Optimizing Price Levels in E-Commerce Applications with Respect to Customer Lifetime Values

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ABSTRACT

In a recent paper we have shown how Internet retailers could optimize their price levels according to their strategy. The discussed method optimizes short-term profitability by determining the exact demand curve. The method involves the application of empirical price tests. For this purpose visitors of an Internet retailer are divided in statistically identical subgroups. Using the A-B testing method different prices are shown to each subgroup and the conversion rate as a function of price is calculated. We describe the organizational requirements, the technical approach, and the statistical analysis applied to determine the price optimizing the per-order profit and the average customer lifetime value. In this paper we review the results of a field study carried out with a large Internet retailer and shows that the company was able to optimize a specific price component and thus increase the contribution margin per order by about 7%. In addition we argue that at the same time the customer lifetime value could be enhanced by 13%. We conclude that the discussed method could be applied to answer further research questions such as the temporal variation of demand curves.

Categories and Subject Descriptors

H.4.m [**Information Systems Applications**]: Miscellaneous; K.4.4 [**Electronic Commerce**]

General Terms

Management, Economics, Experimentation

Keywords

electronic commerce, pricing strategy, price optimization, price tests, price dispersion, price partitioning, demand curve, posted prices

1. INTRODUCTION

Over the last years the pricing of products and services in the online channel has attracted significant attention from the research community ([6], [7], [13], [19]). Due to data availability most work has been done on interactive pricing schemes and auction theory with respect to Internet business models ([17]). While interactive pricing schemes mostly apply to consumer-to-consumer scenarios (e.g. eBay) they are rarely used in business-to-consumer scenarios in which fixed prices (sometimes referred to as posted prices) dominate successful business models. In the area of fixed or non-interactive prices some work has gone into the study of price dispersion ([2], [5]) and price discrimination in different circumstances, for example under consideration of privacy issues ([3], [14]).

Brynjolfsson and Smith [5] have shown empirically that the Internet cannot be considered to be a frictionless market but that price dispersion can be observed for a wide range of products (e.g. prices for books differ by an average of 33%). They argue that, with respect to prices, competition in a specific market and brand as well as trust in a specific company remain a source of heterogeneity among Internet retailers.

This result leaves room for companies to adjust their price level for specific products and services to the profit maximizing level. Empirical price tests have been suggested as the appropriate means for finding optimal "one-for-all" fixed prices [1]. To do so we apply the A-B testing method [15] and show that for standardized goods and services this approach supports price optimization.

The contribution of this paper is threefold. First, a method for optimizing fixed prices in e-commerce applications is proposed and discussed in detail for the first time in the scientific literature. Even though the potential of the method has been pointed out before, there has been no such detailed discussion. Second, the method is set into the context of decision problems related to customer acquisition costs and customer lifetime value. Since changes in price levels influence the overall conversion rate of an e-commerce application, it does not only impact the contribution margin of the customer's first order but also the average cost per acquisition. Third, results of and issues encountered during a field study carried out with a large German Internet retailer are presented.

The paper is organized as follows: in the next chapter we review related work, focusing on aspects of non-interactive pricing. In chapter 3 we describe the method and the basic assumptions of our work in general. Chapter 4 deals with the environment of the field study and the organizational and technical implementation. The results section (chapter 5) presents sanitized data from the field study, shows how to derive the optimal price level and discusses the implications with respect to the average cost per acquisition. The conclusion briefly summarizes the major ideas of the paper and directs attention to where further research is needed.

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2. RELATED WORK

2.1 Price Dispersion

With the advent of e-commerce it was assumed that the Internet would reduce consumer search costs and switching costs and that this would finally lead to more competition and lower prices. This argument was expected to take markets closer to the theoretical model of perfect competition [7]. However, price dispersion is observed not only for heterogeneous products but also for homogeneous ones like books and DVDs.

