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Strategic Inattention in Product Search*

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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 for the platform and allows for real-time price discrimination. Consumers face a trade-off: Search intensely and receive better fits at potentially higher prices or restrict search behavior – be strategically inattentive – and receive a worse fit, but maybe a better deal. We study the strategic buyer-seller interaction in such a situation theoretically as well as experimentally. The search technology we use in the laboratory leads by construction to better-fitting products, but we indeed find that only sellers profit from the buyers' use of the offered search tools.

Keywords: strategic inattention, price discrimination, information transmission, consumer choice, experiment
JEL Classification: D11, D42, D82, D83, L11

1 Introduction

The rise of e-commerce websites increases the transparency for consumers in many markets because a multitude of offers can now easily be accessed and browsed through a single web page. It is a widely used practice among online retailers to personalize search results based on data gathered about consumers. There is a rising awareness that this can potentially also be used to prompt consumers towards buying more expensive products, through rearranging the list of product results (*price steering*) or just offering the same product for different prices to different consumers (*price discrimination*). To what extent such practices are actually used is hard to quantify, but Mikians et al. (2012) and Hannak et al. (2014) make first attempts to collect reliable data and observe price steering for users of mobile devices and based on the history of clicks and

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purchases. Price differences were also observed for geographical locations of consumers, and according to a correspondence between the authors of Hannak et al. (2014) and the travel retailer Orbitz, the company stopped steering Mac OS X users towards more expensive hotels.

What has been neglected in this discussion until now is that the search tools provided by these web pages might not be an innocent feature by themselves. *Filters* on a booking website can be used to restrict the offers displayed to hotels that are close to the beach and come with a pool and a gym. While it is obviously beneficial for consumers when they receive more relevant and better-fitting product offers, the use of these search tools does also transmit real-time information to the seller about the valuation a customer might have for certain products. Crucially, these signals reach the retailer (or the algorithm used by the retailer) right before the list of search results and the product prices are displayed to the customer.

This allows for price discrimination based on the transmitted information. Thus, there is a trade-off between fit and price: Consumers might be better off by restricting their search behavior and using fewer filters. And while they might get a worse fit, they might get a lower price and a better deal overall. In this paper, we focus exactly on this trade-off.

Recent theoretical models in information economics also consider situations where a seller learns about the consumer's valuation of a good before setting the price. Roesler and Szentes (2017) investigate how more transparent markets can leave consumers better informed, but facing higher prices. They investigate a situation where the seller observes the precision a buyer learns his valuation with. Carrasco et al. (2017) develop optimal selling mechanisms given that the seller knows different numbers of first moments of the buyer's value distribution. Very close to our paper is the theory of Condorelli and Szentes (2016). A buyer can choose his value distribution for a single indivisible good. He then perfectly observes his valuation. The seller can infer the chosen distribution (but not the actual realization) and condition the product price on it. As a result, the buyer faces a trade-off: He can stochastically increase his valuation and therefore his payoff from the good, but might face a higher price to pay for it.

To allow for an experimental application that mirrors the use of search tools on online retailer websites, we develop a model that imposes a more specific structure than the general results in Condorelli and Szentes (2016). We provide a concise and testable setup that resembles the use of filters to search a multitude of offers.[1] In equilibrium, product prices weakly increase in the intensity of the buyer's filter use. Second, as a consequence, the consumer restricts his filter use. We will call this active decision to restrict his search behavior *strategic inattention*.[2]

[1]Note that the case of a value distribution for a single good offered by a single seller is equivalent to the case where a multitude of goods are available from one seller, which have valuations distributed exactly the same way.

[2]The 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 and empirically by Martin (2016, 2017) to behave as if they are rationally inattentive. In our model, we exclude psychological costs resulting from search. All search costs are of purely strategic nature and are caused through the seller's ability to observe the filter choice of the buyer.

Our theoretical results provide a testable benchmark and we conduct an laboratory experiment to test the predictions of this model. We want to know a.) whether sellers exploit information revealed through consumer search, and b.) whether consumers are indeed strategically inattentive. Additionally, we are interested in c.) how repeated interaction between sellers and consumers impacts the generated surplus. Consumers realistically buy more than once in their life time through an e-commerce website. And from an experimental perspective, repetition might be necessary, since subjects in the lab often approach equilibria only over time. Repeated interaction gives insights into whether potential deviations from the equilibrium are persistent effects or fade out with experience.

In the laboratory experiment, we have a one-to-one interaction between buyers and sellers. The buyer can decide on the use of a certain amount of *filters* to restrict a set of potential offers. Potential low-valuation products are increasingly excluded from the set. The seller can observe the filter choice and then set a price for a product randomly chosen from the remaining offers. For question c.), we test the effect of repeated interaction under two different market conditions. In some markets, one-shot interactions dominate. Therefore, in the first condition, buyers and sellers encounter a sequence of one-shot interactions with random rematching. This also excludes possible confounding factors and resembles the one-shot model, while allowing for learning effects. In the other condition, subjects interact repeatedly with the same partner. This is more realistic in markets where consumers tend to buy repeatedly on the same platform and allows us to quantify effects through costumer retention and reputation. In these markets, sellers might have an incentive to restrict information exploitation.[3]

Our study is closely related to the literature on behavior-based price discrimination (for an overview, see Fudenberg and Villas-Boas, 2006). In these models, the basic setup typically has two periods. In the second period, a monopolist can charge different prices for consumers who bought in the first period and consumers who did not buy in the first period. Consumers recognize that their choice in the first period has an impact on the prices obtained in the later period.[4] Behavior-based price discrimination is dependent on the information buyers reveal through past behavior. In contrast, we consider a single buyer facing a seller in a one-shot interaction. The buyer chooses how to restrict the distribution of his valuation (through filters), which the seller can observe. Thus, our model tries to capture the automatic use of *real-time search data* that reveals information about consumer's valuation. This goes beyond two-period models that capture a recurring customer who can be identified by browser cookies. We will note the apparent similarities and distinctions to these models in the theory section.

