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On Point Predictions and Reference Dependence in Behavior-Based Pricing Experiments

Michel Tolksdorf*
Faculty of Economics and Management, Technische Universität Berlin, Germany
michel.tolksdorf@tu-berlin.de

Abstract: It has been shown that the comparative static results of two-period behavior-based pricing models hold in laboratory experiments, while point predictions do not. This study aims to check whether these findings replicate and to evaluate why observed prices deviate from point predictions. We report observed prices in conformity with point predictions through: (1.) a uniform pricing benchmark, (2.) a replication of a behavior-based pricing experiment, and (3.) a follow-up experiment in which we consider the second period disjointed from the first period. By disjoining the two periods, we show that reference dependence toward first-period prices shifts the second-period pricing behavior of participants upwards. In a post hoc analysis, we show that considering consumers' myopic instead of strategic explains a downward shift in first-period prices and rationalizes prior experimental findings. Volatile price levels affect price-based welfare measures – such as seller profits and total customer costs. We show that transport costs are a robust welfare measure that alleviates the impact of distorted prices. Ultimately, our findings are relevant for the design and assessment of multi-period pricing experiments.

Keywords: *Behavior-based pricing, forward-looking customers, laboratory experiment, myopic customers, reference dependence*.

1. Introduction

Most papers on behavior-based pricing originated from Fudenberg and Tirole (2000, henceforth F&T).[1] Most commonly, the models in these papers are characterized by a two-period structure, where a continuum of consumers are served by two sellers at uniform prices in the first period, and at differentiated prices in the second period. The second-period prices are differentiated according to the first-period purchasing decisions of consumers. Early successors of F&T include Chen and Pearcy (2010) and Shin and Sudhir (2010), who studied the role of varying degrees of preference dependence. As a second dimension, Chen and Pearcy (2010) evaluated the ability of firms to commit to future prices, while Shin and Sudhir (2010) incorporate customer heterogeneity. Behavior-based pricing reemerged as a relevant topic over recent years with the rise of digital markets and associated distribution channels. Recent academic contributions cover behavior-based pricing and advertising.

(Shen and Miguel Villas-Boas, 2018; Esteves and Cerqueira, 2017), behavior-based pricing with vertical differentiation (Garella et al., 2021; Umezawa, 2022), the observability of behavior-based pricing (Li et al., 2020), and fairness concerns when behavior-based pricing practices are observed (Li and Jain, 2016). In response to recent developments in data protection regulations, behavior-based pricing is studied when firms can personalize prices and products (Capponi et al., 2021; Esteves, 2022; Laussel and Resende, 2022), the ability of firms to share customer information (De Nijs, 2017; Choe et al., 2022, 2023), and consumer control over their data (Choe et al., 2018). While there are empirical studies on behavior-based pricing

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[1]See Fudenberg and Villas-Boas (2006) and Esteves et al. (2009) for comprehensive literature surveys of earlier contributions. Behavior-based pricing is also covered in Armstrong's review of recent developments in price discrimination (Armstrong, 2006).

(Asplund et al., 2008; Cosguner et al., 2017), it might prove problematic to disentangle the aforementioned factors and explicitly verify the mechanics of theoretical models. Laboratory experiments allow fine control and adjustment of market features and grant first insights into market dynamics.

However, to our knowledge, only two experiments that explicitly featured behavior-based pricing have been conducted thus far.[2] Brokesova et al. (2014, henceforth BDP) implemented the model of Chen and Pearcy (2010) experimentally by varying the ability of sellers to pre-commit to future prices and the persistence of consumer preferences. Their first case directly corresponds to simple short-term contracts with independent preferences from F&T, while their second case corresponds to poaching under short-term contracts (behavior-based pricing) from F&T. By employing computerized buyers (while participants act as sellers), their set-up closely resembles the structure of underlying theoretical models and is suited to explicitly test point predictions. Mahmood and Vulkan (2018, henceforth M&V) had participants play only the second period of a behavior-based pricing market as sellers against computerized competitors, following a predetermined first period. With their results, BDP and M&V supported the comparative static predictions of F&T and Chen and Pearcy (2010). However, their observed prices are significantly larger than the point predictions of the model. BDP's observed profits and customer costs and the profits in M&V are driven by skewed price levels and predominantly do not reflect theoretical predictions.

The contribution of this paper is twofold. First, we explore why game-theoretic point predictions of prices in behavior-based pricing models do not hold in laboratory experiments and whether there are circumstances under which they do. Second, we show that transport costs are a suitable welfare measure whenever price predictions do not hold (albeit comparative static results do). To this end, we derive the subgame perfect prices of a parameterized version of F&T's model. We then test the predictions of the model by implementing a laboratory experiment where student participants take the role of sellers and interact with computerized buyers. In a benchmark uniform pricing treatment, we observe convergence toward price predictions in both periods. This contrasts the first case of BDP, where participants chose lower second-period prices than were predicted. In our second treatment, where behavior-based pricing is permitted, we observe that first-period prices converge toward price predictions in contrast with BDP's second case, while second-period prices diverge from price predictions in line with BDP. In a follow-up experiment, we only consider the second period using simulated first-period cutoffs.

This resembles the set-up of M&V, albeit allowing for a wider range of first-period cutoffs and not featuring computerized sellers. In contrast to both M&V and our second treatment, we do not observe a divergence in second-period prices. The most puzzling discrepancy is the difference in first-period prices between the second case of BDP and our behavior-based pricing treatment. Unlike BDP, we observe higher prices and a peak in the distribution at the theoretical point prediction. The most likely explanation for this difference is that BDP implemented myopic instead of strategic consumers and participants used experimentation rather than deduction in their pricing decisions. We show that assuming myopic consumers leads to a theoretical prediction, which is in line with observed prices in BDP's second case. Welfare measures – such as customer costs and profits – are directly derived from prices. When prices are volatile and prone to behavioral biases, these measures are directly affected. We show that transport costs serve as a robust welfare measure, which is independent of price levels but captures the impact of price dispersion and poaching efforts by sellers.

