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The Effects of Non-binding Retail-price Recommendations on Consumer and Retailer Behavior

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Abstract

This paper presents results from an experiment on the effects of retail-price recommendations (RPRs) on consumer and retailer behavior. Despite their non-binding nature, RPRs may influence consumers' willingness to pay by setting a reference point. Loss averse consumers will then be reluctant to pay a price higher than the recommended one. Furthermore, at a given price level consumers will demand a larger quantity the higher the RPR is. We find evidence for both effects. They are stronger when the price recommendation contains information about the value of the product to the consumer instead of providing an uncorrelated anchor only. Retailers in this study react to RPRs in a similar way as consumers do, but they do not anticipate consumers' behavior well.

Keywords: recommended retail price, consumer behavior, retailer behavior, experiment

JEL-Classification: C91, D42, D82

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1 Introduction

Non-binding retail price recommendations are prominent in pricing. They can be found on small goods like chocolate bars or big ones like cars. Manufacturers use this measure to suggest their retailer(s) a price at which the product should be sold to consumers. As such price recommendations are non-binding by definition, standard neoclassical theory classifies them as cheap talk and predicts them to have no effect on the market outcome.[1] Behaviorally, however, retail price recommendations may indeed influence consumers' demand by setting an anchor (see, e.g., Ariely et al. 2003, Stewart 2009, Tversky and Kahneman 1974) for an appropriate price of the product.[2] Retail price recommendations are then predicted to affect consumers' willingness to pay via reference points and loss aversion (Rosenkranz, 2003; Fabrizi et al., 2012). If the price recommendation forms a reference point, loss averse consumers are unlikely to pay a price higher than the recommendation.[3] This allows for "moon pricing", the combination of an artificially high price recommendation and a much lower price in order to increase demand (Armstrong and Chen 2012).[4] Retailers may adapt their price setting to the discontinuities in the demand schedule, but may also be subject to own anchoring biases resulting from receiving the price recommendation.

This paper studies the behavioral effects of retail price recommendations on buyer and retailer behavior. Using experimental data it attempts to help answering the following research questions: What is the effect of a price recommendation on consumers' willingness to pay? How does the retailers' price setting behavior depend on whether consumers are informed

[1]There are extensions to standard theory such as Buehler and Gaertner (2013) showing that retail price recommendations can, for example, transmit information about production costs and consumer demand from the manufacturer to the retailer, and thus, serve as a coordination device in a repeated interaction between the two. Similarly, in the model of Lubensky (2010) information transmission goes directly from the manufacturer to consumers where it can help reducing search costs.

[2]The experimental literature (see Falk et al. 2003; Brandts and Solá, 2001) provides evidence for such anchoring effects by comparing Mini-Ultimatum games with different menus of offers from which the proposer can choose.

[3]In the model of Heidhues and Köszegi (2008) past prices set a reference point by determining consumers' expectations about future prices. See also Köszegi and Rabin (2006) for a general model how reference points affect behavior.

[4]Similarly, such reference point effects can help the upstream manufacturer to solve the problem of double marginalization, because the drop in consumer demand at the recommended price makes it less attractive for the retailer to set a price above the price recommendation (Puppe and Rosenkranz, 2011).

about the recommended price? How do demand and price setting depend on whether the price recommendation contains an informative signal about the quality of the product?

To answer these questions, this paper presents results from an experiment modeling the interaction between a retailer setting prices and a consumer deciding on the quantity demanded. To isolate the behavioral effect of the price recommendation on retailer and buyer behavior from any strategic interaction with an upstream manufacturer price recommendations in the experiment are determined by a random mechanism. Four different treatments vary two aspects of the informational setup in a two-by-two design. In the main treatment, both the consumer and the retailer are informed about the price recommendation, which contains an informative signal about the consumer's valuation of the fictitious product. The control treatments either remove the informative content of the price recommendation by making its random draw independent of the consumer's valuation or hold the consumer uninformed about the price recommendation. An additional control treatment tests the robustness of seller behavior with respect to feedback about past demand.

Results show that consumers react in the way predicted to a price recommendation. At a given price, they demand more the higher the price recommendation is and this effect is stronger when the price recommendation is informative about the quality of the product for the consumer. Their demand drops sharply at prices above the recommended one. Retailers' price setting similarly reacts to the recommendations, but they fail to exploit consumers' behavioral patterns.

The structure of this paper is as follows. In Section 2, we present the experimental design and procedures. Section 3 formulates some behavioral hypotheses. The results are described in Section 4. Section 5 concludes.

2 Experimental design and procedures

The experiment studies the pricing decisions of a (downstream) retailer and the demand of consumers, depending on the retail price recommendation r, set by a (computerized) upstream manufacturer, and on costs c. Costs are randomly drawn in each round with $c \in [0, 10]$. Similarly, the retail price recommendation r is determined as costs c plus a random markup drawn uniformly from the interval $[0, 10]$ in each round. The value of the product for the buyer is $v = c + 10$.