Furthermore, our topic is closely related to a stream of literature on strategic information transmission started by Crawford and Sobel (1982). Two recent working papers in this area (Vellodi, 2016; Hidir, 2017) address similar situations as in our project, but use a bargaining model including cheap-talk messages. In

[3] Note that the term 'market condition' relates here to the repeated interaction. The interaction in each period is between a buyer and a monopolistic seller.

[4] Fudenberg and Villas-Boas (2006) consider a continuum of consumers with fixed valuations drawn from a continuous distribution function. Alternatively, two-point distributions have been considered (Hart and Tirole, 1988; Villas-Boas, 2004).

comparison to this, our filter choice is always informative for the seller. The buyer can hide, but not misrepresent, private information. Additionally, sellers in our model can only set the product price. Filter choices of the buyers restrict the portfolio of the seller and the product offered is randomly drawn from the remaining set.

The results of the experimental study are generally in line with our theory. Buyers are strategically inattentive, although not to the extent predicted by theory. Further, sellers set higher prices for higher filter choices. We find only small differences between the two market conditions, but welfare is slightly higher when sellers and buyers interact repeatedly with each other. Finally, over time, sellers profit from higher filter choices of the buyers, while buyers themselves do not. The remainder of the paper is organized as follows: In Section 2, we provide the theoretical framework and derive testable propositions. We then introduce the experimental design in Section 3. Section 4 presents the results of the experimental study, and we conclude in Section 5.

2 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.[5] 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.[6]

The seller provides a search technology for the buyer which we will call $filter$ choice 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.[7]

The truncated distribution $d_a(v)$ with support on $[a, 1]$ is:

$$\frac{g(v)}{1 - F(a)} \ , \tag{1}$$

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

The choice of a and thus $d_a(v)$ is known to the seller. Afterwards the seller makes a take-it-or-leave-it offer to the buyer by setting a price p. Then, 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:

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

[6]We assume risk neutrality. Note that introducing risk aversion on the buyer side would not change equilibrium predictions.

[7]It would also be possible to model this as as the buyer having a taste parameter θ on a Salop circle and his valuation $v = v_{max} - t(\theta - y)$ where $t(\Delta)$ is a non-decreasing function in Δ and y is the chosen product. The buyer then decides on the maximal distance between his target product given by his taste parameter and the offered product that he will receive. In the end, this simplifies to the buyer restricting his value distribution function from below.

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 or not.

We use backward induction to find the subgame-perfect Nash equilibrium of this game and state two propositions which we will later test in the lab. For any function f with a non-decreasing hazard rate, the following two propositions hold.[8]

Proposition 1 (Increasing Price):
Given that the value distribution function $f(v)$ is regular, the optimal seller price is weakly increasing in the filter choice of the consumer a.

Proposition 2 (Strategic Inattention):
Given that the value distribution function $f(v)$ is regular, the buyer is strategically inattentive and restricts his search optimally ($a < 1$).

$t = 3$: Nature draw and buyer decision

Nature draws the buyer's valuation from d_a. We assume that when the buyer is indifferent between buying and not buying he will always buy. That is, he will buy if $v \geq p$.

$t = 2$: Optimal price

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

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

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

$$p^*(a) = max\{\hat{p}, a\}.^{9} \tag{3}$$

Note that $\hat{p}$ is unique with $\hat{p} \in (0, 1)$. In fact, $\hat{p}$ is the optimal price in the unrestricted case (where $a = 0$) 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 higher a. This proves Proposition 1.

$t = 1$: Optimal filter choice

For the buyer, we need to find the optimal filter choice if the seller chooses the optimal price. The optimal filter choice is

$$a^* = \hat{p} < 1. \tag{4}$$

That is, in equilibrium the buyer is (partially) inattentive, proving Proposition 2. This result is – in line with the literature – not efficient and thus constitutes a hold-up problem in that the buyer restricts his search ($a < 1$), whereas searching fully (choosing $a = 1$) would maximize welfare.

[8] We provide the full analysis in Appendix A.1.

[9] This price function translates to the optimal price for 'previous customers' in the Fudenberg and Villas-Boas (2006) model.

2.1 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 $f(v) = U(0,1)$. We obtain $p^* = max\{\frac{1}{2}, a\}$ and $a^* = \frac{1}{2}$ (see Figure 1).

Example 2. For the lab experiment, we choose a discrete distribution, which makes it easier to understand for subjects. We set $f(v) = Bin(5, 0.5)$. The above results translate directly to this discrete distribution (with a now being a discrete choice). Here $p^* = max\{2, a\}$ and $a^* = 2$ (see Figure 2).

