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SHOPBOTS AND INFORMATION QUALITY – RETAILERS’ STRATEGIES FOR PRICE CONCEALMENT

Abstract

ShopBots allow consumers to compare product offerings of online retailers and can thereby significantly reduce consumers’ search costs. Although it was expected that these comparisons would pull prices down to a single market price, prices in online markets have not even come close to those expectations. In this paper we show how retailers influence the quality of data and thereby successfully pursue strategies making products and prices hardly comparable. We find a notable amount of bundles in highly competitive product categories and show how retailers exploit consumers’ biased perception in terms of partitioned prices. Finally, we argue that with recent business models, it is very unlikely that ShopBots fulfil the promise of market transparency.

Keywords: ShopBots, Information Quality, Price Comparison, Price Concealment, Electronic Commerce.

1 INTRODUCTION

The Internet has radically reduced the marginal costs for collecting and distributing information and the resulting price transparency was expected to be a key driver towards an efficient market (Brynjolfsson and Smith 2000). ShopBots are key players in the process of data collection and distribution of product and price information. Such websites allow prospective buyers to search for suitable products and compare price offerings from multiple retailers. Search results are listed on a web site and link directly to the product offering of the corresponding retailer. Since all relevant information is available on the website, it is assumed that consumers can easily compare the offerings and choose the best offer since the results can be ordered by gross price, net price, shipping costs and other important attributes (Grover and Ramanlal 1999).

Presumably, a larger number of retailers included in the listing of ShopBots and thereby a large number of easily comparable product offerings lead to a more competitive market. However, there are several technical reasons for ShopBots to generally cover only a small sample of the Internet, and collect and report information biased in favour of certain retailers (Bradlow and Schmittlein 2000, Lawrence and Giles 1999). Furthermore, this limitation through technology is reinforced by economic motives. ShopBots generate most of their revenues from retailers, either in the form of fees for listings, fees for product placement or better rankings, commissions on referred sales, or advertising.

Although ShopBots have been available for over a decade now, price dispersion is still substantial. Thus, the question may no longer be “When will prices come down to expectations?” but “Will it ever happen?”. Kocas (2002) stated these questions several years ago but focused on the diffusion process of price-comparison tools and thus on the time it would take till prices would come down to expectations. ShopBots indeed turned out to be effective intermediaries in terms of matching demand and supply and therefore both, consumers and retailers, backed up this business model. However, the model of Kocas (2002) omitted to consider the retailers’ reaction to this substantial threat in form of a perfect market. Although retailers were not able to stop the development towards more transparency, they found suitable strategies to counter the total annihilation of information asymmetry (Grover and Ramanlal 1999). Several studies found, that not only price levels but also price dispersions are for some categories still substantially higher online than offline (e.g., Clay et al. 2002, Pan et al. 2002).

Expert interviews with retailers revealed that they came to an arrangement not only with the existence of ShopBots but also with resulting challenges of price comparison on the Internet. Retailers pursue two strategies: Firstly, they avoid the leashing of price wars by making product offerings incomparable and retreat to an area where no competitor is active. This strategy also ensures that the quality of the search results dramatically declines which also leads to frustrated users who then leave the ShopBot’s website. Secondly, even if the search results list easily comparable products, retailers may use partitioned prices. This makes it more difficult to compare prices, exploits consumers’ biased perception of partitioned prices, and is additionally an approach to segment the market. In this paper we conceptualize the strategies retailers pursue to conceal prices and then test our hypotheses in an empirical study.

The remainder of the paper is organized as follows: First, we conceptualize different strategies for the two phases of the product comparison process, which can be influenced by retailers. In an empirical study we then examine the most prominent strategies retailers might pursue for product and price concealment. In a last step we will link the disappointing – from the consumer’s point of view – findings to the business model that nearly all ShopBots pursue.

2 RETAILERS' STRATEGIES FOR CONCEALMENT

The interaction at a ShopBot can be modelled with three different phases. Figure 1 summarizes the process: Phase 0 is rather technically driven. The ShopBot adds offers to the database which can either be submitted by the retailer as XML stream or alternatively the ShopBot actively runs a web crawler that autonomously gathers offer data from external data sources like online shops. The retailer can choose to submit offers with easily identifiable products – which is highly desirable for the consumer – or can submit offers that lower the quality of information making the product search rather difficult.