This phenomenon has often been studied (see the paper from Baye et al. [2] for an overview and [4]) and a number of possible reasons have been suggested. Product differentiation among retailers is one explanation. Differentiation can happen along features, qualities, and services thus softening price competition. In addition the brand of a company and the loyalty of customers to it play an important role in avoiding price competition.

Furthermore, searching and comparing offerings of identical products from different sites is associated with costs. Hann and Terwiesch [11] define these frictional costs as "the disutility related to learning to navigate through websites, the disutility of keying in order and payment information, the cognitive costs of comparing different offerings, and the opportunity cost of time for the online transaction".

Price dispersion in the Internet enables (and forces) companies to set their own prices while taking into account their strategic goals. There is a large body of knowledge on how this can be accomplished in the offline world (see for example the book from Simon and Dolan [18]). Setting prices is based on a customer's willingness to pay, the cost structure of the company under consideration and the pricing policies of relevant competitors. In some cases "strategic" dumping prices or communication reasons (e.g. being perceived as a high quality provider) are involved when setting prices. More often prices are set in order to optimize short or medium-term profit. To do so the demand as a function of price has to be determined. Different methods have been employed to determine the demand curve: (i) customer and expert interviews, (ii) market observation, and (iii) lab and field experiments. Field experiments have two major problems in the offline world: (i) menu costs forbid changing prices often, thus reducing the possible granularity of price tests, (ii) price tests are carried out either at different locations at the same time or at the same location at different times – therefore, interpreting results requires taking into account potentially different environments. Online price tests can overcome these difficulties and lead to accurate and realistic demand curves, which can then be used to find the optimal prices with respect to profit maximization.

2.2 Customer Lifetime Value

Making decisions between alternative options, based on the different discounted cash flow values, has a long standing tradition in managerial economics. The derived concept of customer lifetime value (CLV) is especially used for the valuation of fast growing companies and tactical decisions in marketing ([8], [16]). The latter for example addresses questions like: what customer segments should be targeted and what cost per acquisition c_0 (CPA) is acceptable? In this work we will consider the lifetime value of a cohort of customers which is given by

$$CLV = n_0 \sum_{t=0}^{\infty} m_t \frac{r^t}{(1+i)^t} - n_0 c_0$$

where n_0 is the number of customers, m_t is the margin in time period t per customer, r is the retention rate of customers per time period and i is the constant discount rate per time period. In this paper we will calculate (and optimize) the CLV to determine the optimal price level on long time scales (>several years).

3. METHODOLOGY

3.1 Assumptions and Limitations

Visitors of an e-commerce site form a heterogeneous group in terms of characteristics such as age, sex, education, purchasing power, and, what is important for our work, the willingness to pay for a given product or service. However, provided that the group of all visitors is sufficiently large, dividing visitors randomly into subgroups (not necessarily of the same size) leads to these subgroups having identical characteristics as the base group. That means that for example the fraction of persons between 20 and 30 years old is – within the margin of statistical error – the same for each subgroup. To generate subgroups, visitors are assigned to one of the subgroups randomly (e.g. on a rolling basis) when they enter the e-commerce site. This facilitates the application of A-B tests for several purposes, e.g. the optimization of click-through rates for different landing pages.

The method works for standardized goods only and assumes that the price sensitivity of customers remains constant over time. It is obvious that this is a simplifying assumption which should be examined in more detail. Furthermore, the method requires the e-commerce site to have enough visitors and transactions (what 'enough' means is defined below) as well as to offer enough technical flexibility to vary posted prices. It should be emphasized that we do not address or propose price discrimination and visitor/customer segmentation based on accessible properties such as the internet service provider, the technical configuration of the browser, or the referrer URL, even though A-B tests could also serve this purpose.

3.2 Method Description

An e-commerce service involves several price components such as the prices for the product ordered, a service charge, an express shipping fee, a fee for using specific payment methods but also posted discounts on all these components. At the beginning of a study, using the method described in this paper, it has to be decided what price component should be observed and optimized and what the appropriate price range for this component might be. The price range may depend on e.g. competitor's prices and own cost structures.