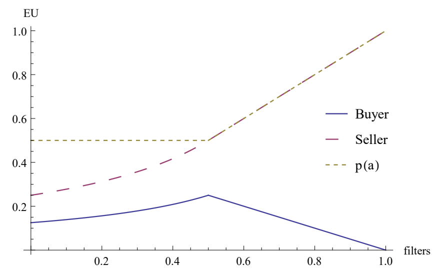

Figure 1: Expected payoffs given filter choice $a \in [0,1]$ with $v \sim U(0,1)$

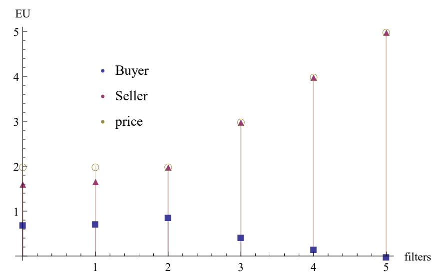

Figure 2: Expected payoffs given filter choice $a \in \{0, 1, ..., 5\}$ with $v \sim B(5, 0.5)$

3 Experimental Design

We conducted eight experimental sessions in the Laboratory for Experimental Economics at the University of Bonn (BonnEconLab) in June 2017. The experiment was computerized with oTree (Chen et al., 2016) and participants were invited using hroot (Bock et al., 2014). We had 24 subjects per session with a total of 192 participants. Subjects played 15 periods of the game in exactly one of two possible conditions, either under *stranger-matching* (STRANGER) or under *partner-matching* (PARTNER). In both conditions, participants are assigned either to the role of a *buyer* or a *seller* and they keep their role for the whole experiment. Buyers and sellers are 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.

Under stranger-matching, buyers are randomly and anonymously re-matched to sellers in the beginning of each period.[10] This excludes any reputation effects, as well as long-term strategies to influence the behavior of the other party. Under partner-matching, buyers and sellers are matched in the beginning of the first period and then stay together for the whole experiment and interact repeatedly.

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

For parametrization we use the discrete distribution pictured in *Example 2* above. We use a portfolio of fictitious products with 5 different binary characteristics. The portfolio consists of all possible combinations of characteristics, which makes a total of $2^5 = 32$ products. This portfolio is the same in all periods of the experiment.

At the beginning of each period, the computer randomly draws from the set of all products to identify the so called *target product* of the buyer. All participants are told that the target product is the ideal product the buyer could buy and that each product in the portfolio has the same probability to be selected, but only the buyer gets to know the actual target product. The value of a drawn product is determined by the number of matching characteristics with the target product. Hence, the drawn product is of value x if x characteristics are matching with the target product.

The buyer can then set a discrete number of filters $F = \{0, 1, ..., 5\}$, which reduces the number of products remaining in the product portfolio. Only products stay in the portfolio that have a minimum number of characteristics in common with the target product, equal to the number of filters used.

All remaining products will get the same price, which is determined by the seller. We use the strategy method to elicit the whole pricing strategy (the price vector) of the seller. Hence she sets 6 prices, and each price can freely be set between 0 and the maximum valuation of 5 in steps of 1 Euro Cent.[11] The strategy method ensures that we obtain pricing data for all possible choices of buyers even when some options are chosen only irregularly.

Once the seller is done with setting the prices, the computer draws randomly one of the remaining products from the portfolio. 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 the product has for him minus the price chosen by the seller. In case she sold the product, 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 as well as the final payoffs for this period. The buyer does not obtain information about the rest of the pricing strategy of the seller.

In the end, the payoff of one of the 15 periods is paid out to prevent hedging between the periods.[12] We also collect data on an incentivized additional task against the computer, which is only generally announced as a second part before (see next paragraph for a detailed description). We also have two incentivized post-tests, the "bomb" risk elicitation task (Holzmeister and Pfurtscheller, 2016) and the SVO slider measure (Murphy et al., 2011). The experiment ends with a standard post-experimental questionnaire containing demographics. The money earned by each participant is paid out in cash privately directly after the experiment.

3.1 Computer Task

The optimal reaction to an irrational counterpart's decision might be different from equilibrium choices. In the main experiment, a buyer might not choose

[11] All values and prices in the experiment are directly calculated in Euro.
[12] Also those where the buyer cancelled the buying process without a purchase.

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. To be able to disentangle the strategies of buyers and sellers and to observe one-sided behavior, in this additional task subjects play the same game as before, but now against the computer. This also excludes any possible effects of social preferences and we fix beliefs about the sophistication of the other party.

As in the main experiment, subjects play for 15 periods and also keep their role as buyers or sellers as before. Sellers set again the full price vector and buyers choose an amount of filters and whether they buy the product in the end. Subjects are aware that they are playing against a computer. 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 are aware that 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^*.

3.2 Hypotheses

We test hypotheses based on the two propositions drawn from our model. First, we test Proposition 1, using realized prices in the experiment, as well as the individual price vectors of the sellers.

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. We also analyze the additional computer task to be able to see one-sided behavior and to control for social preferences as well as (potentially distorted) beliefs about the sophistication of the other party.

Hypothesis 2 *Buyers restrict their search optimally.*

In the model, we make the implicit assumption that buyers take rational buying choices and buy if their net value from the deal is greater or equal to 0. However, it might be that buyers choose not to buy even when they have a positive net value. We will take this into account in our analysis of the two market conditions.

Compared to multiple one-shot interactions with different counterparts (as in the STRANGER condition), strategic uncertainty might be lower in a market were buyers repeatedly meet the same seller (as in the PARTNER condition). Sellers and buyers get a chance to learn about each other and sellers might have an incentive to set lower prices to build up reputation and to ensure consumer retention. In our experiment with a monopolistic seller, buyers cannot switch between sellers but nevertheless can react to high prices. Unreasonably high prices might lead to higher rejection rates of buyers even when their net value might be positive. The buyer might sacrifice some short-term payoff in order to ensure a higher consumer surplus in future periods. When product prices are considered reasonable by buyers and sellers do not fully exploit the information gained from the filter choice to discriminate prices, buyers might make higher filter choices than predicted by the equilibrium. This would lead on average to higher valuations of the offered products, which in turn can be sold at higher prices compared to the equilibrium. That is, even when selling at reasonable prices, sellers could be able to gain a higher surplus. Overall this would then lead to more efficient outcomes.