The quality of the data in the database heavily depends on the applied XML schema or the power of the web crawler. Data quality is thus a function of the data entry application and the chosen strategy of the retailer. The application for data entry can definitely apply some plausible checks but e.g. bundles are usually not considered by definition as poor data.

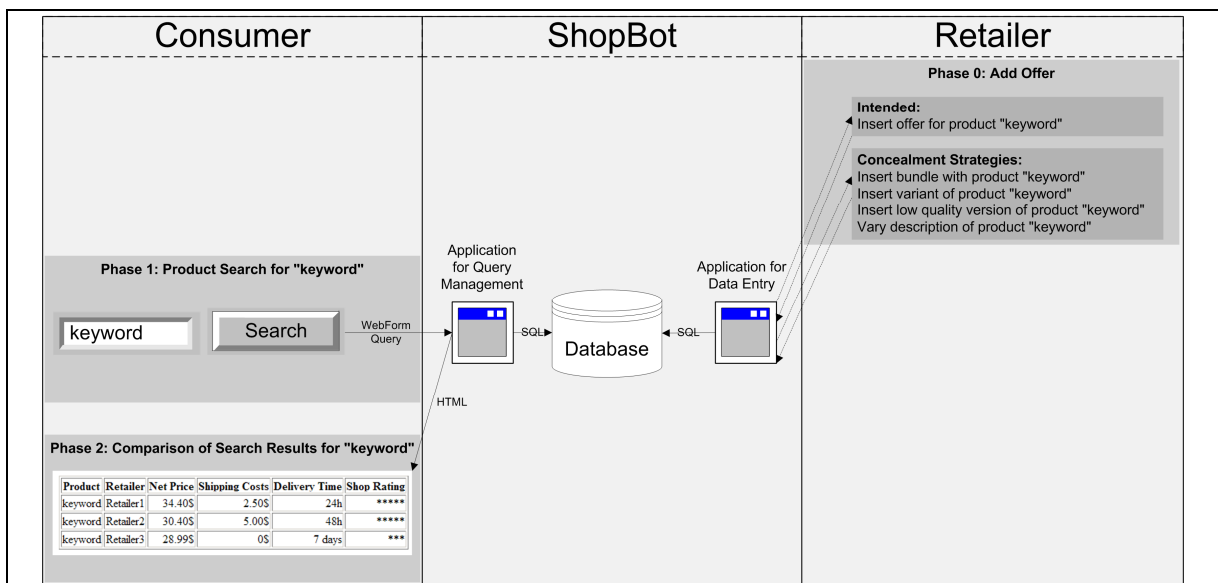


Figure 1. Phases of Product Comparison

In phase 1 a consumer searches for a product. The search engine (here called “Application for Query Management”) composes and sends a more or less complicated SQL query to the database. The resulting rows may again be filtered and are finally listed on an HTML website. Depending on the application for data entry, the quality of the stored data and the quality of the application for query management, the HTML website contains useful or less useful information for the consumer. The capabilities of these components determine the quality of the ShopBot and in the long term the attractiveness for consumers. However, the best ShopBot for consumers may not be the best ShopBot for retailers and thus, depending on the business model, the most sophisticated technology may not be a selling point for the ShopBot’s operator.

In phase 2, the consumer compares the listed offers. The purchase decision depends on the consumer’s preferences then and can be influenced by the quantity and quality of information. Since the influence of information is well-researched in the domain of consumer behaviour, retailers design their offers to successfully target as many consumers as possible and thereby increase profits. We expect to find evidence for these strategies in our empirical study in the next section.

By adding offers in phase 0, retailers can influence phase 1 and phase 2 and thus influence the consumer’s purchase decision. It also allows retailers to create countless micro markets where product comparison is rather impossible. Hence, consumers do not choose the cheapest product but the product

that matches their preferences best. Price is thus not the exclusive decision factor allowing retailers to survive on a market that otherwise would be highly competitive and probably ruining for them. Nowadays, information systems allow retailers to implement strategies in an easy and cost-effective way. Many of these systems monitor the consumers' behaviour and provide valuable decision support for retailers or even decision automation.