During the study, customers from each subgroup are provided with different (discrete) prices chosen from the above price range. Then conversion rates – that is the ratio of buyers to visitors – are calculated for each subgroup. This allows us to find the demand curve, which does not calculate the absolute amount as a function of price as is usually done, but instead the conversion rate as a function of price. If we disregard temporal changes of the demand curve due to, for example, seasonal or weather related fluctuations (see assumptions and limitations) we can determine the conversion rate with as much precision as desired, with the only limit being the statistical error which is related to the number of visitors and buyers in each subgroup. Given a range of prices to be tested the number of subgroups corresponds to the granularity of the price test. The number of possible subgroups in turn depends on the number of visitors and buyers in the period of time of the price test and the desired precision of the conversion rate.

Online price tests overcome the two major problems stated in the previous chapter: (i) once the proposed method in this paper is technically implemented the menu costs, and thus the cost of changing prices, decrease substantially, (ii) since the different prices are displayed virtually at the same time in (with respect to

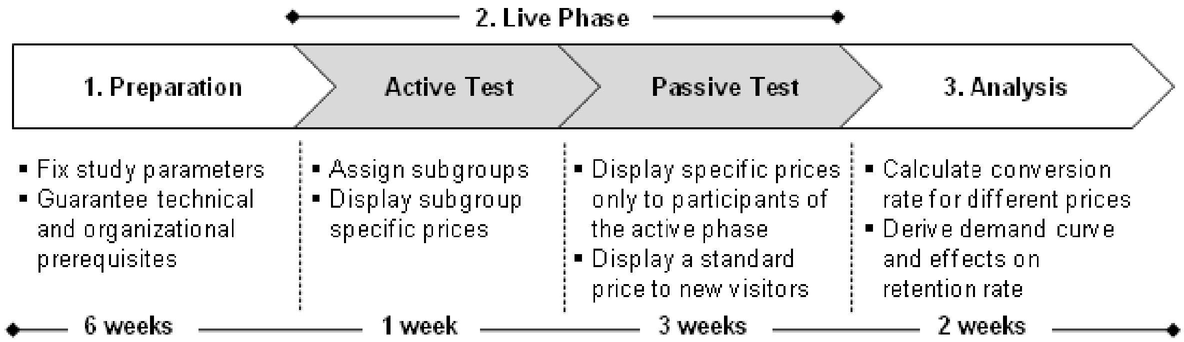

Figure 1: Overview of the actions in the three main phases, the time periods refer to the field study

their characteristics) identical subgroups there are no differences between the environments.

	P_1	P_2	P_3	P_4
S_1	$CR_{1,1}$	$CR_{1,2}$	$CR_{1,3}$	$CR_{1,4}$
S_2	$CR_{2,1}$	$CR_{2,2}$	$CR_{2,3}$	$CR_{2,4}$
S_3	$CR_{3,1}$	$CR_{3,2}$	$CR_{3,3}$	$CR_{3,4}$
S_4	$CR_{4,1}$	$CR_{4,2}$	$CR_{4,3}$	$CR_{4,4}$

Table 1: P_i und S_j represent the different prices charged in the price test. $CR_{i,j}$ is the observed conversion rate at prices P_i und S_j. The price test involves using 16 subgroups.

Recent research has shown that partitioning prices into mandatory price components can increase the willingness to buy while leaving the revenue per sale unchanged. In a series of laboratory experiments Hamilton and Srivastava [10] found out that consumers are more sensitive to prices of product components which provide a lower consumption benefit. These insights and others (e.g. Hossain and Morgan [12]) could be used to generate hypothesis about optimal price partitioning and then test them using our approach. For example, the interplay between the product price P_i and a standard service charge S_j and how these prices are perceived by customers might be studied. This involves offering the subgroups a number of combinations regarding the individual price components and calculating the conversion rate (Table 1). This also allows the study of price-dependent substitution effects between products. These studies are only limited by the number of visitors and buyers per subgroup needed for a statistically valid statement, and so the number of possible subgroups.