Hypothesis 3 *In the* PARTNER *condition, more efficient outcomes are obtained compared to the* STRANGER *condition.*

4 Results

In this section, we provide the analysis for testing our hypotheses. First, we will discuss seller behavior. Then, we will provide an analysis of buyers' filter choices. Finally, we will discuss welfare effects and dynamics. Note that all tests are two-sided.

4.1 Price Setting

Realized Prices

Let us first look at actually chosen prices in the experiment. The realized prices depend on the actual filter choices of the buyers. Sellers charge higher prices in the STRANGER (2.68) compared to the PARTNER (2.49) condition. Taking averages over all periods and treating each matching group as one observation, this difference is not significant, though (rank-sum test, $p > 0.1$). [13]

In both conditions, the realized prices react to the filter choice. The left picture of Figure 3 shows that the average price is increasing in the filter choice. The increase in prices is confirmed in a mixed effects regression controlling for condition differences and the period of play (see columns (1)-(4) in Table 1).

Price Vector

The analysis above takes only the actual choices of buyers into consideration. With the use of the strategy method, we are able to observe pricing strategies of the sellers for all potential decisions of the buyers, i.e., we obtain the full price vectors for each seller. The right-hand side of Figure 3 shows the average price vector in both conditions in comparison to the price vector as predicted by theory. [14] Again, price vectors are increasing. This is confirmed by the regression (see columns (5) - (8) in Table 1). This confirms our first hypothesis and we conclude:

[13]This is based on the comparison of 12 matching groups in STRANGER and 48 buyer-seller pairs in PARTNER. The same holds true when taking the average price per seller over all periods as an independent observation (which it is not). We have 15 (periods)*48 (sellers)*2 (conditions) = 1440 data points for the individual periods, and 96 data points when taking the average for each seller.

[14]see Appendix A.3 for the individual average price vectors of each seller.

Table 1: Regression of realized prices and price vectors on filters

	realized price				price vector			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Filter	0.442^{***}	0.442^{***}	0.438^{***}	0.438^{***}	0.470^{***}	0.470^{***}	0.470^{***}	0.470^{***}
	(28.65)	(28.68)	(28.78)	(28.61)	(84.73)	(84.73)	(85.24)	(84.44)
Partner		-0.219	-0.219	-0.201		-0.195	-0.195	-0.171
		(-1.64)	(-1.64)	(-1.49)		(-1.59)	(-1.59)	(-1.34)
Period			-0.0336^{***}	-0.0344^{***}			-0.0221^{***}	-0.0228^{***}
			(-6.09)	(-6.20)			(-10.13)	(-10.35)
Risk-taking				0.0164^{+}				0.00830
				(1.68)				(0.90)
Controls	No	No	No	Yes	No	No	No	Yes
Constant	1.382^{***}	1.516^{***}	1.794^{***}	0.917^{+}	1.325^{***}	1.442^{***}	1.619^{***}	1.415^{**}
	(17.47)	(13.66)	(14.99)	(1.66)	(20.96)	(15.17)	(16.75)	(2.72)
Observations	1440	1440	1440	1425	8640	8640	8640	8550

z statistics in parentheses
$^{+}$ $p < .10$, * $p < .05$, ** $p < .01$, *** $p < .001$

Note Linear mixed effects regression with errors nested in matching groups, nested in individuals. Dependent variable is the realized price (1)-(4) and the conditional price according to the strategy method (5)-(8). 'Partner' is a dummy taking the value 1 in the Partner condition. 'Filter' is the filter choice or potential filter choice and 'Period' is the period of play. Risk-taking is obtained from the risk task. Controls contain age, gender, SVO angle, and answers to questions about online shopping from the questionnaire.

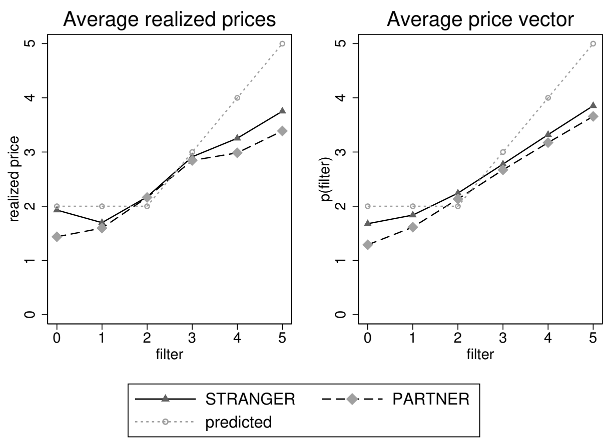

Figure 3: Average realized prices and price vector conditional on filter choice

Result 1 *Realized and conditional prices are increasing in the filter choice.*

Note that sellers who take more risk, on average set higher prices. This makes sense since higher prices increase the probability of the buyer receiving a product with a valuation that is lower than the price and thus of the buyer not buying the product. More risk-averse subjects should thus reduce their prices. Importantly, this effect is only weakly significant and only seems to play a role for the realized price.

The graphs suggest that prices are on a slightly lower level in the PARTNER condition. However, this difference cannot be confirmed in the regression. Considering the conditional price vectors, we do not find any clear difference between market conditions either. The graph suggests that there might be a difference for the average price given a low filter choice. Indeed, taking each price vector of sellers as an individual observation, prices for a filter choice of 0 are higher under STRANGER compared to the PARTNER condition (1.84 vs. 1.52, $p = 0.0027$), which is significant (Bonferroni corrected p-value of $0.05 * 6 = 0.0083$). However, this does not translate into summarizing measures like the average price (STRANGER vs. PARTNER, 3.37 vs. 3.23, $p > 0.1$). Also, the difference nearly disappears when taking averages over all periods as an observation ($p = 0.0703$). Price vectors and realized prices are lower than predicted for low and for high filter choices. Prices are very close to the predicted prices for intermediate filter choices.