The input in phase 0 can not be evaluated in our dataset. However, we are able to evaluate the resulting quality of information in phase 1 and phase 2. We therefore derive hypotheses for phase 1 and phase 2 and will afterwards test them in an empirical study.

2.1 Reducing Utility of Product Search

In the first phase of price comparison, the product search, literature reveals three different strategies making product comparison rather difficult for the consumer: Firstly, Ellison and Ellison (2004) and Baye et al. (2005) state that ShopBots cannot categorize bundles correctly. The search for the key words "Digital IXUS 40" also yields "Digital IXUS 40 plus 512 MB SD-Memory-Card" and "Digital IXUS 40 + Soft Leather Case" which ultimately shows two different bundles which are not easy to compare. Furthermore, bundling itself leads to higher page impressions for the offer since the bundled offer pops up in search results for much more search queries (Baye et al. 2005). Bundling may also enable retailers to extract value from a given set of products by allowing to price discriminate (e.g. McAfee et al. 1989). Literature in marketing and economics has dealt with the promises of bundling extensively (see e.g., Eppen et al. 1991, Varian 1997, Bakos and Brynjolfsson 2000). Bundling is thus advantageous for the retailer for four different reasons: making comparisons difficult; lowering the search quality and thus the utility of ShopBots; increasing the number of page impressions for the offer; and finally allowing price discrimination.

As a second strategy, a retailer might choose to develop additional product variants, e.g., different package sizes, more exclusive equipment or different colours. Monroe (2003) identifies product differentiation as a suitable strategy eluding online consumers' price sensitivity. The availability of a plethora of product variants also leads to an information overflow and finally to hardly comparable product alternatives (Shankar et al. 1999, Baye et al. 2005).

Finally, as a third strategy, retailers can vary the description text of a product. Baye et al. (2005) hold that this makes it hard for the consumers to compare the search results. In particular the comparison is difficult when retailers also offer product bundles. "Canon Digital IXUS 40 Battery" is likely to be the same as "Digital IXUS 40 Power Supply" but could also be descriptions of two different products.

In this paper, we focus on the most prominent strategies in the product search phase. First, we qualitatively examine the bundling strategy since it has several desirable properties that make it especially beneficial for retailers on the electronic marketplace. Thus, we expect a substantial number of bundles in the database of a ShopBot in our descriptive results.

Further on, it can be assumed that a competitive situation increases the propensity to bundle. A product category with high margins attracts numerous retailers. An increasing number of retailers in a specific product category puts stress on all online retailers afterwards and bundling opens up a lucrative way of differentiation and is expected to be better than price wars. Thus bundles appear to be advantageous as part of a concealment strategy (see e.g., Eppen et al. 1991, Bakos and Brynjolfsson 2000). We use the number of retailers to represent the intensity of retailers' competition and claim that an increasing number of retailers is a proxy for an increase in competitive intensity (Xie and Chen 2004). Therefore we enunciate hypothesis H1:

H1: Product categories with a higher number of retailers have a higher fraction of bundles.

As stated before bundling is one strategy to make product search and price comparison less efficient. One reason is that retailers mark bundled offers ambiguously, sometimes using phrases like "bundle", "kit", "set" or "pack", but sometimes omitting such phrases. This makes it hard for consumers to rec-

ognize all bundles and finally to compare the offers. Consequently the list of results for a certain product will be more confusing with pervasive bundling (see e.g., Ellison and Ellison 2004, Baye et al. 2005). We distinguish the items of the search result into hits and misses. Items that exactly list the product we are looking for are considered as hits. Bundles etc. are therefore considered as misses. We define hit rate as the ratio of hits to all items in the search result.

H2: The hit rate of the search is significantly lower than 100%.

2.2 Hampering Price Comparison

After the first phase, the search for a certain product, the ShopBots list relevant offers. These results may actually be distorted by bundles, different products, and product variants as described in the last section. The quality of data at this point could be increased due to sophisticated filter or search technology. However, our empirical study will reveal that the quality of data is unsatisfactory for the consumers.