3.3 Phases

The price test is carried out in three phases (see Fig. 1). In the first phase we fix the price component to be studied, the range containing the expected profit-maximizing price and the duration of the test needed for statistical validity. In addition the technical (generating subgroups, providing them consistently with different prices, collecting data) and organizational requirements (communication policies, customer service training) have to be taken care of. The second phase, which we call the live phase, is subdivided into two time periods. In the first period all visitors are assigned to one of the subgroups at their first visit and are shown the respective price for the subgroup. Alternatively, for high traffic sites only a fraction of all customers are selected to participate in the price test (as in the field study), since this fraction is already large enough to allow for valid conclusions. In the second period of the live phase the changed prices are only shown to those visitors who already visited the site during the first period of the live phase (how visitors are identified is discussed in the next chapter). Visitors who 'enter' the store for the first time in the second period are shown a standard price. This procedure allows recording the effect of changed prices on the customer retention rate. The third phase concerns data analysis and interpretation.

4. IMPLEMENTATION

4.1 General Aspects

The kind and scope of technical changes required for the price test depend on the technical system being used in the front- and backend and its flexibility. The two most important technical requirements for a successful price test consist of the reliable identification of visitors (as far as possible) as well as a consistent communication of the specific price per subgroup based on their identification. These requirements have to be fulfilled for both the front- and the backend. In the frontend cookies and URL encoded session IDs can be used for the identification of visitors and their assignment to a subgroup, in the backend only customers are handled and thus, the identification is easy. Visitors that do not permit persistent cookies should be excluded from the price test and be shown a standard price. If visitors delete cookies regularly they may be quoted different prices for the same product in consecutive visits. An alternative approach to using cookies for identifying subgroups is to use a so-called fingerprint, which is generated based on the technical configuration of a visitor's browser (user agent, operating system, version, resolution). This approach is robust against cookies being deleted, but may lead to subgroups not being identical in their characteristics. For example Firefox users could share a greater willingness to buy a given product than users of Internet Explorer and so influence the conversion rate independently of the price. To avoid displaying different prices to a visitor who uses different computers is almost impossible and would require the visitors to identify themselves by login before seeing prices, which is uncommon in B2C systems.

Besides ensuring the re-identification of visitors the system must guarantee that the posted prices are the ones that are actually processed in the financial system and that a customer is charged accordingly. The posted prices also have to be taken into account, both in electronic (confirmation email, FAQs) and in paper-based (invoice) communication with the customer. Ensuring these technical requirements are fulfilled can, depending on the technical platform being used, involve considerable expense.

4.2 Field Study

We will illustrate the technical implementation of the price test using a field study [8]. The research site is a German e-commerce