The experiment lasts 10 rounds with fixed matching. Participants receive no feedback while making their decisions in the 10 rounds, but learn the full history of prices, traded quantities and profits at the end of the experiment. In all treatments, the retailer knows costs c and sets a price p. The buyer can buy up to 10 units in each round. The buyer's demand is elicited using the strategy method to avoid having an additional reference point formed by the price of the retailer and to collect more informative data. For all possible prices $p \in [0, 20]$ the buyer has to state how many units he would like to order.

Treatments vary with respect to whether the buyer knows the price recommendation and whether the price recommendation is informative about the value of the product for the buyer (see Table 1). In treatment BothInfo, both the retailer and the buyer know the price recommendation when making their decision and the price recommendation is determined as $r = c + random(0, 10)$, which provides an informative signal about the value $v = c + 10$ of the product for the buyer. In particular, the buyer can infer a lower bound for the value of the product from the price recommendation. In treatment BothRandom, again both the retailer and the buyer are informed about r, but r is determined independently of c (and, thus, v), as the sum of two random draws, $r = random(0, 10) + random(0, 10)$. The comparison between these two treatments allows to study whether an effect of the price recommendation on buyer's demand is driven by its informational content about the value of the product or by pure anchoring. The two treatments SellerInfo and SellerRandom have the same mechanism how the price recommendation is determined, but do not inform the buyer about r. Thus, by comparing Both treatments with Seller treatments, we can disentangle direct anchoring effects the price recommendation has on retailers' price setting behavior from indirect effects of their anticipation of buyer's anchoring.

Finally, there is a control treatment BothInfoFeedback. In this treatment, there is feedback for the retailer about p, r, c and, most importantly, demand in the first five rounds

	RPR known to Seller	Buyer	RPR informative	Feedback	# Participants
BothInfo	x	x	x	-	48
BothRandom	x	x	-	-	48
SellerInfo	x	-	x	-	48
SellerRandom	x	-	-	-	48
BothInfoFeedback	x	x	x	x	82

Table 1: Treatments.

after the fifth round of the experiment. This treatment tests whether information about buyers' behavior improves retailers' ability to exploit potential biases their buying decision.

The experiment was computerized using z-Tree (Fischbacher 2007). A total of 274 students from various disciplines took part in the experiment. They were recruited via ORSEE (Greiner 2004). The experiment took place in the *Lakelab*, the laboratory for experimental economics at the University of Konstanz, between May and October 2013. The experimental currency was points. 40 points were converted into 1 euro after the experiment. To cover potential losses during the experiment, participants received an initial endowment of 200 points. On average, participants earned 11-12 euros in the experiment which lasted for about one hour. The protocol during the experiment was as follows: After welcoming participants and explaining the main rules for participation in the experiment, they were randomly assigned seats in the laboratory. Subjects received instructions[5] on their computer screen. Roles were assigned only after reading the instructions. Next, they were given the possibility to familiarize themselves with the computer screens. Then the experiment started. At the end of a session, they were asked to complete a short questionnaire.

3 Hypotheses

In the main treatment BothInfo, the price recommendation r contains a signal about the value v of the product for the buyers, and r is known to the buyers. Buyers can use the signal of r about v to adjust their demand function according to the expected value of the

[5] An English translation of the instructions can be found in the appendix.

product. More precisely, risk neutral buyers will order the maximum amount of 10 units for prices $p < r/2 + 10$ and zero units for prices $p > r/2 + 10$. For $p = r/2 + 10$ they are indifferent with respect to the amount ordered. Risk averse buyers may start reducing their demand at a lower level of prices already, but should follow a similar pattern. Given the findings of Rosenkranz (2003) and Fabrizi et al. (2012), we furthermore expect that r forms an anchor for the buyers with respect to what a reasonable price is. This behavioral effect of having a retail price recommendation relates to the idea of moon pricing: the larger the difference $r - p$ is, the more will buyers perceive p as a bargain. Put differently, at any price p demand will be larger the larger the recommended price r is.

While in BothInfo both effects – rational reaction to the informational content of r and simple anchoring – result in a higher demand the higher r is, in BothRandom only anchoring can take place. In BothRandom the price recommendation is drawn independently from cost, and therefore also the value of the product does not depend on the recommended price. In this treatment we therefore expect no rational reaction of consumers to the price recommendation. However, the anchoring effect holds irrespective of whether r is informative about the value of the product for the buyer or not. We therefore expect the effect of r on demand to be weaker in BothRandom than in BothInfo.