But even with high-quality data, the retailers can pursue strategies that exploit the consumers' behaviour in the second phase of the price comparison: First, retailers can use the delivery time and availability as discriminating property of the offer. This is especially interesting for electronic goods where prices decay quickly over time. A product with longer delivery time can then be sold more cheaply and the consumer has to discount the offer correctly. Moreover, the utility for a product in the future is usually different from the utility for a product now. Several discounted utility models have been proposed in economics and psychology (see Frederick et al. 2002 for a comprehensive overview). Amongst different discount functions, it is well accepted that consumers with high willingness to pay have higher search costs and opportunity costs of time, are more impatient (Tellis 1986) and thus delivery time can also be used as an instrument for market segmentation.

With the help of shipping costs, retailers can sell the product for different prices (Ellison and Ellison 2004). Schindler et al. (2005) and Morwitz et al. (1998) find that consumers have a biased perception of shipping costs. Being aware of this irrational behaviour, retailers exploit shipping costs to make price comparison difficult (Scholten and Smith 2002).

Shipping costs can be used to influence price comparison for two different reasons: When charging consumers for goods or services, many retailers divide the price into two components, a large base price and a comparatively small surcharge, for example shipping costs. Although this should not change the behaviour of a rational consumer, Morwitz et al. (1998) state that this strategy can lead to increasing demands and higher profits. Schindler et al. (2005) have conducted an experiment and notice that shipping-costs sceptics prefer direct retailers' offers in a bundled price format, whereas non-sceptics prefer them with partitioned prices. This allows retailers to target different segments with this strategy. Consumers also have the feeling to get more insights into the retailer's cost structure when shipping costs are shown separately although this is not the truth for many cases (Xia and Monroe 2004).

As a second reason the use of partitioned prices leads to higher ranks in the ShopBots' result list (Daripa and Kapur 2001). Many retailers exclusively submit the net price to a ShopBot with an additional note that shipping costs can be found at the retailer's websites. This leads to a higher and presumably better rank for the offer. A recent study reveals that many online shops expose shipping costs not until the end of the purchase process to generate high lock-in costs for the consumer (Handelsblatt 2006). Such surcharges can also be taxes and restocking fees. For our empirical study, these surcharges are irrelevant, since there were no different levels of sales taxes and since restocking fees were not permitted in Germany at the time of data collection. We hence focus on shipping costs and define the gross product price as: *Gross Product Price = Net Product Price + Shipping Costs*.

Morwitz et al. (1998) examine the effects of partitioned prices, i.e., the division in net product price and surcharge for shipping and handling. They test hypotheses of how consumers process partitioned prices and how partitioned prices affect their purchase intentions. Partitioned prices decrease consum-

ers' recalled total costs and increase their demand. Subjects exposed to partitioned prices recall significantly lower gross product prices than subjects exposed to combined prices. Thus, the consumers' biased perceptions of partitioned prices create opportunities for retailers to exploit this irrational behaviour by charging lower net product prices but comparably high shipping costs. This effect is amplified when retailers can conceal the shipping costs and on top of this, as outcome of this exploit such offers are rewarded with higher rankings at ShopBots.

If retailers exploit consumers' biased perceptions of partitioned prices and thereby pursue a price concealment strategy, then shipping costs on the one hand have a negative effect on the net product price and on the other hand positive effect on gross product prices. Separated shipping costs are used to achieve better positions at the Shop Bot rankings. Lower net product prices will be listed on top and the loss resulting from a lower net product price is captured in the separated reported shipping costs. Retailers have another motivation using partitioned prices. In sum they are able to gain a surplus with their increased gross product price, resulting from a smaller decrease in net product prices than the amount of increased shipping costs. Thereby retailers imply that using separated shipping costs also exploit consumers' perception of total prices (Morwitz et al. 1998, Chakravarti et al. 2002, Burman and Biswas 2007). Accordingly, we enunciate the following two hypotheses:

H3: Separated Shipping Costs have a negative effect on the Net Product Price.

H4: Separated Shipping Costs have a positive effect on the Gross Product Price.

3 EMPIRICAL STUDY

3.1 Data Description

To test our hypotheses, we analyze the database of a leading German ShopBot. Our copy of the database includes tables for offerings, retailers and shipping costs and was made at the end of 2004. 18 product category-tables retain the information for different offers. We focused on the seven most popular product categories with 481,000 offers. We use the original product categories and product classes determined by the ShopBot. The following section describes the structure of the data, market concentration in different categories and shipping costs, before we test our hypotheses.

