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Conference Paper

Strategic Inattention in Product Search

Beiträge zur Jahrestagung des Vereins für Socialpolitik 2018: Digitale Wirtschaft - Session:
Empirical Industrial Organization, No. F07-V2

Provided in Cooperation with:

Verein für Socialpolitik / German Economic Association

Suggested Citation: Hippel, Svenja; Hillenbrand, Adrian (2018) : Strategic Inattention in Product Search, Beiträge zur Jahrestagung des Vereins für Socialpolitik 2018: Digitale Wirtschaft - Session: Empirical Industrial Organization, No. F07-V2, ZBW - Leibniz-Informationszentrum Wirtschaft, Kiel, Hamburg

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Strategic Inattention in Product Search*

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November 24, 2017

Abstract

Online platforms provide search tools that help consumers to get better-fitting product offers. But this technology makes consumer search behavior also easily traceable and allows for real-time price discrimination. Consumers face a trade-off: Search intensely and receive a better fit at a potentially higher price or restrict search behavior – be strategically inattentive – and receive a worse fit, but maybe a better deal. We study the resulting strategic buyer-seller interaction theoretically as well as experimentally. Our experimental results show that it is the sellers and not the buyers who profit from these search tools.

Keywords: strategic inattention, price discrimination, information transmission, consumer choice, experiment

JEL Classification: D11, D42, D82, D83, L11

The rise of online platforms increases the transparency for consumers in many markets because a multitude of offers can now easily be accessed and browsed through at a single web page. Essentially all online platforms provide search tools for the consumer. For example, filters on booking

*We would like to thank Phil Brookins, Christoph Engel, Lars Freund, Dominik Grafenhofer, Lisa Lenz, Daniel Martin, Anne-Katrin Roesler, Sebastian Schaub and Fabian Winter, as well as audiences at the Max Planck Institute for Research on Collective Goods, the Summer Meeting of Young Philosophers and Economists 2016, the 33rd annual NABE Economic Policy Conference, ESA Meetings in San Diego and Vienna and the 12th Nordic Conference in Gothenburg for helpful comments and discussion. Financial support of the Max Planck Society is gratefully acknowledged

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platforms can be used to restrict the offers displayed to hotels that are close to the beach and come with a gym. At first sight this is beneficial for consumers since they receive more relevant and better-fitting product offers.

But online platforms can easily gather data about the consumer and his search behavior and personalize search results based on this real-time information. The use of provided search tools potentially transmits information about the consumer’s valuation for the filtered products. Crucially, this data is available to the seller before the list of search results and the product prices are displayed to the consumer. Consequently, this information can be used to price discriminate and to steer consumers towards buying more expensive products. Search tools might thereby not be an innocent feature by themselves.

Therefore, consumers face a trade-off between product fit and price: They can search intensely for a good-fitting product but, due to the information transmission to the seller, might face a higher price. Thus, they are potentially better off by restricting their search behavior. While they might then receive a worse fit, they might end up with a lower price and a better deal.

In this paper, we study the resulting strategic buyer-seller interaction when the seller can observe the buyer’s search behavior. In a stylized market, we investigate whether sellers extract information rents and whether buyers restrict their information search. Throughout the paper we will call this active decision to restrict product search *strategic inattention*.¹

Given that the market for online travel sales alone is an estimated 564.87 billion U.S. dollars and expected to grow by 45% until 2020 ([eMarketer, 2017](#)), it is important to understand how consumers adapt to these rising markets. Technological advancements will further simplify information ex-

¹The term ‘strategic inattention’ is different from ‘rational inattention’ which is discussed in the literature started by the seminal papers of [Sims \(2003, 2006\)](#). These papers deal with the unobservable psychological costs of processing information based on a Shannon entropy (see [Caplin et al. \(2017\)](#) for a behavioral characterization). Subjects are already shown, theoretically as well as empirically, to behave as if they are rationally inattentive by [Martin \(2016, 2017\)](#). In our setup, we exclude psychological search costs. All search costs are of purely strategic nature and are caused through the seller’s ability to extract information of the buyer’s valuation by observing the search behavior.

traction from consumer’s search behavior. This paper is a first attempt to investigate whether consumers show suitable reactions and are strategically inattentive to protect themselves from this form of real-time price discrimination.

Recent models in information economics provide theoretical insights into situations where a monopolistic seller learns the information choice of the buyer. [Roesler and Szentes \(2017\)](#) discuss the buyer-optimal information structure and [Condorelli and Szentes \(2016\)](#) the buyer-optimal demand function (see also [Carrasco et al., 2017](#)). [Bergemann et al. \(2015\)](#) discuss the limits of price discrimination and describes the set of possible market outcomes.

While there is lots of anecdotal evidence, empirical findings on the extent of real-time price discrimination on online platforms is scarce. Field data (see [Mikians et al., 2012](#); [Hannak et al., 2014](#)) can only provide hints on the extent of the use of consumer data. Furthermore, given the volatility of prices in these markets, price discrimination and other causes for price changes are hard to distinguish ([Vissers et al., 2014](#)). Consequently, using field data alone is not sufficient to understand causes for specific buyer search behavior, i.e., to study strategic inattention.

In this paper we make use of a laboratory experiment that allows us to analyze buyer and seller behavior in a controlled environment. In particular, we can fix which information sellers receive about buyers’ search behavior and ensure that buyers are aware of this, i.e., that the information transmission is common knowledge. To receive testable predictions, we first analyze the situation theoretically. Our setup is thereby close to [Condorelli and Szentes \(2016\)](#) in that the buyer’s choice directly determines his value distribution. However, we impose a specific structure on the buyer’s decision space. This concise model then provides testable hypothesis for our experimental study.

In the experiment, sellers offer one product out of a given set of products with different characteristics. Buyers can make use of a search technology in the form of filters to restrict this product set beforehand by removing bad options. Sellers observe the number of filters chosen and set a fixed price for all the remaining products. This allows them to condition their pricing behavior on the buyer’s filter choice. Finally, buyers receive a random

product from the remaining set and decide whether to buy it at the price set by the seller.

In equilibrium, product prices increase weakly in the buyer's filter amount and the buyer consequently restricts the number of filters used. The results of our experimental study are generally in line with this theoretical prediction: Sellers set higher prices for higher filter choices and the buyers are strategically inattentive, although not to the extent predicted by theory. Interestingly, it is only the sellers that profit from the buyer's use of the search technology: Their surplus increases with higher filter choices of the buyers. Buyers themselves though, do not gain from more extensive use of the search technology.