Hypothesis 1 *(i) For a given price p, demand increases with r. (ii) This effect is weaker in* BothRandom *than in* BothInfo*.*

On top of this rather continuous decline in average demand with r we expect that it will sharply drop at prices above the recommended one. This is because of loss aversion. At any price below or at the recommended one loss averse buyers in treatment BothInfo can be sure that they will not make a loss (because $v = c + 10$ is weakly larger than $r = c + random(0, 10)$), while at prices above the price recommendation losses for the buyers are possible. Anchoring predicts a similar effect, because buying at prices above r – even if r is smaller than p – is perceived as a relative loss compared to the reference point.

Again, we expect that the behavioral effect will be weaker in treatments with entirely randomly drawn r than with informative r. This is because in BothInfo the expectation is backed up by two behavioral phenomena while in BothRandom only the second effect can influence behavior.

Hypothesis 2 *(i) Demand drops at $p = r + 1$. (ii) This effect is weaker in* BothRandom *than in* BothInfo.

Sophisticated retailers anticipate the behavioral reaction of consumers to the price recommendation and are able to exploit it. However, retailers may also be subject to behavioral irregularities themselves. With respect to "moon pricing" effects, the expected behavioral biases of retailers and buyers are aligned. Retailers will react to high price recommendations (relative to their costs) with setting a high price, no matter whether anticipation of buyer behavior or personal anchoring guide their decisions. A comparison of treatments with and without buyer information allows disentangling to which extent any reaction of retailers is driven by direct anchoring of the retailers or by anticipation of buyers' anchoring. In Both treatments both the retailer and the buyer are informed about the retail price recommendation r. In Seller treatments, only the retailer knows r. In Seller treatments there cannot be anchoring of the buyers, because buyers receive no anchor. If buyers cannot anchor their decisions on a price recommendation, retailer also cannot anticipate anchoring of the buyers. Thus, any anchoring effects in Seller treatments is driven by direct anchoring of the sellers. Finally, whether or not r is informative about v should have a similar, indirect effect on the pricing decisions of sophisticated retailers. If they anticipate that buyers' reaction to the price recommendation is stronger in BothInfo than in BothRandom, the effect of r on p as set by the retailers should be strongest in BothInfo.

Hypothesis 3 *(i) For a given cost c, the retailer price p increases with r. (ii) The increases of the retailer price p with r is weaker in* Seller *information treatments than in* Both *treatments. (iii) The increases of the retailer price p with r is weaker in* BothRandom *than in* BothInfo.

Sophisticated retailers will be reluctant to set prices just above the price recommendation, because their loss from the drop in demand will most likely outweigh the gain from a higher revenue per unit. However, naive retailers in the experiment may themselves exhibit similar behavioral biases to the buyers in their reaction to learning a price recommendation. Such retailers may perceive any price below the recommended price as a loss relative to their reference point. To give a good chance for sophistication, we framed the experiment in terms of buying and selling and we assigned roles of retailers and buyers only after reading the instructions. The BothInfoFeedback treatment furthermore tests whether feedback about buyers' reaction to different combinations of r and p improves sophistication.

