.1551***	0.2607***
	(0.0016)	(0.0085)	(0.0179)	(0.0399)
Pricelevel	-0.3773***	-1.0575***	-0.9622***	-0.3212
	(0.0121)	(0.0604)	(0.1218)	(0.2572)
Miss. ship. cost	0.1256***	0.1873***	0.2527***	0.3624***
	(0.0025)	(0.0095)	(0.0187)	(0.0413)
#evaluations	0.0003***	0.0006***	0.0007***	0.0009***
	(0.00001)	(0.00001)	(0.00001)	(0.0001)
Observations	847641	158843	73187	29375
Products	34139	20611	14845	9233
χ^2	89682	15904	6840	2233
LL	-422771	-108389	-52715	-21183
rel. Importance of price over service	47.0	19.5	12.6	8.6

Method of Estimation: Negative Binomial with product fixed effects - marginal effects with respective standard errors are shown. *, ** and *** indicate statistical significance at the 10-percent, 5-percent and 1-percent level. Constant is not shown in Table. Marginal effects for dummy variables represent discrete change from 0 to 1.

Table 5: Purchase Clicks

		Type LCT		
	all clicks	prod-week	subsubc-week	subc-week
Rel. Price	-1.3210***	-1.48647***	-1.61231***	-1.61925***
	(0.0098)	(0.03755)	(0.05816)	(0.1172)
Firm evaluation	-0.0281***	-0.05018***	-0.04296***	-0.04580***
	(0.0014)	(0.00414)	(0.00495)	(0.00743)
Rel. Shipping costs	0.0127***	0.00948**	0.01276***	0.0082
	(0.0014)	(0.0037)	(0.00435)	(0.00608)
Germany	-0.2202***	-0.26541***	-0.27207***	-0.24097***
	(0.0024)	(0.00805)	(0.01126)	(0.01918)
Availability	0.0990***	0.14722***	0.14358***	0.12140***
	(0.0016)	(0.00539)	(0.00702)	(0.0111)
Pick Up	0.0495***	0.08132***	0.07975***	0.08005***
	(0.0016)	(0.00478)	(0.00597)	(0.00959)
Pricelevel	-0.3773***	-0.25630***	-0.16887***	-0.18842***
	(0.0121)	(0.03335)	(0.03935)	(0.05695)
Miss. ship. cost	0.1256***	0.11645***	0.13371***	0.10464***
	(0.0025)	(0.00679)	(0.00885)	(0.01268)
#evaluations	0.0003***	0.00033***	0.00033***	0.00028***
	(0.00001)	(0.00001)	(0.00001)	(0.00002)
Observations	847641	400841	306764	157748
Products	34139	11239	8624	4028
χ^2	89682	15027	10696	4143
LL	-422771	-74727	-45813	-17889
rel. Importance of price over service	47.0	29.6	37.5	35.4

Method of Estimation: Negative Binomial with product fixed effects - marginal effects with respective standard errors are shown. *, ** and *** indicate statistical significance at the 10-percent, 5-percent and 1-percent level. Additional variables as in Table 2.

Table 6: Censored Purchase Clicks

		Type LCT		
	ALL CLICKS	PROD-WEEK	SUBSUBC-WEEK	SUBC-WEEK
Rel. Price	-1.3210***	-1.20991***	-1.60663***	-1.61672***
	(0.0098)	(0.07018)	(0.09541)	(0.14524)
Firm evaluation	-0.0281***	-0.12654***	-0.08137***	-0.09036***
	(0.0014)	(0.0156)	(0.01684)	(0.02026)
Rel. Shipping costs	0.0127***	0.00005	0.01653	0.01306
	(0.0014)	(0.01387)	(0.01488)	(0.01718)
Germany	-0.2202***	-0.19232***	-0.22925***	-0.18690***
	(0.0024)	(0.01711)	(0.01993)	(0.02499)
Availability	0.0990***	0.22887***	0.22498***	0.15518***
	(0.0016)	(0.01509)	(0.01719)	(0.02061)
Pick Up	0.0495***	0.15470***	0.14852***	0.12998***
	(0.0016)	(0.01589)	(0.01785)	(0.0221)
Pricelevel	-0.3773***	-0.04051	0.00189	-0.15841
	(0.0121)	(0.12088)	(0.13176)	(0.15555)
Miss. ship. cost	0.1256***	0.17042***	0.21094***	0.14228***
	(0.0025)	(0.01999)	(0.02297)	(0.02681)
#evaluations	0.0003***	0.00038***	0.00044***	0.00035***
	0.00001	0.00003	0.00003	0.00004
Observations	847641	90638	73691	43436
Products	34139	10910	8086	3841
χ^2	89682	1299	1307	643.5
LL	-422771	-51610	-32658	-13478
rel. Importance of price over service	47.0	9.6	19.7	17.9

Method of Estimation: Negative Binomial with product fixed effects - marginal effects with respective standard errors are shown. *, ** and *** indicate statistical significance at the 10-percent, 5-percent and 1-percent level. Additional variables as in Table 2.

Table 7: Choice Among Close Substitutes

Data Sample	all offers within sub-subcategory	top-listed 120 firms within subsub-category	top-listed 80 firms within subsub-category	top-listed 40 firms within subsub-category
Rel. Price	-0.04651***	-0.04038***	-0.03080*	-0.01768
	(0.01251)	(0.01419)	(0.01717)	(0.02565)
Firm evaluation	-0.01112***	-0.01111***	-0.00985**	-0.01484**
	(0.00406)	(0.00425)	(0.00466)	(0.00592)
Rel. Ship. costs	0. -0.00127	-0.00275	-0.00328	-0.00313
	(0.00403)	(0.0042)	(0.00457)	(0.00585)
Germany	-0.02974***	-0.02919***	-0.03145***	-0.03923***
	(0.00426)	(0.00458)	(0.00529)	(0.00742)
Availability	0.03243***	0.02936***	0.02709***	0.02703***
	(0.00424)	(0.00445)	(0.0049)	(0.00632)
Pick Up	0.01878***	0.01893***	0.01806***	0.01413**
	(0.00408)	(0.00432)	(0.00486)	(0.00648)
Pricelevel	-0.03174	-0.01822	0.00172	-0.04506
	(0.03136)	(0.0338)	(0.0383)	(0.0498)
#evaluations	0.00006***	0.00006***	0.00006***	0.00005***
	(0.00001)	(0.00001)	(0.00001)	(0.00001)
Observations	23472	21501	18324	11782
Subsubcategories	366	366	366	366
R^2	0.01	0.009	0.008	0.008
LL	-1926	-1867	-1936	-1611
rel. Importance of price over service	3.7	3.6	3.1	1.2

Method of Estimation: Ordinary Least Squares Estimation with product fixed effects - marginal effects with respective standard errors are shown. Dependent Variable: Firms' average of Last-Click-Throughs for all products within subsubcategory. *, ** and *** indicate statistical significance at the 10-percent, 5-percent and 1-percent level. Constant is not shown in Table. Marginal effects for dummy variables represent discrete change from 0 to 1.

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