Since we expect an influence of the product category on the retailers' propensity to pursue concealment strategies and different categories may have individual characteristics like average price level, we analyze the categories separately.

Our sample from the database consists of seven different product categories which were given by the ShopBot: computer accessories, computers, consumer goods, electronics, films, cellular phones and software. Each of the chosen categories captures quite homogeneous, standardized products.

Each data row, i.e., offer, consists of a unique dataset identifier, product group, product class, product, product description, product net price, name of retailer, name of manufacturer and shipping costs. Note that the column "product" is not standardized and is simply a text field for the product's name.

As first part of our descriptive analysis, we determine the market concentration which is definitely an important factor for price concealment at ShopBots. Our expert interviews with retailers and operators of ShopBots revealed that a tough competitive situation has a notable impact on pricing and consequently concealment strategies.

Product Category	# of Retailers	# of Offers	Ratio Retailers/Offers (in %)	Minimum ... of the # of Products per Retailer	Maximum	Mean	Standard Deviation
Comp. Accessories	57	85,820	0.07	2	11,294	1,506	2,031
Computers	72	34,444	0.21	1	5,589	478	960

Consumer Goods	81	81,007	0.10	1	17,126	1,000	2,234
Electronics	35	29,522	0.12	8	4,396	844	1,027
Films	14	108,752	0.01	60	19,724	7,768	6,324
Cellular Phones	51	90,643	0.06	3	14,916	1,777	3,148
Software	42	50,812	0.08	4	4,973	1,210	1,505

Table 2. Market Concentration in Different Product Categories

Table 2 depicts the different product categories in our sample, name of the category, followed by the number of retailers for each category, which is already an indicator for market concentration. Further on, we calculate the ratio of retailers and offers and use this ratio as an additional indicator for competition. However, we think that the total number of retailers is a better measure for competition. Table 2 also lists the number of products each retailer offers in our sample, their minimum, maximum and standard deviation.

As preparation for the upcoming analysis Table 3 summarizes means and standard deviations of shipping costs as well as net and gross prices. As stated before in this paper, we defined the gross product price as: Gross Product Price = Net Product Price + Shipping Costs.

Product Category	# of Offers	# of Products	Net Product Price (in EURO)		Shipping Costs (in EURO)		Gross Product Price (in EURO)	
			Mean	Standard Deviation	Mean	Standard Deviation	Mean	Standard Deviation
Comp. Accessories	276	88	104.13	115.35	6.84	1.74	110.97	115.05
Computers	243	49	1457.55	793.66	4.35	4.40	1461.90	791.79
Consumer Goods	688	76	147.32	173.33	6.22	2.34	153.54	173.48
Electronics	1,096	175	497.04	402.14	19.40	20.24	516.43	405.53
Films	2,621	416	15.10	9.52	3.22	1.40	18.32	9.35
Cellular Phones	177	12	387.96	190.09	4.47	3.64	392.43	189.59
Software	864	155	195.10	295.64	4.25	2.63	199.35	295.86
All Categories	5,965	669	218.92	412.54	6.94	10.73	225.86	415.10

Table 3. Description of Net Product Price, Shipping Costs and Gross Product Price

3.2 Bundling and Quality of Search

We now examine the data described in the previous section and determine the propensity to bundle products. We expect to find a noticeable fraction of bundles amongst the offers. We first determine the number of bundles per category by running a SQL query flagging all offers that contain the keywords “set”, “kit”, “pack” or “bundle” in the product description. Note that this search is not available for consumers using the web frontend for product search. Our search criteria are rather conservative and the number of flagged offers is definitely lower than the actual number of bundles in the data set. However, we find a substantial number of bundles as depicted in Table 4.