Hypothesis 4 *Sellers do rarely set prices just above r.*

4 Results

4.1 Demand of buyers

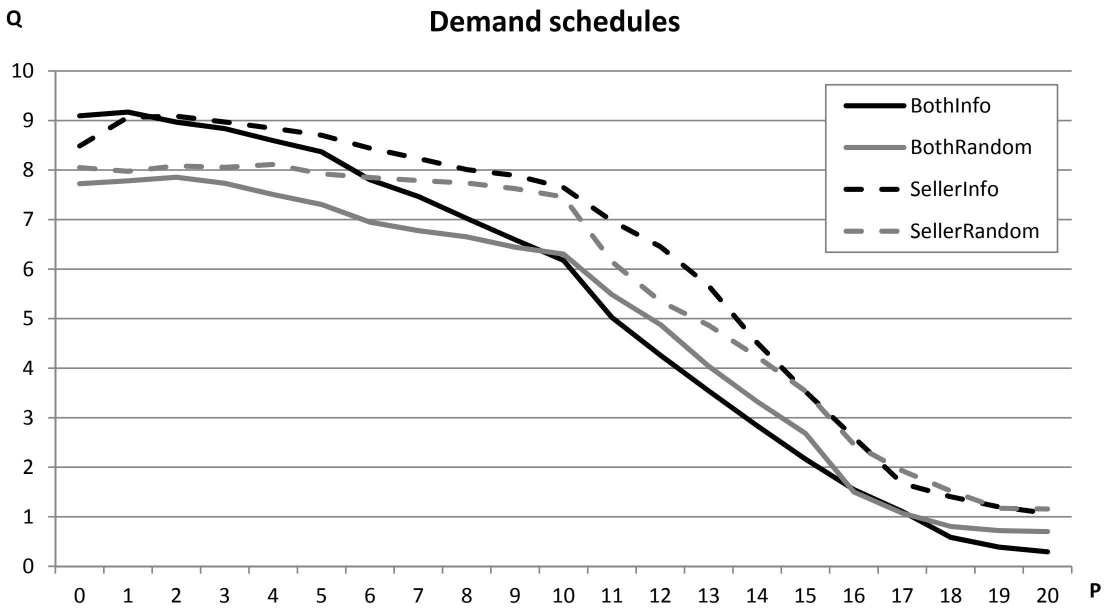

Figure 1: Demand schedules as elicited by the strategy method by treatment

Figure 1 illustrates the demand schedules submitted by participants for all prices between zero and 20 in all treatments. The most prominent element in the demand schedules is a downward kink at $p = 10$. This kink can be explained with loss aversion playing no role for buying decisions at prices up to 10. Irrespective of the treatment, buyers know that the value of the product is always larger than or equal to 10 (because $v = c + 10$ and $c \geq 0$). Thus, even strongly loss averse buyers can buy the maximum of 10 units at prices not larger than 10 without running the risk of making a loss. With respect to testing our hypotheses, we may therefore expect buyers to be less sensitive to any reference point or anchor in the range of prices up to 10. Our analysis of buyer behavior will therefore put a special focus on the upper half of their submitted demand schedules.

The treatment differences in aggregate demand are rather small. This is not surprising, because we expect treatment differences rather locally at prices around the level of the price recommendations, which are distributed over the whole range of prices. However, there is a tendency towards lower demand in treatments with buyer information about the price recommendation. Comparing average demand at prices between 10 and 20, we find that demand is significantly lower in BothInfo than in SellerInfo ($p = 0.01$), while the difference between BothRandom and SellerRandom is statistically not significant ($p = 0.24$).[6]

The regression in Table 2 reports the parameter estimates of an OLS regression of the main treatment differences in average demand. The dependent variable in this regression is the average demand per subject per round for prices in the range between 10 and 20. r is the size of the price recommendation in the respective round. In line with the setup of the treatments, the price recommendation only has a (positive) impact on demand if it is known to the buyers. "Buyer knows r" and "Seller knows r" are dummy variables capturing the information structure of the treatment. Whether the buyers learn a price recommendation reduces their average demand by about 2.6 units, but the interaction of the dummy with the size of the price recommendation is positive. "r contains Info" is another dummy variable distinguishing between treatments with informative and uninformative price recommendations with respect to the value of the product for the buyer. An informative price recommendation reduces demand in the BothInfo compared to the BothRandom treatment. However, the interaction of the dummy with the size of the price recommendation shows that the larger the

[6]If nothing else is stated, the reported p-values in this paper refer to two-sided Wilcoxon rank sum tests using averages at the subject level as the unit of observation.

Average demand at $p \in [10, 20]$	All data	Buyer knows data
r	-0.0219	0.0887***
	(0.0182)	(0.0213)
Buyer knows r	-2.602***	
	(0.433)	
r contains Info	-0.652	-1.894***
	(0.433)	(0.597)
r * Buyer knows r	0.151***	
	(0.0211)	
r * r contains Info	0.0580***	0.148***
	(0.0211)	(0.0316)
Constant	4.001***	1.968***
	(0.374)	(0.415)
Obs.	960	480
Ind. Obs.	96	48

Table 2: Random effects regression on treatment differences in average demand at prices between 10 and 20. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

price recommendation is, the larger is average demand. Taking all these results together, we can confirm hypothesis *1*.

Result 1 *Demand increases the larger the recommended price is. This effect is weaker when the price recommendation is randomly drawn than when it is informative about the value of the product.*

Figure 2 illustrates demand around the price recommendation r. For this illustration, prices p are shown relative to the price recommendation r. Thus, the figure shows the average demand of subjects normalized on the difference $p - r$.[7] Extreme values where p differs by more than five units from r are not shown. The Figure shows a drop in demand at $p = r + 1$ in treatments where the recommended price is known to the buyers. This drop is clearly visible in treatment BothInfo when r is informative about the value of the product to the buyers. In BothRandom, where any effect of r on demand could only be driven by pure anchoring, the downward movement of demand at $p = r + 1$ is still visible but smaller. When only the sellers are informed about r, demand does not exhibit any noticeable movement around $p = r$.

[7]Demand for prices below 10 is excluded in the representation. However, including it yields similar results.