Our paper allows first behavioral insights into the growing market of online platforms and new challenges that might arise with further technological advancement. Our results shed a critical light on the added value for consumers through the rise of online platforms. They call the benefits of the access to a multitude of offers through search tools and the progressing personalization of online search results into question.

Related literature Our study is related to the theoretical literature on behavior-based price discrimination. [Fudenberg and Villas-Boas \(2006\)](#) provide an overview over these models, in which the seller can charge different prices based on past buying decisions of consumers (see also [Hart and Tirole, 1988](#); [Villas-Boas, 2004](#)). These multi-period models can capture situations where a recurring customer can be identified for example through the use of browser cookies. Our model goes beyond this in capturing the use of search data that reveal information about the consumer's valuation in real-time.

Furthermore, there is a related stream of literature on bargaining models with strategic information transmission started by [Crawford and Sobel \(1982\)](#). For the seminal experimental paper on ultimatum bargaining see [Güth et al. \(1982\)](#). Two recent theoretical working papers in this area ([Velodi, 2016](#); [Hidir, 2017](#)) address similar situations as in our project using cheap-talk messages. In contrast to these models, our filter choice is always informative for the seller. The buyer can hide, but not misrepresent, private information.

1 Theoretical Framework

There is one seller (she) and one buyer (he). The seller possesses one good with value normalized to 0 for her, which she wants to sell to the buyer. The buyer's value v of the product is determined by a value distribution f with support on $[0, 1]$. This is equivalent to assuming that the seller has an (infinitely) large portfolio of products with different valuations for the buyer and the buyer receives one random product.² With $F(v)$ denoting the cumulative distribution function of v , we assume that the hazard rate $\frac{f(v)}{1-F(v)}$ is non-decreasing and thus f is regular. The buyer's outside option of not buying the product is also normalized to 0.³

The seller provides a search technology for the buyer which we will call *filter*. The filter choice is denoted by $a \in [0, 1]$. By choosing a , the buyer restricts the value function from below, securing him a value of at least a .⁴

The truncated distribution with support on $[a, 1]$ is:

$$d_a(v) = \frac{g(v)}{1 - F(a)}, \quad (1)$$

where $g(v) = f(v)$ for $v \in (a, 1]$ and 0 otherwise.

The buyer's choice of a and thus d_a is observed by the seller. The seller then makes a take-it-or-leave-it offer to the buyer by setting a price p . Finally, nature draws the buyer's valuation for the product v from d_a and the buyer decides on whether to buy or not. The timing of the game is therefore:

- t=0 • $F(v)$ is common knowledge
- t=1 • Buyer chooses filter a and truncates $f(v)$
- t=2 • Seller sets price $p(a)$
- t=3 • Nature draws v from d_a and the buyer decides whether to buy

²Note that there is no objective ex-ante ranking of the products. Differences in buyer valuation stem from taste, not from quality differences.

³We assume risk neutrality, but introducing risk aversion on the buyer-side would not change equilibrium predictions.

⁴Alternatively this could be modeled as a buyer having a taste parameter θ on a Salop circle with a valuation of $v_{max} - t(\theta - y)$. Here y would be the chosen product and $t(\Delta)$ a function that is non-decreasing in Δ . The corresponding filter choice for the buyer would be to decide on the maximal distance between his target product and the offered product.

We state the following two propositions, which we then test in a lab experiment. The propositions hold for any regular value distribution function $f(v)$ with a non-decreasing hazard rate.

Proposition 1 (Increasing Price):

The optimal seller price is weakly increasing in the filter choice a of the consumer .

Proposition 2 (Strategic Inattention):

The buyer is strategically inattentive and restricts his search optimally such that $a < 1$.

The propositions follow from the subgame-perfect Nash equilibrium of the game, which we derive by using backward induction. The full analysis is provided in Appendix [A.1](#).

Nature draw and buying decision (t=3). Nature draws the buyer's valuation from d_a and the buyer makes his buying decision. We assume that when the buyer is indifferent between buying and not buying he will always buy. That is, he will buy as long as $v \geq p$.

Optimal price (t=2). The seller sets a price p given the buyer's choice of a , to maximize his payoff:

$$\Pi_S = p \text{Prob}(v \geq p). \quad (2)$$

The optimal price function for the seller, dependent on a , is

$$p^*(a) = \max\{\hat{p}, a\},^5 \quad (3)$$

where $\hat{p} \in (0, 1)$ is the optimal price in the unrestricted case ($a = 0$) and thus equal to the standard monopoly price without a search technology available. The price is flat and equal to \hat{p} for $a \leq \hat{p}$ and increasing for $a > \hat{p}$. This proves Proposition 1.

⁵This price function translates to the optimal price for 'previous customers' in the two-period model discussed in [Fudenberg and Villas-Boas \(2006\)](#).

Optimal filter choice (t=1). For the buyer we finally need to find the optimal filter choice, given the seller chooses the optimal price in t=2. The optimal filter choice is

$$a^* = \hat{p}. \quad (4)$$

Since $\hat{p} < 1$, in equilibrium $a^* < 1$, that is the buyer is (partially) inattentive, proving Proposition 2.

The derived equilibrium filter choice a^* is not efficient and constitutes a hold-up problem in that the buyer restricts his search ($a < 1$), whereas searching fully (choosing $a = 1$) would maximize efficiency.

1.1 Examples

To visualize the above results, we provide two examples with different distributions. In the first one we use a uniform distribution and in the second one a discrete distribution which we also used for the parametrization of the lab experiment.

Example 1. Let v be uniformly distributed with $f(v) = \mathcal{U}(0, 1)$. We obtain $p^* = \max\{\frac{1}{2}, a\}$ and $a^* = \frac{1}{2}$ (see Figure 1).

Example 2. For the lab experiment, we chose a discrete distribution to make it easier to understand for subjects. We set $f(v) = B(5, 0.5)$. The above results translate directly to the Binomial distribution, where the filter choice a becomes discrete. Here $p^* = \max\{2, a\}$ and $a^* = 2$ (see Figure 2).