4.2 Filter Choice

Buyers choose on average 2.64 filters in STRANGER vs. 2.70 in PARTNER. Taking filter choice averages over all periods and treating each matching group as one observation, this is no significant difference (ranksum-test, $p > 0.1$).[15] Recall that the optimal filter choice based on the Nash equilibrium predictions is a choice of 2. Buyers choose on average more filters than predicted (ttests, $p < 0.01$ for both conditions). Therefore we can only partly confirm our second hypothesis:

Result 2 *Buyers restrict their search behavior, but search more than predicted by the Nash equilibrium.*

Buyer choices are quite diverse in both conditions. Figure 4 shows a histogram of all filter choices in all periods.

Subjects choose 5 filters most often (22.4% in STRANGER and 26.39% in PARTNER). The other filter amounts are chosen about equally between 11% and 18% of the time. In fact, on average only about 15 % of subjects choose 2 filters. This does not necessarily mean that buyers act non-optimally. Rather, given a certain non-equilibrium pricing scheme of sellers, a different filter choice might be optimal and lead to higher payoffs.

4.3 Buying Decision

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

[15] Again, this is the conservative test. Taking each individual buyer averages over all periods as one observation still does not affect the results(ranksum-test, $p > 0.1$).

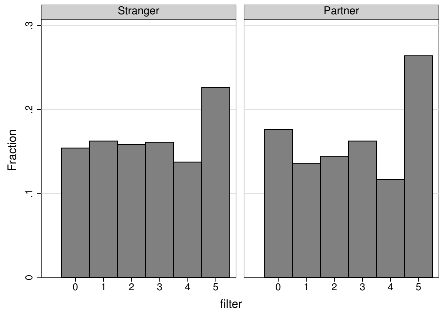

Figure 4: Histogram of all filter choices

conceivable, though, that subjects in the experiment will not buy if the net value is low. The reason might be that they perceive the price as too high. Indeed, we find that some subjects reject offered products that would give them a positive net value. If we focus on decisions where the net value is weakly positive, we find that the average net value of the rejected products is higher in PARTNER than in STRANGER (0.35 vs. 0.21, ranksum-test, $p = 0.0486$). That is, buyers require a higher net value to accept the offered product in the PARTNER condition. They might reject offered products in the hope of lower prices in future periods.

These results can also potentially explain why prices are lower than predicted, especially for high filter choices. Taking a choice of 5 filters, for example, ensures a value of 5 to the buyers. Charging a high price close to 5 would lead to a very low net value for the buyer and could prompt them not to buy.

4.4 Welfare

Total welfare, defined here by the sum of the payoffs of seller and buyer, is driven by two factors, filter choice and buying probability. Higher filter choices always lead to higher expected welfare as long as the product is bought.

Welfare is higher in PARTNER (2.61) compared to the STRANGER condition (2.44). Treating each interaction between seller and buyer as one observation (720 observations in each condition), this difference is weakly significant (ranksum-test, $p = 0.0811$).

	Buyers	Sellers	Total welfare
STRANGER	0.99	1.46	2.45
PARTNER	1.13	1.48	2.61

Table 2: Average payoffs and total welfare (sum of payoffs) between conditions

Considering sellers and buyers separately (see Table 2 for an overview), we find that sellers have, on average, higher payoffs than buyers (sign-rank test with a within-match comparison, $p < 0.001$ in both conditions). Importantly, for sellers there is no difference between the conditions (ranksum-test, $p > 0.1$). On the other hand, buyers in the PARTNER condition earn more than buyers in the STRANGER condition ($p = 0.0235$). However, this difference is only significant when considering each outcome in each period as an observation. Taking average payoffs of subjects over all periods as an observation, we find no difference for buyers or sellers ($p > 0.1$) between conditions. Taken together, we find only weak evidence for our third hypothesis:

Result 3 *Total welfare is on average only slightly higher in the* PARTNER *condition compared to the* STRANGER *condition. This is driven by higher payoffs for buyers in the* PARTNER *condition.*

4.5 Dynamics

In this section, we will provide an explorative overview on the dynamics over time. In short, we find no clear difference between conditions in these dynamics. Further, average prices and filter choices seem to be relatively stable. Figure 5 shows that the average amount of filters chosen as well as the average prices realized are relatively stable over time.

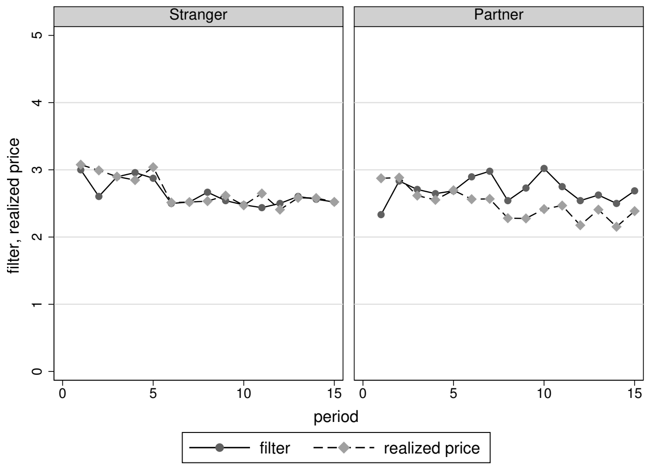

Figure 5: Average filter choice and average price realized

However, in this case the average is slightly misleading. When we look at the distribution of filter choices over time, we see a small but clear movement towards the extremes of 0 or 5 filters (see Figure 6). This dynamic seems to be even more clear in the PARTNER condition. In the last period, about 35% and 21% of buyers choose 5 or 0 filters, respectively compared to 21% and 15% in the STRANGER condition.