Product Category Product Class	Number of Offers	Thereof Flagged as Bundle	Ratio Offers/Flagged Bundles
Comp. Accessories	85,820	6,537	7.62 %
Computers	34,444	1,411	4.10 %
Consumer Goods	81,007	6,355	7.85 %
Digital Camera	6,722	906	13.48 %
Camcorder	3,021	572	18.93 %
Electronics	29,522	1,111	3.76 %
Films	108,752	98	0.09 %
Cellular Phones	90,463	4,122	4.56 %

Software	50,812	1,585	3.12 %
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Table 4. Offers Identified as Bundles in Different Product Categories and Product Classes

We find a particular high frequency of bundling for the product classes “Digital Camera” and “Camcorder” which are currently top-selling product classes (in 2006 retailers sold 7.1 Million Digital Cameras in Germany). Moreover these products have some properties making them especially appropriate for bundling: Cameras and Camcorders are highly standardized and these commodity type products are therefore easy to compare. Furthermore, the price is high enough to compensate the bundling efforts.

To test hypothesis H1 we need to operationalize competition first. We use the number of active retailers in the category as measure for competition. The bivariate correlation between the number of active retailers and the propensity to bundle is positive and statistically significant ($p < 0.02$). This means that high competition is correlated with a high number of bundles, thus we can not reject H1. Although we cannot prove that high competition is causal for the propensity to bundle, this conclusion seems reasonable.

The frequency of bundling is only a first indicator for the quality of search. Even in the absence of bundles, other strategies can lower the search quality. We therefore run a series of searches for distinct products, and then calculate the hit rate for this product. A hit is thereby an item in the search result that links to the actual product we were looking for. We expect that not all items in the search results are hits. A low hit rate is thus a measure for poor search quality. We are not able to calculate the hit rate for all products since the misses and hits have to be evaluated manually at this point of time. We therefore draw a random sample of products and evaluate the hit rate.

Table 5 shows that the hit rate is rather low for some products. At best only 3 of 4 results describe the product that we have been searching for, e.g., laptops are usually sold with carry cases or additional mouses making it very difficult to compare the results. Similarly, retailers added memory cards or additional power packs to digital cameras. In the category software, we find lots of OEM products and versions with disabled features. Outstanding is the product category “Cellular Phones” with a hit rate below 20%. For this category it is very easy to design new variants with a combined call plan. This can be seen as a result of a product variant strategy.

Product Class (Product Category)	Product	Hits	Number of Offers	Hit Rate
Computer Keyboard (Comp. Access)	Logitech LX 700	19	26	73.08 %
Laptop (Computers)	Fujitsu Siemens Amilo A 1640	14	48	29.17 %
Digital Camera (Consumer Goods)	Canon Digital IXUS 50	34	75	45.00 %
Beamer (Consumer Goods)	3M Nobile X55	6	8	75.00 %
Answering Machine (Consumer Goods)	Siemens Gigaset S 100	38	249	15.26 %
Washing Machine (Electronics)	Siemens WXLM 1400	16	22	72.73 %
Coffee Machine (Electronics)	Siemens TC 91100	20	21	95.24 %
Cellular Phone (Cellular Phones)	Nokia 7610	36	184	19.57 %
Cellular Phone (Cellular Phones)	Nokia 6210	34	204	16.67 %
Cellular Phone (Cellular Phones)	Nokia 6230	44	533	8.26 %
Application (Software)	Microsoft Windows XP Pro.	27	76	35.53 %
Game (Software)	Fifa Street Playstation 2	17	44	38.64 %

Table 5. Search Quality for Random Sample

For our random sample of 12 products, the hit rate is significantly ($p < 0.01$) different from 100% and we hence find support for H2 in our empirical study. This finding is a strong indicator for poor quality of data which results from different retailer’s concealment strategies. For this reason the product search has proven to be difficult and tedious. Although the use of ShopBots is easy, the interpretation of results is not and takes a notable amount of time. Thereby the use of ShopBots can be considered as

criterion for market segmentation. Only consumers with low search costs are willing to make the effort to sort out the “misses” from the search result and compare the remaining “hits”.

3.3 Partitioned Prices

We analyze seven product categories: computer accessories, computers, consumer goods, electronics, cellular phones, films and software. We enhanced the data set by adding a unique identifier for distinct products to the data set. This analysis must be done manually but allowed us to have a unique id for a product and therefore no distortion by bundled offers, product variants, etc.. Further, we looked up all missing shipping costs at the offering retailer’s website. We picked the cheapest shipping costs for the product by default if more than one shipping type was available.