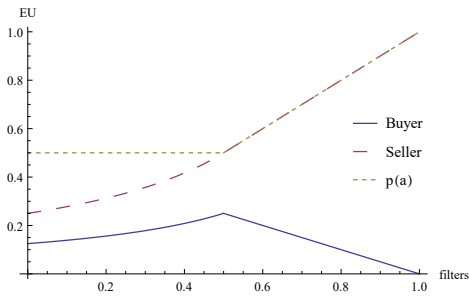


Figure 1: Expected payoffs given $a \in [0, 1]$ and $v \sim \mathcal{U}(0, 1)$

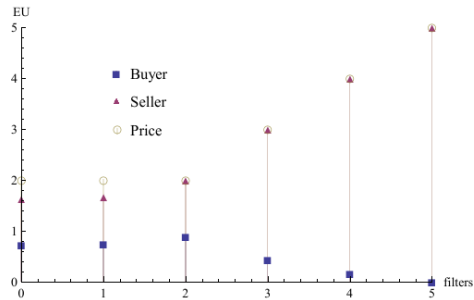


Figure 2: Expected payoffs given $a \in \{0, 1, \dots, 5\}$ and $v \sim B(5, 0.5)$

2 Experimental Design

In the experiment, subjects played 15 periods of the game described in Section 1. For parametrization we used the discrete distribution $B(5, 0.5)$, already explained in Example 2 above. The distribution was presented to the participants as a set of fictitious products with 5 different binary characteristics. In all periods, this set consisted initially of all 2^5 possible combinations of characteristics, which makes a total of 32 products.

Participants were assigned either to the role of a *buyer* or a *seller* and kept this role for the whole experiment. Buyers and sellers were told that in each period the seller can sell at most one good and the buyer has the possibility to buy at most one good, and that the outside option for both buyer and seller is 0.⁶

At the beginning of a period, the computer randomly draws from the set of all products to identify the so called *target product* of the buyer. This is the ideal product for the buyer and only he observes the actual characteristics of the target product. The value of each product in the set is determined by the number of matching characteristics with this ideal product. Hence, a product is of value x if x of the 5 binary characteristics are identical with the target product.

The buyer can then set a discrete number of filters $a \in \{0, 1, \dots, 5\}$ to reduce the number of products remaining in the set such that all products left have a minimum value of a for him.

All remaining products will cost the same price, which is then deter-

⁶The full instructions presented to the participants can be found in Appendix A.3.

mined by the seller. We use the strategy method to elicit the whole price vector of the seller, dependent on the number of filters the buyer chose. Hence she sets 6 independent prices, each between 0 and the maximum possible valuation of 5 Euros.⁷ The strategy method ensures that we obtain pricing data for all possible choices of buyers even when some filter options are chosen only rarely.

Finally, the computer draws randomly one of the remaining products from the set and the buyer gets a take-it-or-leave-it offer to buy this randomly drawn product for the price that the seller set. The buyer is free to buy the product or not. When he buys, his payoff is calculated as the value of the product minus the price and the seller gets the price she demanded. When the buyer does not buy, both get 0. Both seller and buyer get feedback on the number of filters chosen by the buyer, the actual price set by the seller, the buying decision as well as their own payoffs for this period. The buyer does not obtain information about the rest of the pricing strategy of the seller and the seller does not obtain information about the valuation of the chosen product for the buyer.

For each session we used one of two matching protocols to determine which seller interacts with which buyer over different periods. Under *stranger-matching*, buyers were randomly and anonymously re-matched to sellers in the beginning of each period.⁸ The alternative was a *partner-matching* protocol, where buyers and sellers interacted repeatedly for the whole experiment. We used both protocols to be able to account for different market situations. This way we can also control for the impact of reputation effects, which are only possible under a partner matching.⁹

Computer task. As a robustness check all subjects participated afterwards in an additional part where they played the same game, but now against the computer. Subjects knew that there was a second part but learned about the details only at the beginning of the computer task where

⁷All values and prices in the experiment are directly calculated in Euro. Prices can be adjusted in steps of 1 Eurocent.

⁸We used matching groups of 8 subjects (4 sellers and 4 buyers) to increase the number of independent observations.

⁹Reputation effects are considered important in the IO literature. See for example [Kreps and Wilson \(1982\)](#) for a seminal paper.

they were informed that they are now playing against a computerized counterpart. As in the main experiment, subjects played for 15 periods and also kept their role as buyers or sellers.

The additional part enables us to disentangle the strategies of buyers and sellers and to observe one-sided behavior. The optimal reaction to a counterpart's non-equilibrium decision might be different from equilibrium choices. In the main experiment, a buyer might not choose the optimal filter choice against a human seller, because he believes that the seller is not sophisticated enough to extract rents. At the same time, a seller might choose prices lower than in equilibrium, because he anticipates that buyers might not buy the product if the net value is too low. Playing against the computer though fixes beliefs about the sophistication of the other party and also controls for possible effects of social preferences.

Sellers set again the full price vector and buyers choose an amount of filters and whether they buy the product in the end. Sellers are told that the computer chooses every filter with equal probability and that it buys when the resulting net value is at least 0. Here the seller should set the optimal price p^* . The buyers from the main experiment now play against a computerized seller that plays the equilibrium strategy with a small random error term attached to the price. They know they play against an algorithm programmed to maximize profits from selling. They are also informed that the algorithm can use their filter decision for the calculation of the prices, but cannot recover information from former periods. Buyers in this part should choose the optimal number of filters a^* .

Procedures. We conducted eight experimental sessions in the BonnEcon-Lab at the University of Bonn in June 2017. Sessions lasted about 75 minutes and we had 192 participants in total (63% female, on average 24.4 years old). The experiment was computerized with oTree (Chen et al., 2016) and participants were invited using hroot (Bock et al., 2014). For each of the two parts of the experiment, one of the 15 periods was randomly chosen by the computer.¹⁰ The payoff of both selected periods were paid out in

¹⁰This includes also those periods where the buyer decided against buying the product and both players received the outside option of 0. Hence the computer draw could result in a payment of 0 € for the part.

cash to the participants in private directly after the experiment ended. Average earnings summed up to 8.25 €, including a show-up fee of 4 € and payments of post-tests. We collected data on two incentivized post-tests, the “bomb” risk elicitation task (Crosetto and Filippin, 2013; Holzmeister and Pfurtscheller, 2016) as a measure of risk-aversion and the SVO slider measure (Murphy et al., 2011). The experiment ended with a standard post-experimental questionnaire containing demographics.

2.1 Hypotheses

Our hypotheses are based on the two propositions drawn from our model described in Section 1. First we test, in line with Proposition 1, whether the sellers’ price vectors are upward sloping in the filter choice.

Hypothesis 1 *Sellers set higher prices for a higher filter choice.*

Our second main hypothesis is directly derived from Proposition 2, where we test whether buyers choose an optimal filter amount.

Hypothesis 2 *Buyers restrict their search optimally.*

The computer task allows us to see whether facing a human counterpart fundamentally changes behavior compared to the interaction with an automatized computer algorithm. We can observe one-sided behavior and control for social preferences as well as (potentially distorted) beliefs about the sophistication of the other party. We expect that facing a computer should move subject’s behavior closer to the equilibrium predicted by our model.