2. An Experiment on Uniform and Behavior-Based Pricing

BDP analyzed behavior-based pricing while varying two dimensions: the ability to price pre-commit and the extent of preference dependence. We step back from this by contrasting whether sellers can employ behavior-based pricing or otherwise. We do not consider price pre-commitment and only consider perfectly

[2]Mahmood (2014) conducted an experiment motivated by Shin and Sudhir (2010) with participants taking the roles of sellers and buyers. However, their experimental set-up is rather reminiscent of a heterogenous goods Bertrand competition. Instead of a continuum of consumers they consider two discrete locations. Due to this there are no pure strategy equilibria.

dependent preferences. Taken together, our set-up consists of a comparison of uniform and behavior-based pricing, as detailed by F&T. We proceed by deriving subgame perfect prices for both pricing regimes, which serve as predictions for our experiment. We then introduce our experimental design and close by discussing the results.

Theoretical Background: The market structure underlying this experiment closely follows F&T. Two sellers $i, j \in \{A, B\}$ with $i \neq j$ are located at endpoints of a linear city model in the manner of Hotelling with length $\bar{\theta}$. We assume that A is located at 0 and B is located at $\bar{\theta}$. Both sellers produce nondurable goods at constant marginal costs of c over two periods $n \in \{1,2\}$. Consumers are distributed uniformly over the interval $[0, \bar{\theta}]$ and demand a maximum of one unit per period. Consumer valuation of the good is v, and they incur transport costs which correspond to the distance travelled. Thus, a consumer located at $\hat{\theta}$ receives utility $v - p_A - \hat{\theta}$ when buying from seller A, and $v - p_B - (\bar{\theta} - \hat{\theta})$ when buying from a seller B. Both sellers and consumers do not discount the second period. Throughout, we assume v is sufficiently high to ensure full market coverage.

Uniform Pricing: In the first case, both sellers post a uniform price p_i^n in each period n. After observing prices p_A^n and p_B^n, there is a consumer at θ_n who is indifferent between buying from A or B. The location of the indifferent consumer is:

$$\theta_n = \frac{p_B^n - p_A^n + \bar{\theta}}{2}. \#(1)$$

In each period, sellers face a static optimization problem:

$$\text{Seller A: } \max_{p_A^n} \, (p_A^n - c) \cdot \theta_n, \quad \text{Seller B: } \max_{p_B^n} \, (p_B^n - c) \cdot (\bar{\theta} - \theta_n). \#(2)$$

Solving the maximization problems, we find the following symmetric equilibrium prices:

$$p_i^n = \bar{\theta} + c. \#(3)$$

This aligns with the theoretical prediction for Case 1 "Independent preferences and no price pre-commitment" of BDP, as every price is the one-shot Nash equilibrium price.

Behavior-Based Pricing: In the second case, both sellers post a uniform price in period 1 (p_A^1 and p_B^1) and employ behavior-based pricing in period 2. Behavior-based pricing allows them to set differentiated prices for old customers (p_A^O and p_B^O) and new customers (p_A^N and p_B^N), dependent on the first-period purchasing decisions. A consumer who purchased from firm i in the first period is considered an old customer for firm i and a new customer for firm j – and vice versa. We solve the game via backward induction. When entering the second period, first-period prices p_A^1 and p_B^1 determines the location of the indifferent consumer θ_1, which sellers observe. Consumers on the interval $[0, \theta_1]$ bought from seller A in period 1 and are denoted as A's turf, while consumers on the interval $[\theta_1, \bar{\theta}]$ bought from firm B and are denoted as B's turf. Both sellers charge the old customer price (p_A^O and p_B^O) toward their turf and the new customer price (p_A^N and p_B^N) toward the other seller's turf.

Given these prices, the locations of the indifferent consumers on A's and B's turf are

$$\theta_A = \frac{p_B^N - p_A^O + \bar{\theta}}{2}, \qquad \theta_B = \frac{p_B^O - p_A^N + \bar{\theta}}{2}. \#(4)$$

In the second period, sellers solve the following optimization problems as functions of θ_1:

$$\text{Seller A: } \max_{p_A^O, p_A^N} \, (p_A^O - c) \cdot \theta_A + (p_A^N - c) \cdot (\theta_B - \theta_1),$$
$$\#(5)$$
$$\text{Seller B: } \max_{p_B^O, p_B^N} \, (p_B^O - c) \cdot (\bar{\theta} - \theta_B) + (p_B^N - c) \cdot (\theta_1 - \theta_A).$$

Using the first-order conditions we can derive the optimal second-period prices as:

$$p_A^O = \frac{1}{3}(2\theta_1 + \bar{\theta} + 3c), \qquad p_A^N = \frac{1}{3}(3\bar{\theta} - 4\theta_1 + 3c),$$
$$\#(6)$$
$$p_B^O = \frac{1}{3}(3\bar{\theta} - 2\theta_1 + 3c), \qquad p_B^N = \frac{1}{3}(4\theta_1 - \bar{\theta} + 3c).$$

In the first period, forward-looking consumers can anticipate these pricing strategies. The first-period cutoff θ_1 denotes the consumer who is indifferent between *i*) buying from seller A in the first period and switching to seller B in the second period and *ii*) buying from seller B in the first period and switching to seller A in the second period. Following F&T, using p_A^N and p_B^N from (6), we find that the location of the indifferent consumer is

$$\theta_1 = \frac{3}{8}(p_B^1 - p_A^1) + \frac{\bar{\theta}}{2}. \#(7)$$

In the first period, forward-looking sellers face the following optimization problems:

$$\text{Seller A: } \max_{p_A^1} \, (p_A^1 - c)\theta_1 + (p_A^O - c)\theta_A + (p_A^N - c)(\theta_B - \theta_1),$$
$$\#(8)$$
$$\text{Seller B: } \max_{p_B^1} \, (p_B^1 - c)(\bar{\theta} - \theta_1) + (p_B^O - c)(\bar{\theta} - \theta_B) + (p_B^N - c)(\theta_1 - \theta_A).$$

We insert the expressions for θ_1 from (7) and for p_A^O, p_A^N, p_B^O and p_B^N from (6), and solve the resulting first-order conditions for p_A^1 and p_B^1 to yield the symmetric equilibrium prices as:

$$p_i^1 = \frac{4}{3}\bar{\theta} + c \qquad p_i^O = \frac{2}{3}\bar{\theta} + c \qquad p_i^N = \frac{1}{3}\bar{\theta} + c. \#(9)$$

This is equivalent to Case 2 "Constant preferences and no price pre-commitment" of BDP.