With this completion we end in a sample consisting of 5,965 offers for 669 products. We applied a fixed effect regression to control for price variances between products. Fixed effect models are usually used for panel data and other combinations of longitudinal and cross-sectional data.

3.3.1 Influence of Shipping Costs on Net Product Price

In our first analysis we determine the impact of shipping costs on the net product price. We have been expecting that an increase in shipping costs should decrease the net product price. We estimate the following model: $NPP_i = \alpha_i + \beta \cdot C_i + \varepsilon_i$ where NPP_i is the net product price for the i-th product, α_i covers individual effects, β captures the influence of shipping costs on the gross product price, C_i are the observations of shipping costs for the i-th product and ε_i is the product specific error term.

Product Category	Shipping Costs (Sign.)	Adj. R ²	F-value	# of Offers	# of Products
Comp. Accessories	-0.665 (0.1777)	0.990	307.99 (0.000)	276	88
Computers	-6.461 (0.0008)	0.981	251.75 (0.000)	243	49
Consumer Goods	-1.582 (0.0000)	0.987	692.67 (0.000)	688	76
Electronics	-0.827 (0.0000)	0.975	245.05 (0.000)	1,096	175
Films	-0.291 (0.0000)	0.751	19.95 (0.000)	2.621	416
Cellular Phones	-1.304 (0.0023)	0.995	405.61 (0.000)	177	12
Software	-27.536 (0.0054)	0.929	15.34 (0.000)	864	155
All Categories	-0.888 (0.0000)	0.990	370.43 (0.000)	5,965	669

Table 6. Regression Results for Net Product Price

First of all, the high adjusted R²-values become evident but this is not unusual for fixed effect regressions due to the use of dummy variables capturing inter-product variations and rather low degrees of freedom for the product groups. Secondly our results in Table 6 hold even if controlling for merchant ratings, stating that the influence of shipping costs on gross price is not distorted by the effect of merchant brands given by consumer ratings.

The results depicted in Table 6 strongly support our hypothesis H3. We find a negative influence of shipping costs on the net product price for all categories and the entire sample as well. The results are highly significant and indicate that a raise of shipping costs leads to lower net product prices. The coefficient of the entire sample also indicates that the net price only decreases under proportionally with an increase of shipping costs. An increase of 1 EUR in shipping costs lowers the net product price by 89 Cents only. This is exactly what we expect and may be an indicator for price concealment at Shop Bots. The decrease of net product prices leads to higher ranks in search results and since shipping

costs do have not to be reported, retailers increase shipping costs over proportionally and lower net product prices under proportionally.

3.3.2 Influence of Shipping Costs on Goss Product Price

As outlined in the previous sections, retailers exploit the consumer's biased perception of partitioned prices or even conceal shipping costs altogether. We therefore concluded that we must find a positive effect of shipping costs on gross product prices.

In order to test our hypotheses, we analyzed the effect of shipping costs on gross prices while controlling for the product id. Let GPP_i denote the observed gross price of the i -th product. We specify our model as follows to the test hypothesis H4: $GPP_i = \alpha_i + \beta \cdot C_i + \varepsilon_i$

The gross product price GPP_i for the i -th product is the dependent variable. On the right side of the equation we have α_i which captures all inter-product actions, the individual effect respectively, β captures the influence of shipping costs on the gross product price and is a vector of coefficients. Further, C_i denotes the observations of shipping costs for the i -th product and is a vector of regressors. ε_i is the product specific error term. Table 7 reports the result of this regression:

Product Category	Shipping Costs (Sign.)	Adj. R ²	F-value	# of Offers	# of Products
Comp. Accessories	0.335 (0.4969)	0.990	306.35 (0.000)	276	88
Computers	-5.461 (0.0046)	0.981	250.54 (0.000)	243	49
Consumer Goods	-0.582 (0.0915)	0.987	693.87 (0.000)	688	76
Electronics	0.173 (0.1176)	0.975	249.29 (0.000)	1,096	175
Films	0.709 (0.0000)	0.741	19.05 (0.000)	2,621	416
Cellular Phones	-0.304 (0.4724)	0.995	448.21 (0.000)	177	12
Software	-26.536 (0.0074)	0.929	15.36 (0.000)	864	155
All Categories	0.112 (0.1054)	0.991	375.07 (0.000)	5,965	669

Table 7. Regression Results for Gross Product Price

Our hypothesis H4 can only be supported partially. In three of seven categories we find a positive influence of shipping costs on gross price. But we also find a significant negative influence of shipping costs on the gross product price for two product categories. This effect is the result of a high fraction of “no shipping cost” offers in these categories. For the categories yielding a negative influence of shipping costs on gross prices the fraction of “no shipping cost” is 20.94%. The categories with an expected positive influence of shipping costs on gross prices, only 5.49% of the offers are free of charge. The difference is highly significant (ANOVA, $p < 0.01$).