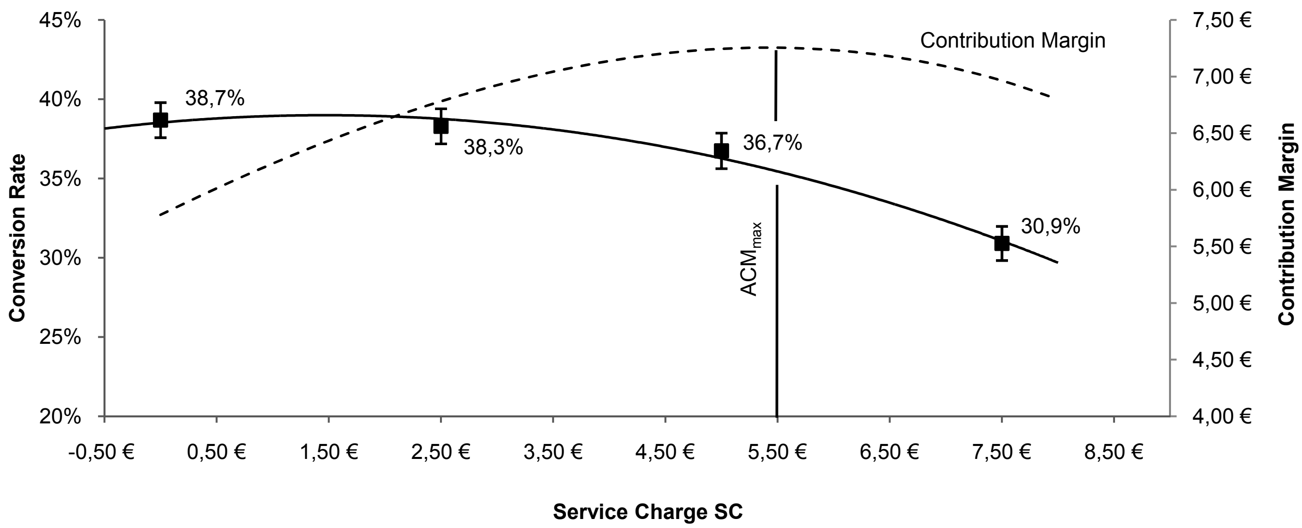

Figure 2: For each of the 4 subgroups there is one data point shown in the figure above covering the range from €0.00 to €7.50. The sample size is about 1,900 for each data point and so the error is about +/- 1.1%, slightly above the planned value of 1.0%, which is due to the fact that the sample size turned out to be a bit lower than expected. The dashed line shows the average contribution margin per visitor who has seen the seen the electronic basket.

site with an annual revenue of about 100 million euros at the time of the study. The site offers a large number of products (>10,000), whose individual prices vary only slightly between the company's and its competitors. The technical platform is a Java-based, proprietary web application which is operated, maintained and further developed by the IT department of the company. The backend system was also individually developed for the company.

In the preparatory phase (outlined in section 3), we decided at the beginning of the project that rather than test individual product prices we would study the optimization of the service charge collected with each order. With respect to the technical implementation we decided to use cookies to identify users participating in the price test. When a visitor arrived on the web site during the live phase it was checked whether he already had a cookie related to the price test. If not, a cookie was set containing information about which subgroup the visitor had been assigned to. If there was already a "price test cookie", it was used to show the appropriate service charge for the subgroup. In addition to the cookie, a session ID was generated that contained an ID referring to the appropriate subgroup (SGID). Since the shop system supported URL rewriting (hence URLs contained the SGID), users who bookmarked the site and deleted the cookies could still be identified as belonging to a particular subgroup. Furthermore the SGID was used to communicate and use prices consistently throughout the shopping process of the visitor, even when cookies were not enabled by the user.

The first time the visitor saw the service charge was in the electronic basket. Therefore the conversion rate for each subgroup was not determined as the plain ratio of buyers to total visitors but as the ratio of buyers (with a certain SGID) to visitors (with the same SGID) who entered the electronic basket at least once during their session and so were able to see the service charge (in the following chapter this value is referred to as CR_{Basket}).

The first phase (including project set-up, software design and implementation as well as internal communication and preparation) took about six weeks. The first part of the live phase took about 6 days, the second part about 3 weeks. Results were presented 3 months after the beginning of the project.

Alongside the technical requirements there are also organizational ones. Obviously price tests should be managed by the department/ people responsible for price management in the company taking into account what the limits with respect to strategic positioning and competitors are. Furthermore, before starting the price test employees who actively enter into contact with customers of the website (especially service staff) or who are contacted by customers need to be informed and trained in how to deal with price enquiries by telephone and email, canceling orders and possible complaints about different prices caused by the price test. In the latter case the service staff was asked to communicate the display of different prices as a technical error and to apologize by sending out a €5 gift certificate to the complaining visitor/ customer. As long as the number of gift certificates sent out is small it does not impact the price test.