Experimental Design: We implemented an experiment in line with BDP using two treatments, corresponding to our two cases from Section 2.1. Similarly to BDP, we chose $\bar{\theta} = 120$ and $c = 50$, so that results are easily comparable. As shown in Table 1, our predictions for Treatment 1 "Uniform pricing" correspond to the predictions of Case 1 of BDP, where the two-afternoon prices (*Price for loyal customers* and *Price for new customers*) of BDP are condensed into the singular *Second-period price*. Treatment 2 "Behavior-based pricing" is a replication of BDP's Case 2.[3]

Table 1: Comparison of Price Predictions

Treatment	**1 Uniform pricing**	**2 Behavior-based pricing**	**Case Buyer Preferences Price pre-commitment**	**1-Baseline Independent No**	**2 Fixed No**
Introduction price	170	210	*Morning price*	170	210
Old customer price		130	*Price for loyal customers*	170	130
New customer price		90	*Price for new customers*	170	90
Second-period price	170				
(a) Price predictions by Treatment.			**(b) Excerpt from Table 1 in BDP.**		

There are two minor differences between our experiment and that of BDP. First, BDP framed the task as "ice-cream vendors on a beach", whereas we kept the task general, where the participants assume the role of a seller who is positioned at location 0 of a line, with another seller at the opposing end (at 120). As in BDP, sellers learned that they were competing for computerized buyers who were uniformly distributed along the line. They were informed that buyers make decisions considering prices and transport costs of both periods and seek to minimize their total expenditures.[4] Second, in contrast to BDP which used matching groups of 4, we used the whole group of 20 participants in the first and 18 participants in the second treatment as matching groups. As in BDP, participants played over 20 rounds, where one round lasted for two periods and corresponded to the theoretical market.

Hence, in our experiment, participants were matched with each other slightly more than once on average, decreasing reputation effects that could lead to tacit collusion. The experiment was programmed and conducted with the experiment software z-Tree (Fischbacher, 2007). We conducted the experiment in the experimental laboratory at TU Berlin in November 2016, with student participants drawn from the WZB ORSEE pool (Greiner, 2015), with experiments lasting around 90 minutes. On average, participants earned

[3]Our *Introduction price* corresponds to the *Morning price*, our *Old customer price* corresponds to the *Price for loyal customers* and our *New customer price* corresponds to the *Price for new customers*.
[4]Instructions and review questions were handed out in print and are available upon request.

€7.20 in the first treatment and €7.75 in the second, in addition to a €5 show-up fee. Participants were aged 25 on average, with around one-third of the participant female. Around two-thirds of all participants were in currently enrolled in undergraduate studies, with industrial engineering and natural sciences as the most common fields of study.

3. Results

Table 2 shows aggregated behavior between our two treatments on the left and two cases of BDP on the right, where p-Values are based on Random Effects GLS regressions on the difference between observed and predicted prices at the subject level. While BDP observed no significant difference in their "Case 1" between both second-period prices, they did find a difference between second-period prices and the first-period price (see *Afternoon price effect* in Table 3b). We do not find a significant difference between the corresponding introduction price and the second-period price in Treatment 1 (see Table 3a). Likewise, the distributions of introduction and second-period prices are extremely similar in our Treatment 1 (as shown in Figure 1a) in contrast to Case 1 of BDP (as shown in Figure 1b).

Table 2: Comparison of Observed Prices

Treatment	**1 Uniform pricing**	**2 Behavior-based pricing**	**Case Buyer Preferences Price pre-commitment**	**1-Baseline Independent No**	**2 Fixed No**
Introduction price			*Morning price*		
Observed mean	147.3	174.2	Observed mean	141.5	138.2
Model prediction	170	210	Model prediction	170	210
p-Value	<0.001	<0.001	p-Value	0.002	<0.001
Old customer price			*Price for loyal customers*		
Observed mean		149.77	Observed mean	119.7	129.2
Model prediction		130	Model prediction	170	130
p-Value		0.013	p-Value	0.002	<0.001
New customer price			*Price for new customers*		
Observed mean		114.6	Observed mean	116.5	114.1
Model prediction		90	Model prediction	170	90
p-Value		<0.001	p-Value	0.002	<0.001
Second-period price					
Observed mean	141.4				
Model prediction	170				
p-Value	<0.001				
(a) Observed prices by treatment.			**(b) Excerpt from Table 2 in BDP.**		

Table 3: Comparison of Price Effects

	Uniform pricing	**Behavior-based pricing**	**Follow-up experiment**	**Case Buyer Preferences Price pre-commitment**	**1-Baseline Independent No**	**2 Fixed No**
Second-period price	-5.890	-59.54***		Afternoon price effect	-25.028**	-24.041***
Effect	(4.484)	(5.393)			(7.227)	(3.094)
Old customer price		35.13***	41.41***	Loyal customer price	3.250	15.022**
Effect		(5.751)	(4.371)	effect	(7.889)	(3.857)
Constant	147.3***	174.2***	83.65***	Constant	141.512***	138.172***

	(3.795)	(7.104)	(3.685)
Observations	800	1080	796

Standard errors are in parentheses. Estimation by OLS regression with standard errors clustered at the subject level. ***denotes significance at the 0.1% level.

(a) Analysis of prices within treatments.