We also look at the buyer’s final buying decision. Our model assumes implicitly that buyers make rational buying choices and buy whenever their net value is weakly larger than 0. However, it might be that buyers choose not to buy even when they would profit from the deal. A potential reason might be fairness considerations when they find the seller’s price unreasonably high and would make only a small gain. We therefore suspect deviations from the rational choice mainly to happen for small positive net values.

Finally we test whether the matching protocol and potential reputation effects play a role in subjects' decisions. As explained at the end of Section 1, the equilibrium predicted by the model is not efficient. The possibility to build up a reputation is known as a simplifying factor for market transactions. Fairness considerations with regard to unreasonably high prices might be more apparent under a partner-matching and a seller's reputation for setting moderate prices might create room for higher filter choices of the buyers and reduce irrational offer rejections. We therefore expect that the partner-matching increases the outcome efficiency compared to the stranger-matching.

3 Results

In this section, we provide the analysis for testing our hypotheses. First note that we did not find any robust differences between the partner- and the stranger-matching protocol. To provide a concise analysis we thus pool the data from both matching protocols.¹¹ For a discussion of potential reasons why the matching did not significantly influence our results, please refer to Section 4.

3.1 Seller

Figure 3 shows the average price vector in comparison to the price vector predicted by theory.¹² The graph shows that price vectors are on average increasing in the filter choice. This is also supported by the regression depicted in Table 1.¹³ This confirms our first hypothesis and shows that sellers use the information about the filter choice to price discriminate.

Result 1 *Prices are increasing in the filter choice.*

Prices are lower than predicted for very low and very high filter choices, but very close to the predicted prices for intermediate filter choices. Thus,

¹¹If not mentioned otherwise, we use matching group averages as individual observations for the sessions with the stranger-matching protocol.

¹²For theoretical predictions compare also Figure 2 in Section 1.

¹³The analysis still holds when we only look at the actual prices buyers faced in the experiment instead of the whole price vector. The table also shows that the matching protocol has no influence on the price vector.

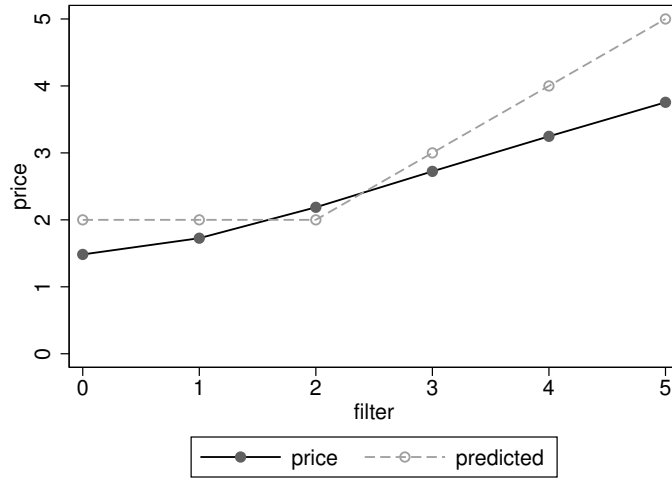


Figure 3: Average price vector (price conditional on filter choice)

Table 1: Regression price vector

	(1)	(2)	(3)
Filter	0.470 (.006)	0.470 (.006)	0.470 (.006)
Partner		-0.195 (.123)	-0.195 (.123)
Controls			YES
Constant	1.325 (.063)	1.442 (.095)	1.619 (.097)
Observations	8640	8640	8640

Standard errors in parentheses

Note Mixed effects linear regression with errors nested in matching groups, nested in individuals. Dependent variable is the conditional price according to the strategy method. ‘Partner’ is a dummy taking the value 1 under partner-matching and ‘Filter’ is the filter choice or potential filter choice. Controls contain the period of play, the matching protocol, age, gender, risk-taking, svo-angle, and answers to questions about online shopping from the questionnaire.

although our first hypothesis is confirmed, the average price vector for filter choices above 2 is significantly less steep than the equilibrium prediction (two-sided ttest¹⁴ against predicted slope of 1, $p < 0.001$). This might influence the buyers' optimal filter choices and therefore needs to be taken into account for the analysis of the buyer behavior.

3.2 Buyer

Buyers chose on average 2.69 filters while the equilibrium prediction is at 2 filters. Therefore buyers chose on average more filters than predicted (two-sided ttest, $p < 0.001$) and we can only partly confirm our second hypothesis:

Result 2 *Buyers restrict their search behavior, but search more than predicted.*

This does not necessarily mean that buyers act non-optimally given the situation in the experiment. Given actual price vectors of the sellers differed from the equilibrium price vector, a non-equilibrium filter choice might be the optimal response and lead to higher payoffs for the buyer. Taking the observed average price vector as a benchmark, the optimal filter choice turns out to be 5 filters as can be seen in Figure 4.

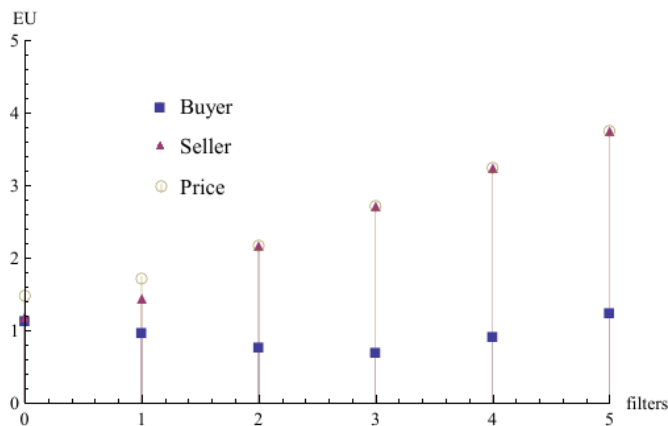


Figure 4: Expected payoffs on filter choice based on observed average price vector

¹⁴Average slopes of each individual seller are taken as one observation.

Looking at the histogram of all filter choices in all periods (Figure 5) reveals that buyer choices do not clearly coincide with either the predicted filter choice nor with the optimal filter choice based on the observed average price vector, but are quite heterogeneous. Indeed subjects chose 5 filters most often (24.51%) but the other filter amounts are also chosen between 12% and 17% of the time. The equilibrium prediction of 2 filters was selected in 15 % of all cases.