5. RESULTS

Before the price test the service charge was €2.50 per order. At the beginning we decided to investigate the price range between €0.00 and €7.50. In order to be able to reach valid conclusions after a short period of time it was decided to test four values for the service charge (€0.00/ €2.50/ €5.00/ €7.50). Following basic statistics with respect to the necessary sample size, the required time period for the test can be estimated by:

$$T_{Test} \approx \frac{N_{Bin}\left(\frac{CI}{e}\right)^2 CR_{Basket}\left(1 - CR_{Basket}\right)}{V_B}$$

where N_{Bin} is the number of subgroups (=4), CI is the chosen confidence interval (=1 σ), e is the allowed error (=1%), CR_{Basket} is the ratio of buyers to visitors who have seen the electronic basket (~40%, as an approximate value before the price test was carried out), and V_B is the number of visitors seeing the electronic basket per day (=1,500 per day, here only a fraction of all visitors to the website participated in the price test). A calculation using company data from the field study leads to necessary time period for the study T_{Test} of 6.4 days. The price test was carried out on 6 consecutive days and yielded the following results.

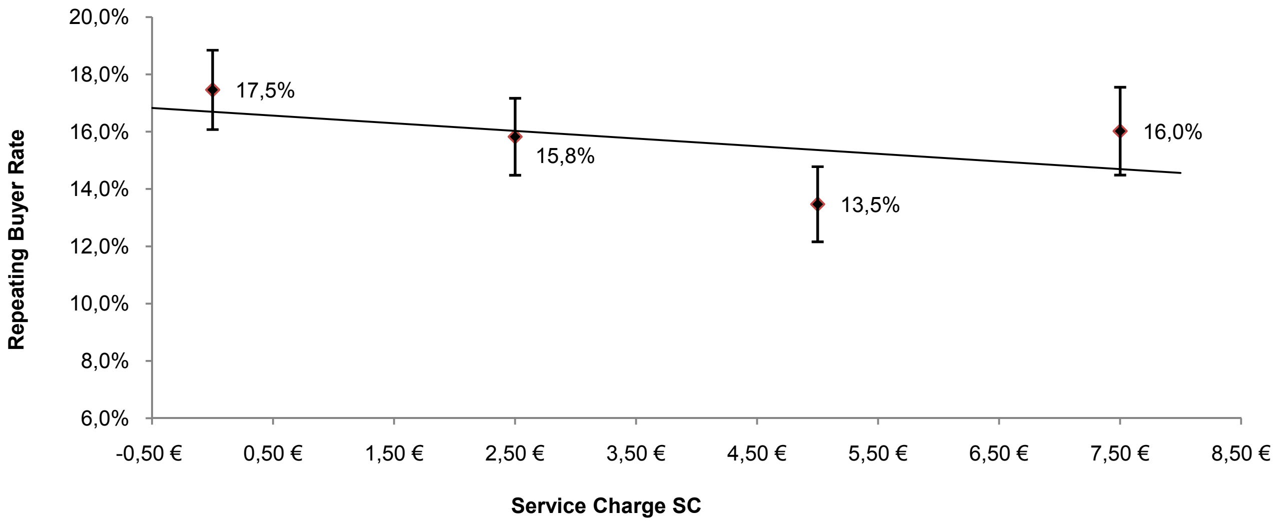

Figure 3: For each subgroup the fraction of buyers that bought again during the test period is determined. The slope of the linear function is statistically consistent with 0. Thus, in the considered price interval no significant dependency of the repeating buyer rate and the service charge could be observed.