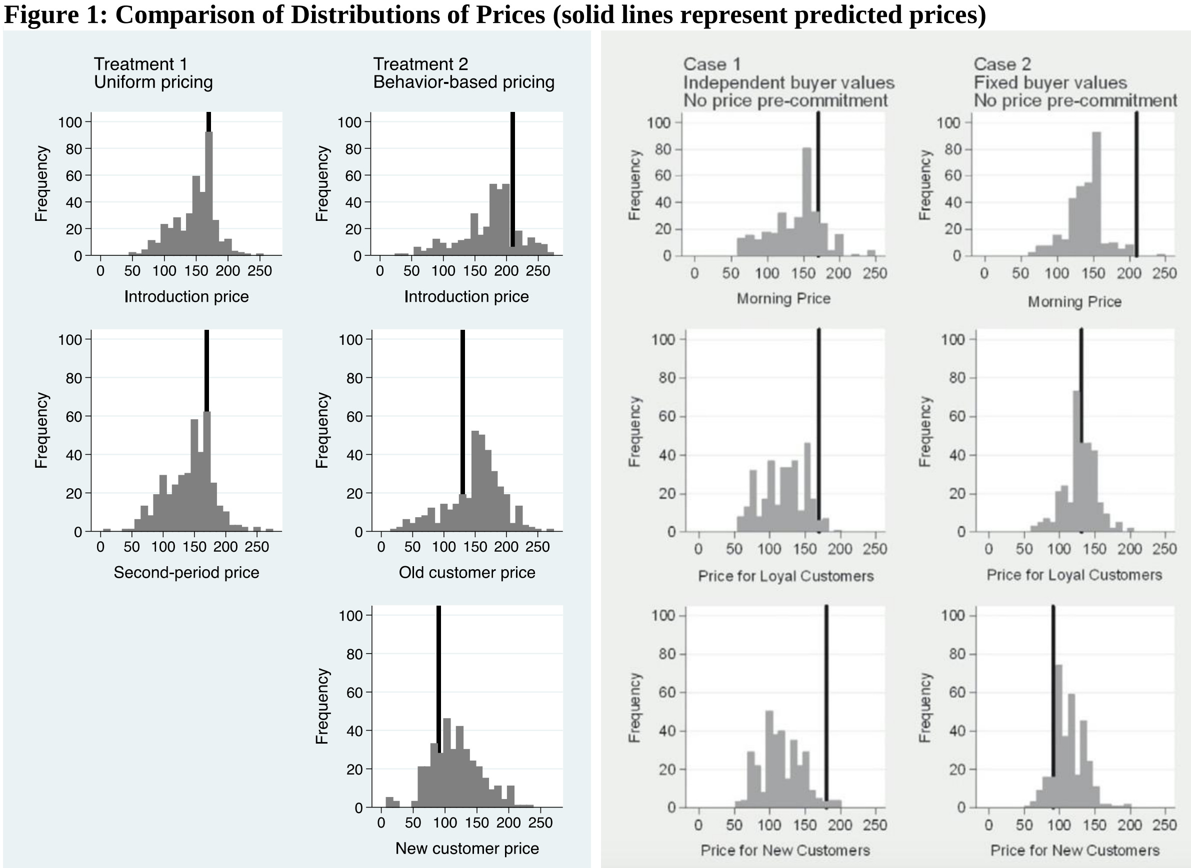
	(9.363)	(1.306)
observations	960	960

Standard errors, clustered by matching group, are in parentheses. ** and *** denote significance at the 1% and 0.1% level, respectively.

(b) Excerpt from Table 2 in BDP.

We observe a substantially larger average introduction price in our Treatment 2 compared with Case 2 of BDP. In addition, we observe a larger old customer price, but a similar new customer price. As shown in the distribution of prices in Figure 1a, we observe similar patterns for the introduction prices in both our treatments, with a left-skewed distribution whose peak is close to the respective theoretical prediction. This is not the case in BDP, as seen in Figure 1b. Accordingly, as shown in Table 3, we observe a much larger second-period price effect compared with BDP's corresponding *Afternoon price effect*, and a larger old customer price effect compared with BDP's corresponding *Loyal customer price effect*. The introduction price in Treatment 2 is significantly larger than in Treatment 1 (see Table 4), confirming a treatment effect on the first-period price in line with the comparative static prediction of the model. This effect was absent in BDP. In contrast to BDP, we see a larger rightwards shift for old customer prices and a wider spread for new customer prices.

Figure 1: Comparison of Distributions of Prices (solid lines represent predicted prices)



(a) Distribution of prices by treatment.

(b) Excerpt from Figure 2 in BDP.

Table 4: Analysis of Prices Between Treatments

	Introduction price	Old customer price	New customer price
Behavior-based pricing	26.85***	24.71**	30.94***
	(7.936)	(8.281)	(7.191)
Constant	147.3***	125.1***	83.69***
	(3.749)	(2.672)	(3.652)
Base case	Uniform pricing	Follow-up experiment	Follow-up Experiment
Observations	760	758	758

Standard errors are in parentheses. Estimation by random-effects GLS regressions with standard errors clustered at the subject level. ** and *** denote significance at the 1% and 0.1% level, respectively.

We find that prices converge toward their prediction in Treatment 1 by performing round-wise OLS regressions on the difference between observed and predicted prices (see Table 5). By the last round, this difference is close to (and insignificantly different from) zero for both the introduction price and the second-period price. We observe a similar pattern for the introduction price in Treatment 2. However, we find a different pattern for second-period prices in Treatment 2. Both old and new customer prices are not significantly different from their predictions in the beginning, but significantly larger than their predictions in the second half of the experiment.[5] In the spirit of backward induction, we first explore the apparent divergence from predicted levels of second-period prices in behavior-based pricing experiments, which are observed in both BDP and our experiment. Subsequently, we will show a potential explanation for the disparity of first-period prices between BDP and our experiment.