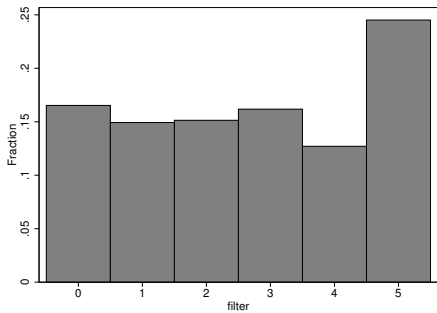


Figure 5: Histogram of all filter choices in the main task

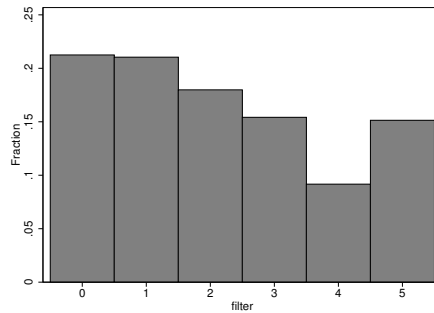


Figure 6: Histogram of all filter choices in the computer task

The same histogram for filter choices in the computer task (Figure 6) suggests that this heterogeneity is not driven by the non-equilibrium behavior of sellers. Against the computer we can observe one-sided buyer behavior whereby seller behavior is fixed and prices are identical to the equilibrium price vector. Overall, the average filter choice in the computer treatment is with 2.16 lower than in the main treatment and closer to the prediction. However, 2 filters were selected in only 17% of all cases and heterogeneity remains large.

Result 3 *Filter choices are heterogeneous, in the main task as well as in the computer task.*

Comparing Figure 5 and 6, there is a shift to choices between 0 and 2 filters. In the computer task, all filters in this range provide a decent expected payoff compared to higher filter choices.¹⁵ Thus, buyers restrict their search but don't search as predicted by the equilibrium.

¹⁵See again Figure 2 in Section 1.

Altogether behavior in the main as well as in the computer task suggests, that buyers do not fully appreciate the impact of the use of the search technology on their payoffs.

3.3 Efficiency and Surplus Distribution

It is not obvious from the separate analysis of buyers and sellers in the experiment which consequences non-equilibrium behavior had on the overall market outcome. Given that the situation constitutes a hold-up problem, deviations from the equilibrium could even increase market efficiency.

We therefore investigate efficiency of outcomes in the experiment, whereby efficiency is defined as the sum of payoffs of the seller and the respective buyer. In the experiment, average efficiency is at 2.53 € which is significantly lower than the 2.89 € predicted by the equilibrium (two-sided ttest, $p = 0.0046$).

There are two driving factors for efficiency in our setup: filter choice and buying probability. Higher filter choices always lead to higher expected efficiency as long as the product is bought. In our theoretical model, buyers always buy the offered product as long as the value is at least as high as the price and the net value is 0 or above. It is conceivable, though, that subjects in the experiment will not buy at very low net values. Indeed, we find that some subjects reject offered products that would give them a weakly positive net value. Buyers facing a net value equal to 0 buy only in 18% of the cases, facing a positive net value the buying probability is 88%. This explains why efficiency is lower than expected in equilibrium even though 5 filters are chosen most often.¹⁶

Surplus distribution The decision not to buy the product if the net value is low should reduce the difference between seller and buyer payoffs. Nevertheless, the distribution of surplus between buyers and sellers is quite unequal: a seller earns on average 1.47 € which is significantly more than the average of 1.06 € a buyer gets (sign-rank test with a within-match comparison, $p < 0.001$). But while sellers get on average less payoff

¹⁶Imposing theoretical buying behavior, efficiency in the experiment would be at 3.71 €.

than predicted (2 €), buyers do earn more than predicted in equilibrium (0.89 €).

One could conclude that buyers actually profit from their higher filter choices in the experiment. Using more filters always increases the expected efficiency and they got a bigger share of the created surplus than predicted by the model. To analyze who actually benefits from filter choice, for buyers we compare average payoffs over all periods in relation to their average filter choice, and for sellers we relate payoffs to the average filter choice that they faced over all periods.

As Figure 7 shows, the buyers' average payoffs are not increasing in the filter choice. In fact it is actually the sellers who profit from an increased use of the search technology provided to the buyers. This dependency is also confirmed in a regression of payoffs on the filter choice (Table 2). The coefficient for filter fails to be significant when we include the interaction term while the other coefficients are significant. That is, while sellers earn less for low filter choices, they are profiting from an increase in the filter choice while buyer's payoffs do not increase.

Result 4 *Higher filter choices lead to higher welfare. But buyers do not profit from using the filter technology. Only the sellers payoff increases with the buyer's filter choice.*

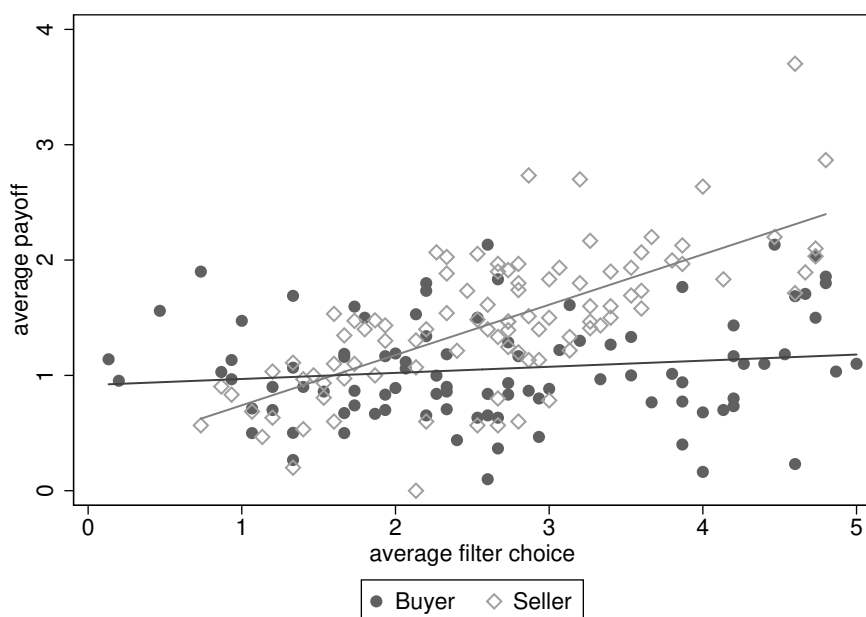


Figure 7: Average payoff on average filter choice (each data point represents one subject and lines are a linear fit)

Table 2: Regression of average payoffs over all periods on average filter choice

	(1)	(2)
Filter	0.199 (.030)	0.0529 (.038)
Seller	0.412 (.079)	-0.611 (.173)
Filter \times Seller		0.383 (.069)
Constant	0.526 (.090)	0.916 (.102)
Observations	192	192

Standard errors in parentheses

Note OLS regression with errors clustered on the matching group level. Dependent variable is average payoffs over all periods. Independent variables are average filter choice / average filter faced, ‘Partner’ is a dummy taking the value 1 under partner-matching.