For consumers these results suggest that “no shipping cost” offers are indeed on average unfavourable since they raise the gross price over proportionally. Our analysis reveals ambiguous results for the influence of shipping costs on the gross product price. We can thus neither reject hypothesis H3 nor find support for it. The sign of influence seems to vary across categories although the influence of shipping costs is positive for the entire sample. Further analyses are necessary to disentangle the effects of different strategies pursued by retailers. In some of the categories, we find the expected influence of shipping costs on the gross price. In others, there is a significant negative effect of shipping costs on gross price. Especially offers with no shipping costs at all increase the gross product price.

4 CONCLUSIONS

Our results indicate that retailers have elaborated strategies to counter price wars. To influence the first phase of price comparison, retailers pursue strategies to lower the quality of the data and thus the utility of product search: By creating bundles retailers move their product out of the commodity type

market, thereby evading direct price comparison and hence competition. Additionally, bundles can be used to price discriminate and lower the quality of the search results. We found a significant positive correlation between the number of bundles and the number of active retailers which may indicate that bundling is a strategy to evade market pressure. Although ShopBots could prevent this loss of quality by introducing unique identifiers for products similar to bar codes or using more sophisticated search algorithms, we do not see any development for improvement here.

In the second phase, retailers exploit the consumer's irrational behaviour, thus making the gross price as an exclusive decision factor less important. Even if the consumer faces a perfect research result in terms of comparability, retailers balance information in their favour and change properties like the delivery time or use partitioned prices to lower the price sensitivity. This also allows retailers to benefit from irrational consumer behaviour which might increase their profits. We found second-order evidence for consumers' biased perception of partitioned prices and additionally our analysis suggests that "no shipping cost" offers raise the gross product price over proportionally in some categories and should thus be avoided by consumers.

Although ShopBots cannot actively influence the second phase of the comparison process, ShopBots could easily improve their algorithms or introduce better identifiers for products and thereby improve product comparability. Consumers might think that results are sorted by store rating or best prices. Actually, at some ShopBots, e.g., BizRate, results are primarily sorted by which retailer has paid for appearing at the top of the list (Mulrean 2001).

In the light of these dependencies, it is not surprising that ShopBots could do better and our study found support for the hypothesis that retailers have elaborated and are able to pursue strategies to conceal prices. Since the business model of common ShopBots heavily relies on the success of their paying customers, i.e., the retailers, it is more than questionable whether ShopBots will ever create market transparency. In the self-interest of ShopBots, the number of participating retailers should be as high as possible. Price wars would certainly decrease the number of retailers in the long term and thus decrease the profitability of ShopBots. Hence, ShopBots are somehow stuck in the middle: On the one hand, the search process has to deliver some kind of utility to consumers and thereby generate significant web traffic. On the other hand, the utility of the search must not be too high to fuel ruining price wars amongst the participating retailers.

Our study has several limitations which can be avenues for further research: First, we focus on retailer strategies and can thus only provide second-order evidence of consumer behaviour to these strategies. It would be interesting to observe the reaction of consumers to the pursued strategies directly. Second, we assume that consumers purchase only one product per shipment. This assumption does not seem critical for products like washing machines, for products like DVDs this assumption may not hold. Third, we do not control for delivery time which may justify some part of the price dispersion.

Our research results indicate a gap between what consumers need and what recent ShopBots deliver (see also The Guardian 2006). This is mainly not due to technical limitations but due to economic motives. Recent business models favour retailers since they pay for advertisement, ranking and product placement. Therefore, it would be interesting whether a ShopBot that charges consumers for search facilities would close this gap.

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