In Appendix A.2, we provide an overview of realized prices and filter choices over time for each individual buyer. Especially in the PARTNER condition, we find a heterogeneous effect. In some groups, filter choices increase and are quite stable at high levels, while in other groups the opposite can be observed. How this translates to payoffs for the corresponding group members is less clear. One would assume that in groups with high average filter choices both sellers and buyers should benefit from this development. For buyers, we analyze 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 face. This analysis provides insights on the effect of the search technology – the filters – on payoffs of sellers

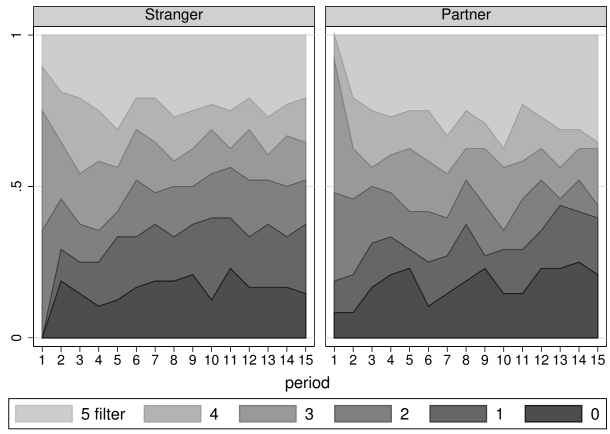

Figure 6: Frequency of filter choices over time

and buyers. Interestingly, as Figure 7 suggests, the buyers' average payoffs are not increasing in the filter choice, while sellers profit from a higher filter choice. This dependency is confirmed in separate regressions for buyers and sellers (Table 3).

Result 4 *Over time, buyers using more filters on average do not profit more than buyers using less filters. On the other hand, sellers profit more when faced with higher filter choices.*

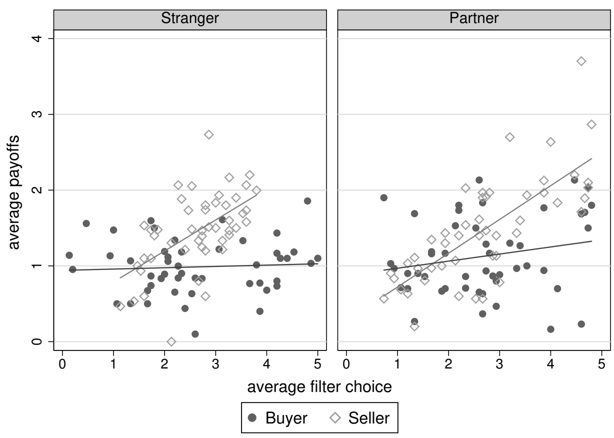

Figure 7: Average payoff on average filter choice (when each data point represents one subject and lines are a linear fit)

4.6 Computer Task

As mentioned above, beliefs or social preferences might influence our results. To control for this, subjects in the additional computer task have the same role,

Table 3: Regression of average payoffs over all periods on average filter choice

	(1) Payoff buyer	(2) Payoff seller
Average filter	0.0517	0.436***
	(1.38)	(9.55)
PARTNER	0.139	-0.00547
	(1.31)	(-0.06)
Constant	0.850***	0.307*
	(7.40)	(2.17)
Observations	96	96

z statistics in parentheses

$^{+}$ $p < .10$, * $p < .05$, ** $p < .01$, *** $p < .001$

Note OLS regression with clusters 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 in the PARTNER condition.

but we fix beliefs by making the computer seller use the optimal pricing strategy (with a small error term) and by programming the buying choice of computer buyers such that they buy whenever they would get a non-negative payoff.

Since the filter choice that sellers face is random (computer buyers make random choices), it is sensible to focus the analysis on price vectors. As confirmed by a mixed effects regression (see Table 4 in Appendix A.4), conditional prices are again increasing in the filter choice. The average price vector tracks the optimal price vector much closer than in the main task (see Figure 12 in Appendix A.4). Clearly, this is driven by the fact that there is no strategic uncertainty here for the sellers. While in the main task buyers can always decide not to buy the product, in the computer treatment, sellers can be sure that the computer buyers buy at all net values equal to or above 0.

In comparison to the main task, the average filter choice over all periods also moves closer to the predicted values (STRANGER: 2.20 vs. 2.64, sign-rank test, $p < 0.001$; PARTNER: 2.12 vs. 2.70, sign-rank test, $p < 0.001$). In both conditions, the average filter choice is now not significantly different from the predicted value of 2 (ttests, $p > 0.1$). This automatically leads to lower welfare in the computer task.[16]

[16] We focus on the buyer side and consider the sum of payoffs of the buyer and the payoff that the corresponding seller would earn if he was not a computer. Treated like this, welfare is lower in the computer task compared to the main task in both conditions (STRANGER: 2.01 vs. 2.45, sign-rank test, $p = 0.0041$; PARTNER: 2.22 vs. 2.61, sign-rank test, $p = 0.0071$).

5 Discussion

We provide a theoretical analysis and an experimental test on the behavior of sellers and buyers when the sellers can observe the product search behavior of buyers. We show theoretically that prices are increasing in the filter choice. Further, buyers are strategic in that they reduce their filter choice below the maximum possible amount. We test the theory in two settings, a STRANGER condition directly capturing the situation of the theory, but allowing for learning and a PARTNER condition where sellers and buyers interact repeatedly, allowing reputation to come into effect.

Our experimental results are in line with the theory. Prices are increasing in the filter choice and buyers choose a medium number of filters. We find only weak differences between the conditions. Sellers seem to take into account that unreasonably high prices will lead buyers to reject the offer. Given that this is a concern already in a single interaction, there is not much room for improvement through repeated interaction.