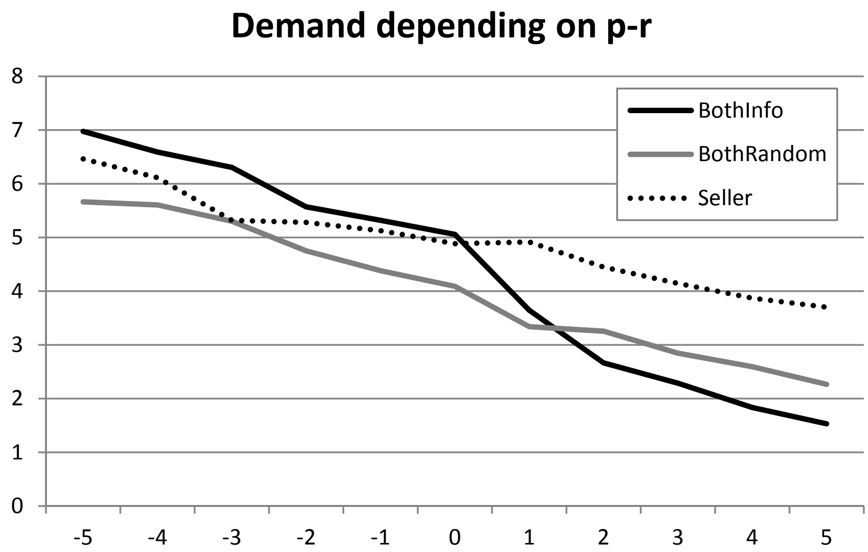

Figure 2: Demand depending on $p - r$

Table 3 supports this finding by reporting results from random effects regressions of average demand per subject depending on the absolute difference between p and r and on an additional dummy variable "$p > r$?" being equal to 1 if the price is larger than the price recommendation. In this regression, we use demand at different prices per round as the unit of observation. In both treatments, there is a significant decline in demand the larger $p-r$ is, a fact that basically reflects the downward sloping demand function. On top of this, the dummy $p > r$? captures a structural break in this downward slope with demand dropping significantly at prices above the recommended one, supporting hypothesis *2(i)*. This drop may contribute to explaining the above reported finding that average demand for prices between 10 and 20 is smaller in treatments with buyers being informed about the price recommendation. In BothRandom the coefficient of $p > r$? is still negative but of smaller size. This finding is confirmed by the interaction of $p > r$? with the "r contains Info" dummy in the third regression, supporting hypothesis *2(ii)*.

Result 2 *Demand drops at $p = r + 1$. This effect is weaker when the price recommendation is randomly drawn than when it is informative.*

Demand	BothInfo	BothRandom	Both Treatments
$p - r$	-0.189***	-0.177***	-0.182***
	(0.0184)	(0.0192)	(0.0133)
$p > r$?	-2.896***	-1.180***	-1.199***
	(0.282)	(0.300)	(0.237)
$p > r$? * r contains Info			-1.682***
			(0.234)
constant	5.753***	4.570***	5.159***
	(0.336)	(0.413)	(0.266)
Obs.	577	595	1,172
Ind. Obs.	24	24	48

Table 3: Random effects regression on demand at prices around r. Data dropped if $p < 10$. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

4.2 Prices set by sellers

Figure 3 illustrates the price setting of retailers depending on the price recommendations they receive. In order to normalize price setting to the different $c - r -$ combinations, the Figure shows price markups over costs $p-c$ depending on the "recommendation markup", the difference $r - c$ between the price recommendation and costs. In all treatments, there is a clear positive relationship between the price markup and the recommendation markup, indicating that sellers generally react to the price recommendation as expected in hypothesis *3(i)*. They seem to feel entitled to claim at least half of the difference between costs and value as the price markup is already for $r = c$ about equal to 5. Comparing the different treatments, hypotheses *3(ii)* and *3(iii)* predict the curve for BothInfo to be the steepest while the curve for SellerRandom should be the flattest. However, the slope of the curves is hardly distinguishable in this Figure.

To enlighten treatment effects in seller behavior more precisely, the regressions in Table 4 test the impact of different price recommendations on sellers' price setting behavior, controlling for differences in costs. The first three columns include all data; the regressions in columns 4-6 omit data with $r - c > 10$ from the two Random treatments, thus making the range of observations comparable across treatments. Prices increase with costs c by a factor of about one half, indicating that sellers on average try to share the burden of a cost increase by one unit about equally with the buyer. The impact of the price recommendation r indicates that an

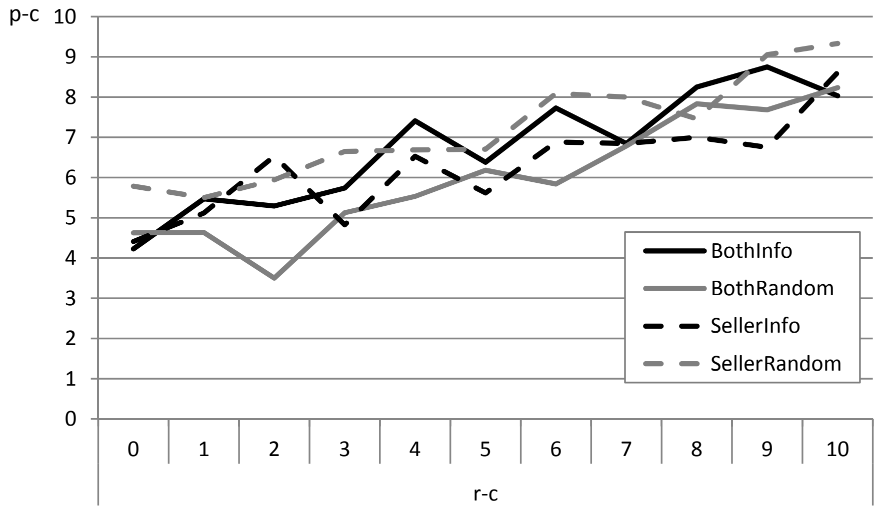

Figure 3: Price markup $p-c$ depending on the difference $r-c$ between the price recommendation and costs.