Table 5: Regressions on Difference between Observed and Predicted Prices Per Round and Treatment

	Treatment 1 Uniform pricing		Treatment 2 Behavior-based pricing			Treatment 3 Follow-up experiment	
	Introduction price	Second-period price	Introduction price	Old customer price	New customer price	Old customer price	New customer price
Round							
1	-46.40***	-51.60***	-69.17***	0.444	7.444	-6.944	-10.56**
	(7.294)	(7.399)	(10.76)	(10.59)	(8.632)	(7.839)	(5.269)
2	-41.75***	-52.30***	-69.78***	2.833	14.97	1.500	-3.750
	(7.820)	(8.163)	(10.40)	(11.90)	(11.98)	(8.390)	(7.626)
3	-39.65***	-43.00***	-60.39***	9.333	9.111	-14.85*	-13.55*
	(7.093)	(7.408)	(12.72)	(14.25)	(10.85)	(7.953)	(7.033)
4	-28.85***	-40.90***	-50.89***	15.22	11.58	0.400	-5.250
	(7.071)	(7.376)	(11.11)	(12.01)	(8.244)	(6.517)	(10.09)
5	-27.75***	-47.55***	-53.06***	3.333	25.31*	-2.000	-5.700
	(6.486)	(8.890)	(13.16)	(13.83)	(14.77)	(8.470)	(10.78)
6	-33.35***	-40.50***	-50.22***	6.778	17.78	-1.300	-3.250
	(6.932)	(6.771)	(10.60)	(11.94)	(10.81)	(6.641)	(7.775)
7	-27.80***	-38.15***	-36.89***	15.50	26.47***	-5.550	-5.675
	(6.296)	(8.601)	(11.05)	(11.40)	(9.035)	(7.881)	(8.784)
8	-28.65***	-40.10***	-40.56***	17.83	20.11	-3	-6.800
	(7.536)	(9.523)	(10.72)	(11.16)	(13.32)	(5.468)	(4.351)
9	-28.80***	-29.90***	-47.17***	2.444	12.97	-8.000	-6.900
	(7.019)	(8.034)	(11.54)	(10.91)	(9.963)	(5.462)	(8.724)
10	-20.40**	-23.10**	-39.22***	14.11	32.78***	1.300	-5.450
	(8.451)	(10.73)	(7.870)	(8.999)	(10.80)	(6.227)	(5.879)

[5]Results in Table 5 use the subgame corrected predictions which are introduced in Section 3.1 and are even stronger when not using the correction.

11	-18.40**	-24**	-27.39***	17.33	36.00***	-7.750	-7.525
	(9.240)	(11.33)	(7.903)	(12.82)	(11.17)	(7.772)	(9.521)
12	-19.15***	-19.15***	-18.39**	31.61***	45.72***	-7.800*	-10
	(6.986)	(7.304)	(7.867)	(11.82)	(12.40)	(4.690)	(8.398)
13	-16.85**	-14.85**	-27.56***	28.61***	22.78**	-8.150	-4.750
	(6.944)	(7.495)	(9.107)	(9.617)	(11.18)	(5.697)	(10.49)
14	-14.90**	-19.60**	-31.56**	15.78	21.86*	-10.75	-6.650
	(7.376)	(7.917)	(12.19)	(14.08)	(12.56)	(7.283)	(6.883)
15	-11.35*	-21.75***	-21**	17.33	24.36**	-10.40*	-8.000
	(6.140)	(7.465)	(9.986)	(11.94)	(11.01)	(5.540)	(5.410)
16	-16.20**	-20.40**	-18.39***	28.17***	26**	-19.05***	-13.90**
	(7.649)	(8.408)	(7.001)	(9.779)	(11.44)	(6.669)	(6.912)
17	-13.60**	-13.60*	-21.89**	20.11*	22.00**	-8.150	-7.650
	(6.076)	(7.237)	(9.465)	(11.42)	(10.77)	(5.430)	(6.580)
18	-6.850	-11.15	-17.44**	31.44***	28.42***	-1.700	2.200
	(4.343)	(6.787)	(7.375)	(10.51)	(10.96)	(9.692)	(12.20)
19	-7.000*	-11.30**	-11.94	35.94***	38.56***	-7.750	-8.450
	(3.669)	(5.590)	(8.432)	(12.01)	(11.64)	(5.786)	(5.496)
20	-5.950	-8.550	-3.667	30.17**	22.94**	-9.500	-11
	(4.529)	(5.196)	(10.68)	(12.98)	(11.23)	(5.784)	(7.498)

Standard errors are in parentheses. Estimation by round-wise OLS regressions. Coefficients are the difference between observed and predicted prices. *, ** and *** denote significance at the 10%, 5% and 1% level, respectively.

4. Reference Dependence Impacts Second-Period Prices

In the below section we, explore why second-period prices seemingly diverge from their predictions in Treatment 2 by limiting our attention to the second period. We begin by showing that theoretical subgame predictions for second-period prices increase whenever the cutoff is insufficiently centered, but that this increase does not account for observed second-period prices in both BPD and our experiments. We then present the design and results of a follow-up experiment where we simulate the first-period cutoffs based on our previous findings. Using this, we keep the model predictions constant but eliminate the first-period price as a potential reference point for participants when choosing second-period prices.