3.4 Determinants of Filter Change

In this section we provide an exploratory analysis of potential determinants of the observed heterogeneity in filter choices. As outlined in Section 3.2, the number of filters predicted by equilibrium is chosen about as much as the other options. First, the individual filter choices over time (Figure 8 in Appendix A.2) reveals that only few buyers keep on varying their filter choice over the 15 periods in the experiment: In 43% of all individual decisions the filter of the last period was chosen again. For many buyers the number of chosen filters stabilizes after a couple of periods. Seemingly, buyers tend to stop the search for a potentially payoff-increasing filter choice too early, before reaching the optimal amount of filters.

Making use of the panel data structure of the experimental data, we can analyze determinants for changing the number of filters. A logistic random effects regression shows that a higher payoff in the previous period makes it significantly less likely to change the number of filters in the current period. We also find a significant negative effect of the period of play on the propensity to change the filter. This supports the hunch that the filter choice stabilizes over time, although not necessarily at the optimal number of filters.

In the case that buyers do in fact buy the product, the payoff equals the net value, hence the combination of product value and the price set by the seller. In the regression, a higher value of the randomly drawn product in the previous period has a significantly negative effect on the propensity of filter change, while the price does not have a significant influence. When controlling for payoff, subjects attach additional importance to the product value. This suggests that buyers pay too much attention to the fit of a product and less attention to its price.

Table 3: Random effects logit regression for determinants of filter change

	Filter change	
Payoff (t-1)	-0.06 (.025)	-0.058 (.025)
Value (t-1)	-0.044 (.021)	-0.046 (.022)
Price (t-1)	0.029 (.022)	0.030 (.022)
Period	-0.023 (.003)	-0.023 (.003)
Controls		YES
Observations	1344	1344

Standard errors in parentheses

Note Random effects logit regression. Dependent variable is propensity to change filter amount. Independent variables are experienced price and value as well as the payoff in the previous period, ‘Period’ is the period of play. Controls contain the matching protocol, age, gender, risk-taking, svo-angle, and answers to questions about online shopping from the questionnaire.

4 Discussion

The paper provides a theoretical analysis and an experimental test on the behavior of sellers and buyers in a situation where the seller can observe the product search behavior of the buyer. We show theoretically that prices are increasing in the filter choice and that buyers are strategically inattentive and restrict their search optimally.

Our experimental results are mostly in line with the theory. Sellers price discriminate by setting higher prices for a higher filter choice and buyers restrict their search. However, the average price vector is significantly less steep than the equilibrium prediction and this might influence the buyers' optimal filter choice in the main task. Buyers search more than predicted by the equilibrium and the distribution of individual filter choices shows that choices are very heterogeneous. This remains true in the computer task where we can observe one-sided behavior.

The computer task also confirms that buyers react to the environment in the predicted way but, while their choices are decent, they are not optimal. An exploratory analysis suggests that buyers pay too much attention to the fit of a product and less attention to its price. This might leave room for buyers to charge higher prices and to increasingly extract surplus. Our experimental design is not suitable to unequivocally identify the suggested psychological over-fitting effect and we need to defer the answer to this question to future work.

Most importantly, our results show that sellers are profiting from the use of the search technology while buyers' average payoffs are not increasing in the filter choice. This suggests even more that sellers are able to charge relatively high prices for high filter choices and to extract all the additional surplus generated.

We find no clear differences between the two matching protocols – stranger and partner – that we used. We assume that sellers take into account that buyers can reject the offer in each period. Sellers thus seem to be deterred to charge overly high prices already in the one-shot interaction, giving not much room for improvements due to reputation under repeated interaction. The voluntary buying decision might therefore function as an instrument for a natural upper bound to price discrimination.

In this paper we use a monopoly setting, and discuss the situation of a single buyer and a single seller. This allows us to concentrate on the main aspect of information transmission from the buyer to the seller through disclosed search behavior. A natural next step would be to introduce competition (Fudenberg and Tirole, 2000; Chen and Zhang, 2009) between multiple buyers and multiple sellers. In this case, also other aspects of optimal search behavior become relevant. Lock-in effects become possible, because consumers might only consult a limited amount of platforms before making their buying decision. Further extensions could also allow for more complexity in the product domain: Vertical quality differences are an obvious feature to add, but also the introduction of good bundles or the possibility of more complex pricing strategies as for example add-on pricing.

Sellers in our setup can set prices directly in response to the filter choice. In the field, online platforms might use this information in a more indirect way. Blunt price discrimination might come at the risk of boycotts when detected by the consumers. We therefore assume that existing price discrimination is harder to detect for the consumer than in our experiment and that our findings serve as an upper bound for consumers' ability to be strategically inattentive.

There is a rising awareness for the potential need of consumer protection in connection to these emerging markets. Since the 2016 update, the guidelines for the "Directive on Unfair Commercial Practices" (UCPD)¹⁷ of the European Commission contain also guidelines how to apply UCPD to online platforms. A single study cannot give policy recommendation or decide whether extended consumer protection on online platforms is indicated. But our results provide first behavioral insights into the specific aspect of an important growing market and shed a critical light on provided search tools. While the search technology leads to better-fitting products, it is not straightforward who profits from this technology.

¹⁷http://ec.europa.eu/justice/consumer-marketing/files/ucp_guidance_en.pdf

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A Appendix

A.1 Theory – extended

Optimal Price

The seller sets a price dependent on the buyer's choice of a to maximize his payoff

$$\Pi_S = p \text{Prob}(v \geq p). \quad (5)$$

Case 1. Assume $p \leq a$. Clearly, $\text{Prob}(v \geq p) = 1$ and thus the seller increases his profit by setting $p = a$.

Case 2. Assume $p > a$. Then,

$$\Pi_S = p \int_p^1 \frac{g(v)}{1 - F(a)} dv = p \int_p^1 \frac{f(v)}{1 - F(a)} dv = \frac{1 - F(p)}{1 - F(a)} p \quad (6)$$

$$\frac{\partial \Pi_S}{\partial p} = \frac{1 - F(p)}{1 - F(a)} - \frac{F'(p)}{1 - F(a)} p \stackrel{!}{=} 0. \quad (7)$$

This reduces to:

$$p \frac{f(p)}{1 - F(p)} = 1. \quad (8)$$

Because the hazard rate $\frac{f(x)}{1 - F(x)}$ is assumed to be non-decreasing in x , there is a unique solution \hat{p} with $\hat{p} \in (0, 1)$, solving the above equation (8). Taking both cases together, we get $p^*(a) = \max\{\hat{p}, a\}$. This proves Proposition 1.