increase in the price recommendation by one unit translates into a price increase of about 0.3 units. We can thus confirm hypothesis *3(i)*. With respect to treatment differences according to buyer information about the price recommendation, the picture is less clear. Generally, both knowledge of buyers about the price recommendation and its informative content seem to reduce prices, while the interactions of these two dummy variables with the size of the price recommendation are weakly positive. Thus, retailers at least tend to behave according to hypotheses *3(ii)* and *3(iii)*, but not strongly significantly. Retailers in the experiment seem to exhibit direct anchoring effects but do only weakly adjust their decisions to similar effects on the buyer side.

Result 3 *For a given cost c, the retailer price p increases with r. Retailers only weakly adjust their price setting to variations in buyer information.*

Figure 4 illustrates the price setting of sellers relative to the price recommendation. Similar to Figure 2, the two parts of the illustration show the relative frequency of the absolute difference between p and r, where differences of more than five units are omitted. If sellers would correctly anticipate the drop in demand at $p = r+1$ prices at exactly this level should be rare, particularly in comparison to prices just below the recommendation, $p = r-1$, and to the neighboring price

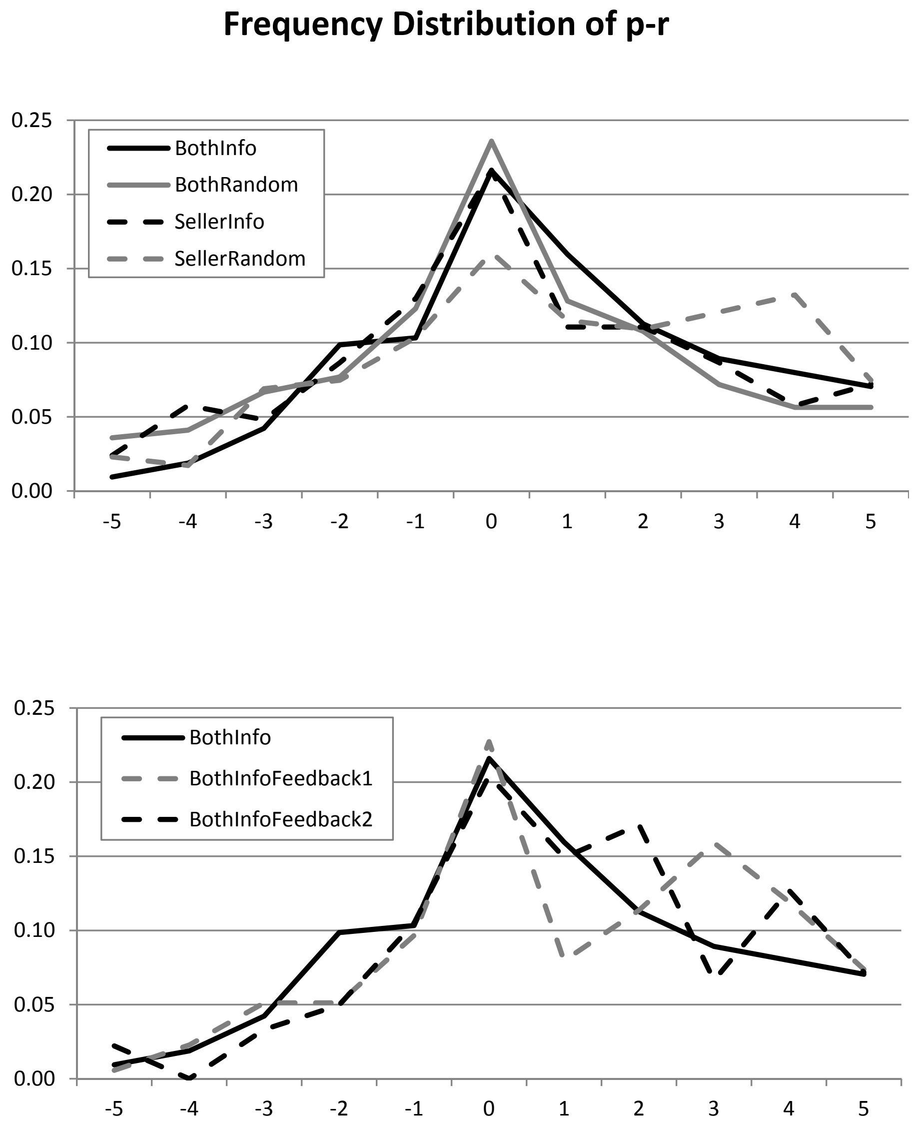

Figure 4: Distribution of prices around the price recommendation in the four main treatments and in the control treatment with feedback.