Results from the additional computer task, where subjects face computer sellers and buyers, are in line with this. Behavior moves closer to the predicted values. Especially, prices on the extreme ends (following very low and very high numbers of filters) are closer to the optimal amount compared to the main task. This can be explained by the absent strategic uncertainty. Computer buyers always buy the product as long as their net value is non-negative. Overall, higher payoffs are reached in the main task.

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 ad, 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, laws already regulate some forms of dynamic adjustments of prices and too obvious price discrimination might come at the risk of boycotts when detected. Still, platforms could use this information in a more indirect way, for example through targeted advertising or by allowing sellers to persuade buyers to buy add-on products or services. In this case, we 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. A possibility to test this effects is to subsequently use more realistic experimental setups that mirror real online platforms more closely.

From a policy perspective, a single study cannot decide whether extended consumer protection on online platforms is indicated. But our results provide first insights into a specific aspect of an important growing market. While the search technology, by construction, leads to better search results, it is not straightforward who profits most from this technology. Our data suggest that buyers on average do not profit from a higher filter choice. On the other hand, sellers earn on average more when facing buyers who choose a higher amount of filters. In other words, while both sides could potentially profit compared to a situation without a search technology, sellers in the end seem to be the main beneficiaries.

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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

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

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

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

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

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

This reduces to:

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

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,

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

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

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

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

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

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

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 Results Buyers

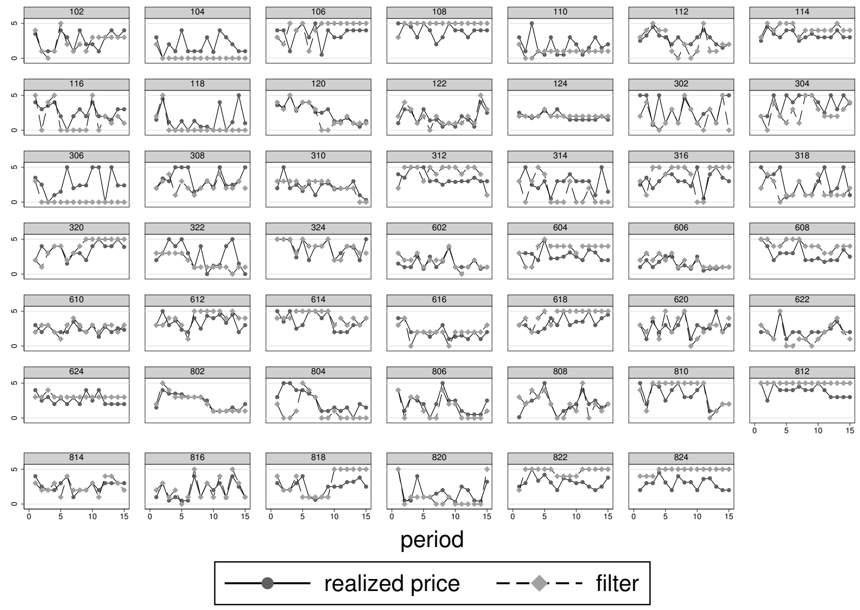


Figure 8: Individual filter choices and realized prices for buyers in STRANGER

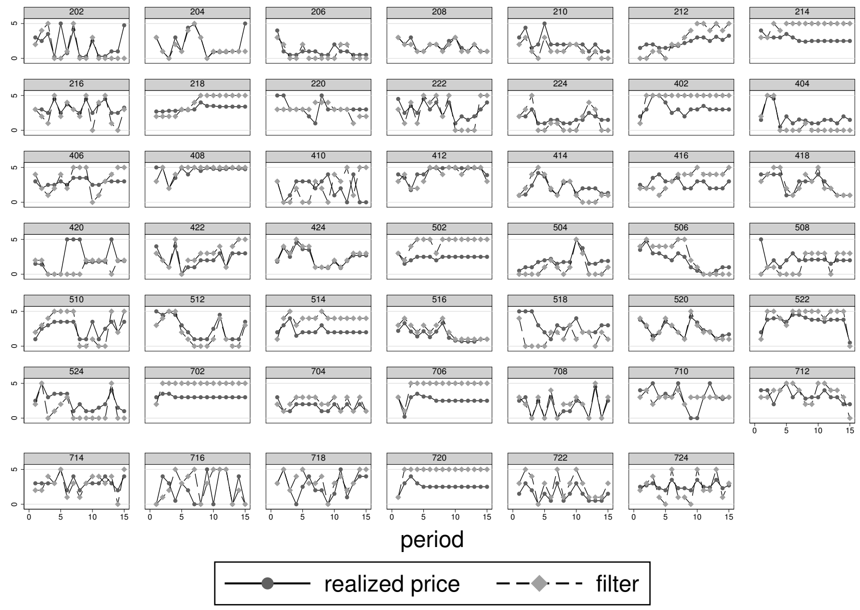


Figure 9: Individual filter choices and realized prices for buyers in PARTNER

A.3 Individual Results Sellers

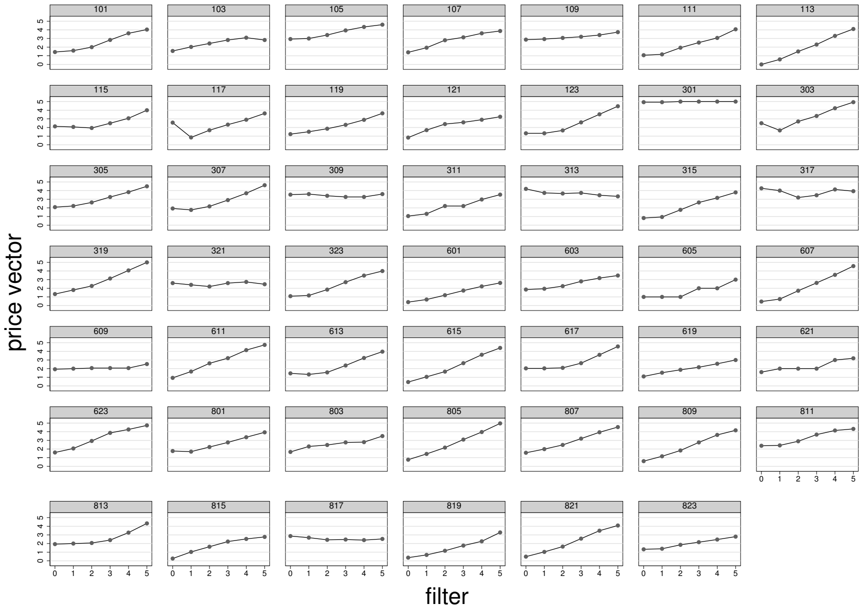


Figure 10: Individual average price vectors for sellers in Stranger

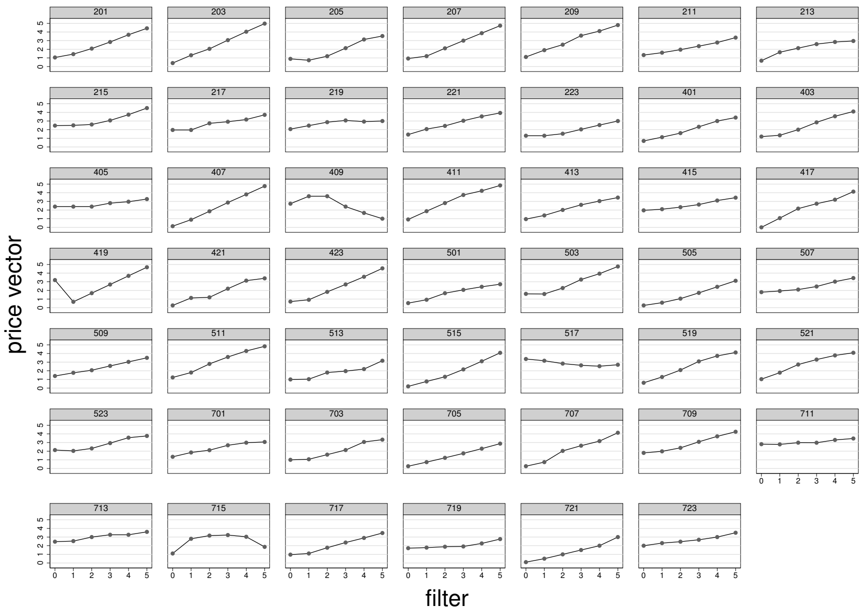


Figure 11: Individual average price vectors for sellers in Partner

A.4 Computer Task

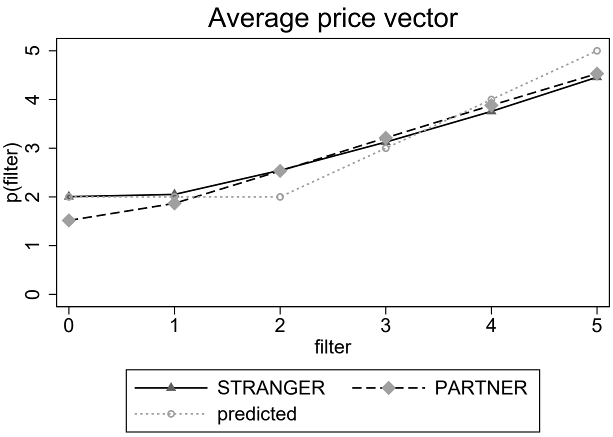


Figure 12: Average price vector in the computer task (when sellers are split by condition from main experiment)

Table 4: Regression of conditional prices on filter

	(1)	(2)	(3)
Filter	0.568***	0.568***	0.568***
	(117.19)	(117.19)	(117.51)
Partner		-0.0667	-0.0667
		(-0.59)	(-0.59)
Period			0.0131***
			(6.87)
Constant	1.538***	1.571***	1.269***
	(26.58)	(19.45)	(13.81)
Observations	8640	8640	8640
Pseudo R^2			

z statistics in parentheses
$^{+}$ $p < .10$, * $p < .05$, ** $p < .01$, *** $p < .001$

Note: Mixed effects regression with errors nested in groups, nested in individuals. Dependent variable is the conditional price according to the strategy method. 'Partner' is a dummy taking the value 1 in the Partner condition. 'Filter' is the potential filter choice and 'Period' is the period of play.

A.5 Instructions

Note: Instructions displayed here are a translation into English. Original instructions where in German and are available from the authors upon request.[17]

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.

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 in* STRANGER *condition:* Further, the computer will rematch, 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

[17] We thank Brian Cooper from the MPI for Collective Goods for the translation.

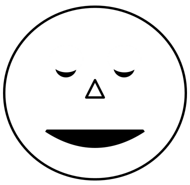
experiment, will you be told with which other people you have been matched.]

[*Only in* PARTNER *condition:* 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:

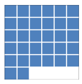
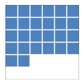
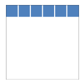
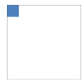


In each round, the buyer is assigned a target product at random by the computer. At no point during the experiment can the seller see this product. The target product would be the optimal product for the buyer and has a value of 5 € for the buyer. No other product has a equivalently high value. The value 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 corresponding 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:

Payoff of the buyer = Value (of product drawn) - Price in €

Payoff of the seller = Price in €

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:

Payoff of the buyer = 0

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.