Theoretical Preamble: In the following section we attempt to rule out asymmetric market shares as the sole driver for the higher than predicted second-period prices in our Treatment 2 and Case 2 of BDP. The equilibrium in (9) is symmetric and implies $\theta_1 = \bar{\theta}/2$. In Treatment 2, we observe first-period cutoffs between the full range of 0 and $\bar{\theta} = 120$, while only 3.89% of the observed cutoffs are exactly $\bar{\theta}/2 = 60$. Hence, we need to check whether first-period cutoffs of $\theta_1 \neq \bar{\theta}/2$ affects second-period prices.
Let us fully specify the optimal second-period prices from (6) for both firms:

$$p_A^O = \begin{cases} \frac{1}{3}(2\theta_1 + \bar{\theta} + 3c) & \text{if } \theta_1 \geq \frac{1}{4}\bar{\theta} \\ \bar{\theta} - 2\theta_1 + c & \text{if } \theta_1 < \frac{1}{4}\bar{\theta} \end{cases}, \quad p_A^N = \begin{cases} \frac{1}{3}(3\bar{\theta} - 4\theta_1 + 3c) & \text{if } \theta_1 \geq \frac{3}{4}\bar{\theta} \\ c & \text{if } \theta_1 < \frac{3}{4}\bar{\theta} \end{cases},$$

$$\#(10)$$

$$p_B^O = \begin{cases} \frac{1}{3}(3\bar{\theta} - 2\theta_1 + 3c) & \text{if } \theta_1 \geq \frac{3}{4}\bar{\theta} \\ 2\theta_1 - \bar{\theta} + c & \text{if } \theta_1 < \frac{3}{4}\bar{\theta} \end{cases}, \quad p_B^N = \begin{cases} \frac{1}{3}(4\theta_1 - \bar{\theta} + 3c) & \text{if } \theta_1 \geq \frac{1}{4}\bar{\theta} \\ c & \text{if } \theta_1 < \frac{1}{4}\bar{\theta} \end{cases}.$$

Now, we denote the average prices for *old* and *new* customers respectively as $\bar{p}^O = (p_A^O + p_B^O)/2$ and $\bar{p}^N = (p_A^N + p_B^N)/2$ dependent on θ_1 and get:

$$(\bar{p}^O, \bar{p}^N) = \begin{cases} \left(\bar{\theta} - \frac{4}{3}\theta_1 + c, \frac{\bar{\theta}}{2} - \frac{2}{3}\theta_1 + c\right) & \text{if} \quad \theta_1 < \frac{1}{4}\bar{\theta} \\ \left(\frac{2}{3}\bar{\theta} + c, \frac{\bar{\theta}}{3} + c\right) & \text{if} \quad \frac{1}{4}\bar{\theta} \leq \theta_1 \leq \frac{3}{4}\bar{\theta}. \\ \left(\frac{4}{3}\theta_1 - \frac{\bar{\theta}}{3} + c, \frac{2}{3}\theta_1 - \frac{\bar{\theta}}{6} + c\right) & \text{if} \quad \theta_1 > \frac{3}{4}\bar{\theta} \end{cases} \# \#(11)$$

A change in the first-period cutoff does not affect the average old and new customer prices while $\theta_1 \in [\bar{\theta}/4, 3 \cdot \bar{\theta}/4]$. When correcting the model predictions for Treatment 2, according to (10) we would expect an average old customer price of 132.55 instead of 130, and an average new customer price of 91.275 instead of 90.[6] The results presented in Table 5 are created under these corrected model predictions. Thus, we can rule out asymmetric first-period market shares as a driver for higher second-period prices as the increase in predicted prices is not substantial and does not explain observed higher prices.

Experimental Follow-Up: We conducted an additional Treatment 3 "Follow-up experiment" in which we omitted the first period of Treatment 2. We provided participants with the required information – the first-period cutoff – without providing them the theoretically unnecessary information on first-period prices. Similar to the previous experiment, participants took the role of sellers and posted prices for "near" and "far" customers. The near customers correspond to the old customers, while the far customers correspond to the new customers in Treatment 2.[7] Participants were presented with randomly simulated first-period cutoffs and learned that these were derived from earlier experiments. Using a Q-Q plot, Shapiro-Wilk tests, and Shapiro-Francia tests, we confirmed that the first-period cutoffs follow normal distributions – both overall and for each period. However, around 60% of the observations were multiples of 3.75, which occur whenever the difference of chosen prices is a multiple of 10. To account for this, we drew the according share of cutoffs from a truncated normal distribution of multiples of 3.75, and the rest from a normal distribution of multiples of 0.375.[8]

Furthermore, we accounted for the fact that 3.75 is a multiple of 0.375 when specifying the respective shares. We did this by first drawing from a uniform distribution on the interval [0,1] to determine from which of the two normal distributions to draw given a critical value. The critical value is derived from the observed share of cutoffs which are multiples of 3.75 named s_{10}, and those that are not s_{-10} by solving the following system of equations:

$$s_{10} = s_{10}^{crit} + \frac{s_{-10}^{crit}}{10},$$
$$s_{-10} = \frac{9}{10} s_{-10}^{crit}, \#(12)$$
$$s_{-10} = 1 - s_{10}^{crit}.$$

For example, if for a given round the first-period price difference was a multiple of 10 in 6 out of 10 markets, i.e., $s_{10} = 0.6$, we would find the critical cutoff value $s_{10}^{crit} = 0.\overline{55}$. To keep the draws as close to the original observations as possible and avoid situations for the participants that did not occur in the original experiment, we fixed the mean at 60.

However, we varied the lower bound, upper bound, standard deviation, and the critical value s_{10}^{crit} for each round according to the original experimental values of the respective round. Truncated normal distributions are achieved by redrawing an observation when it is either below the lower bound or above the upper bound. Given that the lower bounds (upper bounds) are well below (above) the mean at a considerably low standard

[6]First-period cutoffs were not sufficiently centered in 1/6 of our observations and caused a change in the predicted average prices.
[7]For the remainder of this paper, we will refer to the customers in Treatment 3 as "old" and "new" customers.
[8]The most common integer step of differences between two prices is $\frac{3}{8} \cdot 10 = 3.75$. The smallest integer step of differences between two prices is $\frac{3}{8} \cdot 1 = 0.375$.

deviation, this approach is highly efficient (see Robert, 1995; Chopin, 2011). The follow-up experiment was conducted in October 2018 in the experimental laboratory at TU Berlin. As with the first two treatments, student participants were drawn from the WZB ORSEE pool and shared similar demographic characteristics (age, gender, and field of study). The experiment was slightly shorter in duration (at 60 minutes) as no first period was played. 20 participants earned €6.24 on average, in addition to a €5 show-up fee. The exchange rate was increased so that the total payment remained comparable to the first two treatments.