Seller price		All Data			Data with $r - c > 10$ dropped	
c	0.487***	0.487***	0.476***	0.532***	0.531***	0.519***
	(0.0236)	(0.0236)	(0.0252)	(0.0266)	(0.0267)	(0.0274)
r	0.312***	0.313***	0.266***	0.280***	0.281***	0.230***
	(0.0167)	(0.0167)	(0.0273)	(0.0197)	(0.0199)	(0.0339)
Buyer knows r		-0.195	-0.775*		-0.312	-0.484
		(0.326)	(0.459)		(0.336)	(0.473)
r contains Info		-0.317	-0.766		-0.155	-0.910*
		(0.326)	(0.476)		(0.338)	(0.485)
r * Buyer knows r			0.0565*			0.0182
			(0.0317)			(0.0348)
r * r contains Info			0.0438			0.0781**
			(0.0339)			(0.0363)
Constant	6.120***	6.373***	6.908***	6.141***	6.371***	6.901***
	(0.239)	(0.331)	(0.414)	(0.242)	(0.338)	(0.433)
Obs.	960	960	960	877	877	877
Ind. Obs.	96	96	96	96	96	96

Table 4: Random effects regression on prices set by sellers. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

$p = r+2$. Table 5 summarizes the relative frequency of prices around the price recommendation. In all treatments, there is a clear peak at $p = r$, but prices of $p = r + 1$ are everything but rare. This provides first evidence against hypothesis 4. To test whether sellers learn to react to buyer's drop in demand when being informed about it, we consider the control treatment BothInfoFeedback, where sellers receive full feedback about c, r, p and the sold quantity of the past five rounds after round 5. As can be seen in the second illustration in Figure 4 and in Table 5, prices $p = r + 1$ are even more frequent in the second than in the first part of play, and still not significantly less frequent than $p = r - 1$ or $p = r + 2$. We thus reject hypothesis 4. Sellers do not adapt their behavior to consumers' behavioral reaction to receiving an informative or uninformative price recommendation.

Result 4 *Sellers set prices just above r about equally as often as the neighboring prices.*

	(1) $p = r - 1$	(2) $p = r + 1$	(3) $p = r + 2$	p-value (1) vs. (2)	(2) vs. (3)
BothInfo	0.10	0.16	0.11	0.3251	0.9877
BothRandom	0.12	0.13	0.11	0.9398	0.2536
SellerInfo	0.13	0.11	0.11	0.7335	0.9105
SellerRandom	0.10	0.11	0.11	0.3321	0.3811
BothInfoFeedback Part 1	0.10	0.08	0.11	0.5705	0.4830
BothInfoFeedback Part 2	0.10	0.15	0.17	0.6981	0.4924

Table 5: Relative frequency of prices $p = r + 1$, $p = r - 1$, and $p = r + 2$. The p-values refer to two-sided Wilcoxon signed rank tests, taking subjects as the unit of observation.

4.3 Payoff consequences

Buyers in this experiment almost perfectly follow the behavioral biases predicted in our hypotheses. Sellers exhibit similar biases, but they seem unable to exploit the predictable biases of buyers. In the following, we will consider the material consequences. How much do sellers lose in terms of monetary payoffs by not adjusting their price setting to buyers' behavioral biases? To estimate average losses, we first determine buyers' average demand depending on prices and price recommendations in the different treatments. For treatments without buyer information, we simply use average demand depending on price. Next, we ask what sellers would have earned if they correctly optimized their price setting against this average demand function. Finally, we compute the difference between this maximum possible profit and the actually realized profit per round to determine the average forgone profit per round by treatment, summarized in Table 6.

Treatment	Forgone profit	Average profit	Forgone/Average
BothInfo	7.86	28.45	0.28
BothRandom	9.24	31.50	0.29
SellerInfo	11.24	37.64	0.30
SellerRandom	6.51	37.98	0.17
BothInfoFeedback Part 1	10.07	27.42	0.37
BothInfoFeedback Part 2	9.51	28.36	0.34

Table 6: Sellers' forgone profits and average realized profits per round (in points).

Sellers forgo about 6 to 11 points per round on average by not optimizing their prices against buyers' average demand, which amounts to 17 to 37 percent of their total profit. Average profits are lower in the treatments with information of buyers about the price recommendation, which reflects the lower demand in these treatments.[8] The differences in relative losses are not systematic. In BothInfo and SellerInfo the relative losses of retailers are almost equally as large, indicating that retailers' non-adjustment to buyers' reaction to the informative price recommendation has no additional detrimental effect on their profits. However, in BothRandom the relative loss is weakly larger than in SellerRandom ($p = 0.06$), pointing to losses for the sellers by following their own anchoring instead of anticipating similar effects on the buyer side. Again, there also seems to be no improvement from the first to the second part of BothInfoFeedback.