5.1 Interpretation

Figure 2 shows the dependency of the basket conversion rate CR_{Basket} as a function of the service charge SC. As expected, the conversion rate decreases (statistically significant) with the service charge, indicating the customer's decreasing willingness to pay the increasing service charge. It should be emphasized that each data point (and the corresponding samples) consists of sales with a wide variety of products and a wide range of prices. Nevertheless, allowing for standard deviation the samples are identical. At this point the exact functional dependency is not important for the argument and thus we decided not to use theoretical functions from microeconomics. For practical purposes, in the field study the empirical data were fitted using a second order polynomial function CR_{fit}:

$$CR_{fit} = (-2.2 \pm 0.6) \cdot 10^{-3} \bullet SC^2 + (6{,}2 \pm 5.1) \cdot 10^{-3} \bullet SC + (0{,}385 \pm 0.008)$$

In order to find the optimal service charge the full economics of the company under consideration had to be taken into account. In this paper we initially make the following simplifying assumptions[1]: the service charge should be set in such a way that it maximizes the average contribution margin of a visitor who has seen the electronic basket. We assume that the contribution margin of a single order is given by $CM_{prod} + SC - C_S$, where CM_{prod} is the average contribution margin of the products sold in an average order and C_S (= €3.00) is the internal order fulfillment cost (including e.g. postage, wages, machines). For our analysis CM_{prod} (= €18.00) is assumed to be independent of SC, even though the average revenue in a subgroup per visitor (and thus the contribution margin) might be positively correlated with SC, since it is likely that the willingness to accept a higher service charge will rise with increasing revenue. Formally, the problem is to find

$$SC : \max ACM_{visitor} \text{ with}$$
$$ACM_{visitor} = CR_{fit}(SC)\left(CM_{prod} - C_S + SC\right)$$

where $ACM_{visitor}$ is the average margin contributed by each visitor who sees the electronic basket at least once during his visit. Applying the above values the optimal service charge is about €5.50 compared to a service charge of €2.50 at the beginning of the field study. By setting the service charge to €5.50, the average contribution margin per visitor $ACM_{visitor}$ could be increased by 7% from €6.78 to €7.25.

5.2 Accounting for CLV

The procedure described above optimizes the contribution margin of an individual visitor with respect to his first order. The question is whether by taking into account the customer lifetime value as discussed in chapter 2.2 the price decision would change. First of all we focus on the retention rate and try to determine whether it significantly depends on the service charge. As an indicator we use the repeat buyer rate (what fraction of customers comes back after their initial order?) for the respective subgroups. Only the short term repeat buyer rates were calculated as only the data from the test period was available.

Figure 3 shows only a slight dependency of the repeat buyer rate on the service charge. The slope of the linear function in fig. 3 is 0.27 ± 0,31 % per EUR and thus not significantly different from 0. More data would be needed to prove or exclude the statistical significance of this dependency. A negative correlation between the repeat rate and the service charge would indicate that some customers are willing to buy once at a higher service charge but subsequently use alternative offerings. In order to optimize long-term profit this relationship would have to be taken into account in future studies.

From the data we conclude that for the first order the retention rate is independent of the service charge. Neglecting customer

[1] It should be noted that more realistic (and complicated) assumptions about the economics would not change the main results of the study

acquisition costs (as indicated by the prime in the next formula) and assuming that the margin m_t is equal to $ACM_{Visitor}$ and thus constant over time (as stated above) we can estimate the lifetime value of the cohort (resulting from a subgroup and the corresponding service charge) by

$$CLV'_{Bin} = V_B ACM_{Visitor} N_{yo} \sum_{t=0}^{\infty} \frac{r^t}{(1+i)^t}$$

where N_{yo} (about 1 order per year) is the number of orders per year. Since r was assumed to be independent of the service charge we can replace the infinite sum by a constant value T_L (for the field study we used 3.5 corresponding to an average lifetime per customer of 4 to 5 years). How customer acquisition costs are taken into account, depends on the advertising model used by the company. In general there are three basic alternatives (in practice, usually a mixture of them is employed); advertising partners are paid (i) for generating traffic to the website (e.g. search engine marketing or CPM-based bannering) without taking responsibility for the conversion to customers, (ii) a fixed fee C_C for each new customer, or (iii) a fixed fee C_O for each order directly related to the advertising partner.