Findings: Comparisons of aggregate prices in Table 6 and the distribution of prices in Figure 2 reveal that second-period prices are not significantly different from their model prediction, at a 5% significance level in Treatment 3.[9] Both second-period prices are significantly lower in Treatment 3 compared with Treatment 2 (see Table 4). These findings contrast with those of M&V, who observed that prices are significantly higher than model predictions in a similar experiment – also limited to the second period.

Figure 2: Distribution of Prices (Follow-Up)

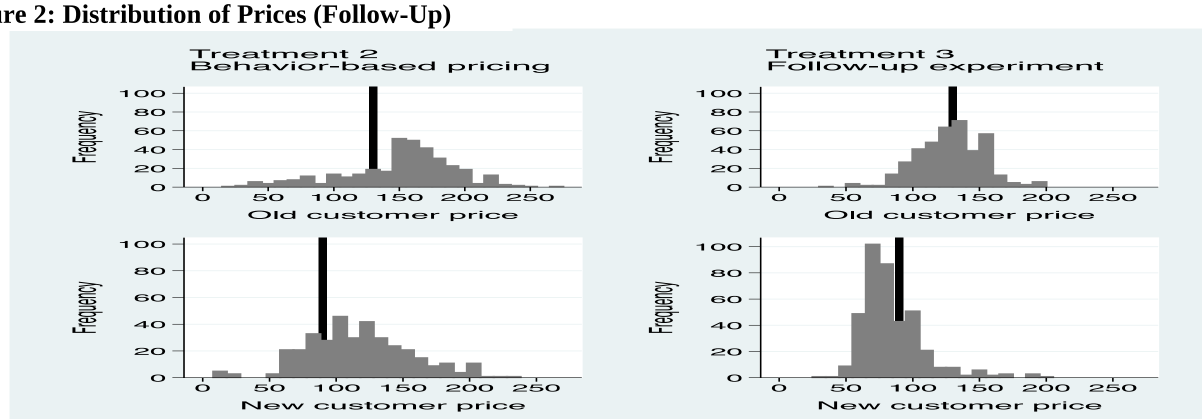


Table 6: Observed Prices (follow-up)

Treatment	**2** **Behavior-based Pricing**	**3** **Follow-up experiment**
Old customer price		
Observed mean	149.77	125.06
Model prediction	130	130
p-Value	0.013	0.068
New customer price		
Observed mean	114.6	83.65
Model prediction	90	90
p-Value	<0.001	0.088

For the subsequent discussion, we correct model predictions by calculating second-period predictions following (10). However, we only find the marginal impact of these corrections with an average predicted old customer price of 131.53, and an average predicted new customer price of 90.76. We have shown that, in Treatment 2, second-period prices increase along with the introduction price. In Treatment 3 (where the first period is absent) there is no considerable change in prices over rounds, as shown by the round-wise OLS regressions in Table 5. We only observe two rounds in which both the old and new customer prices are

[9]Again, p-Values are based on random-effects GLS regressions on the difference between observed and predicted prices at the individual level.

significantly different from their predictions and three instances where one of the two prices is significantly different from the prediction.[10] We still observe a significant old customer price effect with a similar effect size (as in the behavior-based pricing treatment), as shown in Table 3a. This indicates that the presence of the first period does impact overall price levels in the second period but does not affect poaching efforts.

Myopic Consumers Induce Lower First-Period Prices

While we have shown that the upwards price shift in the second period is driven by the availability of the first-period prices, there are remarkable differences between the chosen first-period prices in Case 2 of BDP compared with the second treatment in our experiment. In the following discussion, we conjecture that this may have been driven by a faulty fraction in the computation of the first-period cutoff in the code of BDP's program. We argue that this represents a case of "Behavior-based pricing with myopic consumers". To support this argument, we first derive the subgame perfect prices of a myopic consumer variation of F&T's model. We then show that the result is a better prediction of BDP's observations.

Behavior-Based Pricing with Myopic Consumers: Whether consumers are naïve or strategic only alters their actions in the first period. Hence, we can readily skip the analysis of the second period as it is identical to the case of behavior-based pricing in section 2.1. Due to the naivety of consumers, the location of the indifferent consumer in period one $\theta_1^{'}$ is akin to the location of the indifferent consumer under uniform pricing, i.e.,

$$\theta_1^{'} = \frac{p_B^n - p_A^n + \bar{\theta}}{2}. \#(13)$$

The maximization problems of firms are like (8) with $\theta_1^{'}$ inserted instead of θ_1:

$$\text{Seller A: } \max_{p_A^1} (p_A^1 - c)\theta_1^{'} + (p_A^O - c)\theta_A + (p_A^N - c)\big(\theta_B - \theta_1^{'}\big),$$

$$\#(14)$$

$$\text{Seller B: } \max_{p_B^1} (p_B^1 - c)\big(\bar{\theta} - \theta_1^{'}\big) + (p_B^O - c)(\bar{\theta} - \theta_B) + (p_B^N - c)\big(\theta_1^{'} - \theta_A\big).$$

Solving the maximization problems for p_A^1 and p_B^1 with consideration of $\theta_1^{'}$ from (13) and optimal second-period prices from (6), where we replace θ_1 by $\theta_1^{'}$, yields:

$$p_i^1 = \bar{\theta} + c. \#(15)$$

This result is identical to the result under uniform pricing in (3).[11] Case 1 of BDP and the case of "Behavior-based pricing with the myopic consumer" both share the term $(p_B^1 - p_A^1 + \bar{\theta})/2$ as a first-period cutoff. Case 2 of BDP and our behavior-based pricing case are different in this term, as shown in (7) where the difference in prices $p_B^1 - p_A^1$ is multiplied by 3/8 instead of 1/2. For Treatment 1 and Treatment 2 in our experiment (as well as for Case 1 of BDP), we observe a peak in the price distribution close to the model prediction whenever a uniform price is chosen in the first period (see Figure 1). This only fails for Case 2 of BDP, where prices are similar to their Case 1 and our Treatment 1, with a peak in the price distribution at a similar point – just below 170. However, this would be in line with the price prediction in (15). While this does not fit the instructions of BDP – according to which consumers are strategic in their first-period decision.