5 Conclusion

This paper presented results from an experiment on the effect of a retail price recommendation on consumers' demand and retailers' price setting. Buyers in the experiment buy more at a given price the larger the price recommendation is and their demand drops at prices above the price recommendation. These effects are stronger when the price recommendation is informative about the value of the product than when it is not, indicating that rational responses to the price recommendation explain a large part buyers' demand function. Sellers set higher prices when they receive a higher price recommendation, but they hardly differentiate their pricing with respect to buyers' knowledge about the price recommendation and to the price recommendation being informative. In particular, they do not avoid setting prices just above the price recommendation, where demand drops sharply. Thus, anchoring explains most of sellers' decisions in the experiment, but they fail to adjust their pricing to differences in demand.

With respect to buyer behavior, the results are in line with the hypotheses. In part, retail price recommendations simply serve as an anchor. However, their effect is much stronger if con-

[8] The difference in average profits is statistically weakly significant when comparing BothInfo and SellerInfo ($p = 0.0814$), while the difference between BothRandom and SellerRandom is statistically not significant ($p = 0.3921$).

sumers have rational reason to interpret them as a signal for the value or quality of the product. Thus, when buyers have an appropriate belief about whether the price recommendation informs them about the value of the product, their behavior in the experiment is quite rational. While in the experiment it was clear whether the price recommendation is informative, retail price recommendations in the field may intentionally create the impression to be informative when they are not. In this case, they may distort consumers' decisions by more than they did in the experiment and consumer protection may be needed.

Sellers in the experiment did not adjust their pricing to biases in demand, even when they were given feedback about buyers' behavior. As professional retailers in the real world are doing much more market research when pricing their products than the retailer participants in this experiment it seems likely that they are better in choosing an appropriate price setting strategy. In order to draw conclusions from the experimental findings for retailer behavior in real markets one would have to restrict attention to markets with naive and inexperienced retailers, which may, if at all, be present in markets for newly invented products.

In the experiment in this paper the retail price recommendation was drawn by a random mechanism to determine retailers' and buyers' reaction to receiving such a recommendation. In vertically differentiated industries, it is usually the manufacturer who decides on the price recommendation. A natural next step in the analysis of such industries would be an extension of the experiment where a manufacturer actually sets retail price recommendations.

Appendix A: Instructions for treatment BothInfo

Welcome to the Lakelab. Thank you for participating in this experiment.

From now on we ask you to stay seated and stop communicating with other participants. Please read the instructions carefully. If you have any questions or if anything is unclear to you, please raise your hand. We will come to your place.

Your payoffs in this experiment depend on your decisions, the decisions of other participants and chance. You will not get to know who the other participants are and those participants will also not learn your identity.

This experiment consists of 10 rounds in which you always interact with the same other participant. After completing all 10 rounds of the experiment, we will add up your achieved earnings. Your earnings during the experiment are counted in points. The exchange rate is 40 points for 1 Euro. To account for possible losses during the experiment, you get additional 200 points at the beginning. You get your earnings paid out directly after the experiment in cash. If you achieve a negative payoff at the end of the experiment, your payment will be zero.

In this experiment there is a seller and a buyer. Your role will be randomly assigned to you at the beginning of the experiment.

The seller can produce a fictitious product at certain costs in each round. The costs lie between 0 and 10 points per unit. They will be generated randomly in each round and communicated to the seller. Furthermore, the seller is informed about a recommended retail price which is also generated randomly. The recommended retail price corresponds to the costs plus a randomly drawn number between 0 and 10. Overall the price recommendation will thus lie between 0 and 20 points.

The seller can decide in each round for which price she wants to sell the product. The buyer will be informed about the retail price recommendation, however not yet about the price set by the seller.

The value of the product for the buyer corresponds to the costs plus 10 points. Hence, the value for the buyer lies between 10 and 20 points. On average, the product has a value of 15 points. The buyer is not informed about the value the product has for him in each round before the end of the experiment. In each round the buyer can buy up to 10 units of the fictitious product from the seller. For this, the buyer fills out a table. In this table, the buyer specifies for each possible price between 0 and 20 how many units of the fictitious product he would like to buy. Afterwards the buyer automatically buys the amount he specified for the price the seller actually set.

The number of units the buyer bought for the price set by the seller will not be communicated to you before the end of the experiment. Furthermore, the profits from each round will not be shown to you before the end of the experiment.

The seller's profit per unit is the price set by the seller minus the costs. The buyer's profit per unit is the value of the good minus the price set by the seller. The overall profit for the seller and the buyer results in their profits per unit multiplied by the amount traded.

After having read the instructions, we will ask you to answer some control questions. Only after all participants have answered the questions correctly, we will start with the experiment. After the experiment we will ask you to fill out a short questionnaire.

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