Optimal Filter Choice

For the buyer, we need to find the optimal filter choice if the seller chooses the optimal price. We again look at the two cases separately.

Case 1. Assume $a \leq \hat{p}$ and thus $p = p^* = \hat{p}$. Then,

$$\Pi_B = E[v - p | v \geq p] = \int_a^1 \frac{f(v)}{1 - F(a)} (v - p) dv \quad (9)$$

$$\frac{\partial \Pi_B}{\partial a} = \frac{f(a)}{(1 - F(a))^2} \int_a^1 f(v)(v - p) dv > 0. \quad (10)$$

Case 2. Assume $a > \hat{p}$. Then, $p = p^* = a$:

$$\Pi_B = \int_a^1 \frac{f(v)}{1 - F(a)} (v - a) dv = \frac{1 - a - \int_a^1 F(v) dv}{1 - F(a)}. \quad (11)$$

Again, given that the hazard rate $\frac{f(x)}{1 - F(x)} < 1$, we see that the first derivative is negative:

$$\frac{\partial \Pi_B}{\partial a} = -1 + \frac{f(a)}{1 - F(a)} \frac{1 - a - \int_a^1 F(v) dv}{1 - F(a)} < 0. \quad (12)$$

Taken together, we get that the optimal choice $a^* = \hat{p} < 1$. That is, in equilibrium the buyer restricts his search, proving Proposition 2.

A.2 Individual filter choices

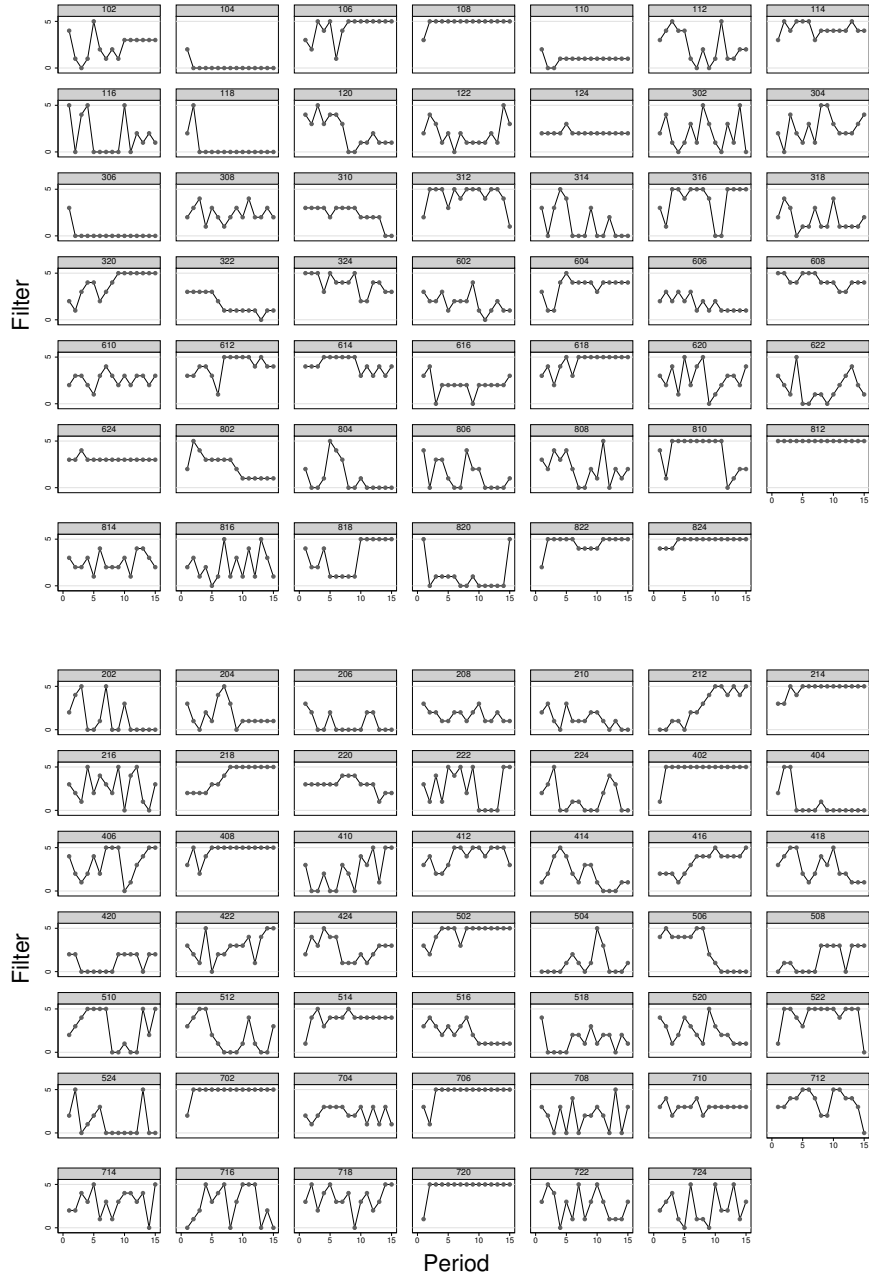


Figure 8: Individual filter choices and realized prices for buyers under stranger matching (top) and partner matching protocol (bottom)

A.3 Instructions

*Note: Instructions displayed here are a translation into English. Original instructions were in German and are available from the authors upon request.*¹⁸

Welcome to our experiment!

You are about to take part in an economic experiment that is financed by the Max Planck Society. It is therefore very important that you read the following instructions carefully. You will receive 4 Euro for showing up to this experiment. During the experiment, you will be given the chance to earn further sums of money. The exact amount will depend both on your own decisions and on the decisions made by the other participants in the experiment, as well as on chance. All sums mentioned during the experiment are calculated directly in Euro. After the experiment, you will be asked to fill in a brief questionnaire. Before you leave, all sums of money you have earned will be paid out to you in cash in Euro.

Please stop talking now, switch off your mobile phone, and remove from your desk anything you do not need for this experiment. Disobeying these rules will lead to exclusion from the experiment and from all payments.

Today's experiment consists of two parts. You will receive the instructions to the individual parts just before each respective part begins. The decisions you make in both parts will have no impact on the respective other part or on the payments you can receive in that other part.

In the following paragraphs, we will describe the exact procedure of the first part of this experiment. At the end of this introductory information, we will ask you please to answer some comprehension questions on your computer screen, which are meant to familiarize you with the decision situation. Should you have any questions, please raise your hand quietly and ask only us. We will then come to you and answer your questions individually.