$$CLV_{Bin} = V_B CR_{fit} \left(\left(CM_{prod} - C_S + SC - C_O f_O \right) N_{yo} T_L - C_C f_C \right) - C_{CPM}$$

where C_{CPM} is the total cost for all advertising actions described under (i), f_O (f_C) is fraction of orders (customers) for which the company pays a fee C_O (C_C) to an advertising partner. Since C_{CPM} does not depend on the service charge it has no influence on the optimization problem for CLV_{Bin}. For realistic values ($f_O = 40\%$, $f_C = 10\%$, $C_O = 6€$, $C_C = 15€$) CLV_{Bin} reaches its maximum for a service charge of €6.00 and thus only slightly higher than for optimizing the initial per-order-profit. However, the customer lifetime value could be significantly increased by 13% which easily justifies the effort of the study.

5.3 Customer Complaints

During the study there were less than 10 complaints from customers by email and telephone related to the observation of different prices. The great majority of these complaints came from existing customers who knew the original service charge and first noticed the supposed increase after ordering. These customers were not told the reason for the change but instead received a €5.00 gift certificate. The overall complaint rate was lower than that expected at the beginning of the field study and had no influence on the outcome. However, it should be emphasized that price tests and subsequent price increases could be associated with the risk of being perceived as an unreliable company by its existing and potential customers. Specifically, for very large retailers which are monitored by active customers (and price bots) our approach may impose additional risks.

For these companies, A-B-tests may be employed to analyze how the active communication of discounts changes the willingness to buy. This could be done by offering visitors gift certificates of different value (e.g. as a layer ad) during the information phase anteceding the transaction phase, in which a fraction of all visitors will buy a product. It remains to be studied how the results from such an experiment could be translated into a demand curve as described in this paper.

6. CONCLUSION AND FURTHER WORK

This paper deals with one of the fundamental questions in economics: what is the optimal price of products and services? The method described in this paper enables e-commerce companies (but also providers of digital content) to determine the exact demand curve represented by the conversion rate as a function of price. Based on the demand curve and the cost structure of a company, optimal price levels for products and services can be determined. The accuracy of this method is only limited by statistical means. In the field study this method has been applied to optimize the service charge of a large German e-commerce merchant. The field study shows that employing the method involves only limited expense and effort while significantly increasing the profitability of the company under consideration.

There is a large body of research around the topic of price dispersion in the Internet but only a limited amount of work has gone into studying what are the resulting degrees of freedom for companies and how they should use them. This paper opens substantial opportunities for future studies on this topic. Research questions include for example:

- How does the demand curve change over time? There are almost certainly seasonal effects. For example, there is an observable increase in the willingness to buy and to pay in Internet stores during the pre-Christmas season. Knowledge of such temporary effects would allow a further optimization as discussed in this paper.
- What consequences do the brand awareness of a company and the uniqueness of its products have on the demand curve? Companies may have market exclusivity for a part of their product range (for example, in Germany the iPhone can only be officially obtained from T-Mobile). This leads to a lower price elasticity. With the help of the method outlined in this paper the changes in demand due to a loss of exclusivity in a market or substitution products[2] can be investigated.
- What kinds of reciprocal dependencies are there between price components of an order? How could these dependencies be employed to optimize the overall profitability based on studies like the one from Hamilton and Srivastava [10]?
- Can user groups be identified that demonstrate varying degrees of willingness to pay? There are numerous criteria possible in e-commerce, for example the IP address can be used for regionally oriented pricing. The access provider, the user agent or the technical configuration of the computer can also provide information about how willing a customer is to pay (price discrimination).
- If it is possible to identify user groups with diverging willingness to pay, the question arises as to how prices could then be differentiated (e.g. by product differentiation) or concealed (e.g. by giving gift certificates to customers who use a certain access provider).

This paper is meant as a starting point for discussion and further research related to optimizing prices in e-commerce by determining the exact demand curve for products and services in different circumstances.

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