¹⁸We thank Brian Cooper from the MPI for Collective Goods for the translation.

Description of the First Part

This part of the experiment consists of 15 rounds. At the end of the experiment, exactly one round will be chosen randomly by the computer for payoff. Since you will only be told at the end of the experiment which round is payoff-relevant, you should make your decision carefully in each round.

Before the beginning of the first round, the computer will assign you either the role of buyer or that of seller. You will keep this role during the entire first part; it will therefore not change.

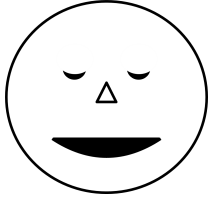
[*Only under stranger-matching protocol:* Further, the computer will re-match, in each new round, one buyer and one seller. In each of the 15 rounds, you will interact with a randomly chosen buyer or seller. At no point, neither during nor after the experiment, will you be told with which other people you have been matched.]

[*Only under partner-matching protocol:* In addition, the computer will randomly match a buyer and a seller at the beginning of the experiment. In all 15 rounds, you will always interact with the same buyer or seller. At no point, neither during nor after the experiment, will you be told with which other people you have been matched.]

In each round, buyers have the chance to buy a product from a large selection of products. The products are depicted through faces that differ in a maximum of 5 characteristics. These characteristics are:

- A white or gray color
- A closed or open left eye
- A closed or open right eye
- A triangular or diamond-shaped nose
- A closed or open mouth.

A total of exactly 32 different products can be made from these characteristics, and each of these possible products occurs just once. For example, a product can be a white face with a closed left eye, a closed right eye, a triangular nose, and an open mouth. This product would then look as follows:









In each round, the buyer is assigned a target product at random by the computer. At no point during the experiment can the seller see this product. The target product would be the optimal product for the buyer and has a value of 5 € for the buyer. No other product has a equivalently high value. The value of each product is determined from the number of matching characteristics with the target product. If, for example, a product distinguishes itself from the target product only by a different nose, then it has a value of 4 € for the buyer. If, on the other hand, a product differs from the target product in all 5 characteristics, then the value of this product is 0 € for the buyer. The products therefore have a value of exactly 0 €, 1 €, 2 €, 3 €, 4 €, or 5 € for the buyer.

At the beginning of each round, the buyer has the chance to diminish the number of products by choosing a number of filters. The buyer may choose between 0, 1, 2, 3, 4, or 5 filters. The number of filters determines the minimum value of the remaining products. In other words, those products remain that have at least as many matching characteristics with the target product as the number of filters chosen. Or, put differently, products with a lower value for the customer are dropped.

Example: If a buyer chooses 0 filters, then all possible 32 products remain. If, for example, the buyer chooses 4 filters, only those products remain that have a value of 4 € or 5 € for the buyer (i.e., a minimum value of 4 €), and all products with a value of 3 € or less are dropped. The number of products remaining – dependent on the number of filters – and the corre-

sponding minimum value can be examined on the decision screen.

Information on the decision screen:

Filter	0	1	2	3	4	5
Remaining products						
Minimum value	0	1	2	3	4	5

In each round, the seller determines a price between 0 € and 5 € for every possible filter choice of the buyer (0, 1, 2, 3, 4, 5). This price can be chosen quite precisely, up to two positions after the decimal point. The seller is also shown the above information. However, the seller is not told the buyer's target product.

The actual filter choice then determines the price that is chosen. This price is then valid for all other products. Hence, if the buyer wishes to buy a product, this price must be paid. The buyer is told the price that was determined by the seller only after the buyer has opted for a number of filters. The buyer is only told the price corresponding to his or her choice of filters, rather than the prices the seller has chosen for the possible other filters.

After the buyer has been told the price for the remaining products, the computer randomly chooses a product from the set of remaining products. The buyer can then either buy or not buy this selected product. The buyer is shown the selected product by the computer, as well as the payoff that beckons in this round if he or she buys the product. The seller is not told which product has been randomly chosen and hence does not know that product's value either.

At the end of each round, the buyer and the seller are shown how high the payoff for this round is. In addition, the seller is told how many filters the buyer chose and whether or not the buyer has bought the product.

The payoff for each round is calculated as follows:

If the buyer buys the product:

$$\text{Payoff of the buyer} = \text{Value (of product drawn)} - \text{Price in } \text{€}$$

$$\text{Payoff of the seller} = \text{Price in } \text{€}$$

Therefore, if the buyer buys the product, he or she will receive as payoff the value of the product minus the price. In this case, the seller will receive a payoff that is the same amount of the price.

If the buyer does not buy the product:

$$\text{Payoff of the buyer} = 0$$

$$\text{Payoff of the seller} = 0$$

Therefore, if the buyer does not buy the product, both buyer and seller will each receive a payoff of 0 € in this round. The seller therefore only receives the price if the buyer actually buys the product.

You will find out at the end of the experiment which round will become payoff-relevant.

Do you have any questions, or is anything unclear? If yes, please raise your hand now. We will then be glad to assist you. You may continue reading the instructions on the next page.

Description of the Second Part

This part of the experiment consists again of 15 rounds. At the end of the experiment, exactly one round of this part will be chosen randomly by the computer for payoff. Since you will only be told at the end of the experiment which round is payoff-relevant, you should make your decision carefully in each round.

[*Only for first part buyers:* The structure of this part is identical to the first part and you keep your role as in the first part – you are again a buyer. However, in this part a computer algorithm takes over the role of the seller.

After setting a number of filters, a computer algorithm determines a product price. Be aware that the computer algorithm saves your choice of the filter number and can use this information for the calculation of the prices. The computer algorithm is programmed with the goal to maximize profits from selling. Additionally, the chosen price will be changed by a random value. The computer algorithm cannot use information from previous periods.]

[*Only for first part sellers:* The structure of this part is identical to the first part and you keep your role as in the first part – you are again a seller. However, in this part a computer algorithm takes over the role of the buyer.

Again, you determine a price for every possible filter choice of the buyer (0, 1, 2, 3, 4, or 5 filters). The computer algorithm receives a target product, as the buyer did before, which you cannot observe. Afterwards the buyer chooses the number of filters (0, 1, 2, 3, 4, 5) randomly, whereas every choice is equally likely. Then, the computer algorithm receives a randomly drawn product from the remaining products. He buys the product if the value for him is at least as high as the price that you set for the chosen filter amount.]

Do you have any questions, or is anything unclear? If yes, please raise your hand now. We will then be glad to assist you.