It is a surprising testament to how powerful price predictions are in this model. It should be noted that BDP's instructions are somewhat vague concerning buyer behavior in the first period. Buyers are described as minimizing their total expenditures with their first-period decision (considering their location and the current prices) while anticipating optimally chosen prices in the second period. On the other hand, second-period behavior is described explicitly, covering precise calculations of the location of the indifferent consumer and the resulting cutoff. It may not be immediately apparent to an uninformed participant that the strategic decision of a consumer in the first period involves a lowered willingness to buy from a far seller. Rather than relying on instructions, participants appeared to have experimented over the course of the experiment to optimize their pricing decisions.

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[10]Four out of the seven significant differences only hold at a complaisant significance level of 90%.
[11]The uniform pricing benchmark is identical for myopic and strategic consumers, due to the independence of the periods.

Transport Costs as a Robust Welfare Measure

As discussed previously, chosen prices are prone to distortions. Therefore, we hold reasonable doubt regarding the reliability of consumer costs and profit as welfare measures, as used by BDP. Both measures are easily shifted by price levels and mask the efficiency of the market. Instead, we propose to measure total welfare directly by means of transport costs. While this is not necessarily the preferred welfare measure in terms of policy recommendations, it is superior when assessing the efficiency of an experimental market. This is sensitive to comparative static implications (such as poaching and efficiency losses due to price dispersion), but insensitive to distorted price levels. Under uniform pricing the transport costs are:

$$T = \int_0^{\theta_1} \theta \, d\theta + \int_{\theta_1}^{\bar{\theta}} (\bar{\theta} - \theta) \, d\theta + \int_0^{\theta_2} \theta \, d\theta + \int_{\theta_2}^{\bar{\theta}} (\bar{\theta} - \theta) \, d\theta. \#(16)$$

Transport costs under behavior-based pricing are:

$$\tilde{T} = \int_0^{\theta_1} \theta \, d\theta + \int_{\theta_1}^{\bar{\theta}} (\bar{\theta} - \theta) \, d\theta + \int_0^{\theta_A} \theta \, d\theta + \int_{\theta_A}^{\theta_1} (\bar{\theta} - \theta) + \int_{\theta_1}^{\theta_B} \theta \, d\theta + \int_{\theta_B}^{\bar{\theta}} (\bar{\theta} - \theta) \, d\theta. \#(17)$$

It is noteworthy that gains are independent of consumer purchasing decisions when the market is fully covered. Hence, it is sufficient to consider losses in the form of transport costs in (16) and (17) to evaluate welfare effects. In Table 7, we show how profits for sellers and total costs for consumers were lower under uniform pricing compared with behavior-based pricing in the first period, in contrast to BDP which found no effect. This finding is driven by higher introduction prices in our Treatment 2 (compared with Case 2 of BDP). However, transport costs were not significantly different in the first period between both treatments. The difference in total costs can be entirely explained by the difference in prices paid (i.e., product costs). Second-period profits and total costs are larger in Treatment 1 compared with Treatment 2 – oppositional to the findings of BDP. Transport costs are significantly different between the uniform pricing and behavior-based pricing treatments in the second period. In contrast, there are no differences in transport costs between the follow-up experiment and the behavior-based pricing treatment, while profits and total costs were significantly smaller in the follow-up experiment compared with the behavior-based pricing treatment. This is a direct consequence of the lower prices chosen by participants.

Table 7: Treatment Effects on Welfare Measures in the First And Second Period

	Seller's Profit	Customers' Total costs	Transport costs	Seller's Profit	Customers' Total costs	Transport costs
Treatment 1	-1374.7***	-2820.8***	-71.48	572.2**	386.1	-758.2***
	(158.5)	(366.8)	(73.40)	(174.0)	(405.9)	(90.28)
Treatment 3				-1396.2***	-2821.9***	-29.46
				(151.6)	(342.5)	(95.54)
Constant	5150.0***	20339.9***	4039.9***	3844.9***	18344.3***	4654.5***
	(324.6	(876.5)	(114.7)	(243.0)	(627.1)	(132.6)
Base case	Treatment 2	Treatment 2	Treatment 2	Treatment 2	Treatment 2	Treatment 2
Considered period	First	First	First	Second	Second	Second
Observations	760	380	380	1158	579	579

Standard errors are in parentheses. Estimation by OLS regressions with round fixed effects. Analysis is done on the individual level for sellers and market level for customers. Treatment 1 - Uniform pricing, Treatment 2 - Behavior-based pricing, Treatment 3 - Follow-up experiment. ** and *** denote significance at the 1% and 0.1% level, respectively.

We show the effect of disjoining the decision process in Table 8. There, we calculated mean profits, mean total costs and mean transport costs for three cases. The first and second case corresponds to the first and second treatment. In the third case, we hypothetically combine the second-period findings of the follow-up experiment with the results of the first period of the behavior-based pricing treatment. Both mean profits and total costs are lower in the combined case compared with the uniform pricing treatment, whereas they were originally larger in the behavior-based pricing treatment (compared with the uniform pricing treatment). In contrast, the sign and the magnitude of the differences in transport costs between both the behavior-based pricing and the uniform pricing treatment and the combined case and the uniform pricing treatment remain similar. This shows that price-based measures (profits and total costs) are volatile and can mask efficiency. Transport costs are independent of prices and reflect the efficiency of the market without distortion.

Table 8: Sum of Mean Profits, Total Costs and Transports Costs Between Cases

Considered treatment in	First period Second period	Uniform pricing + Uniform pricing	Behavior-based pricing + Behavior-based pricing	Behavior-based pricing + Follow-up experiment
Sum of mean	profits	10485.44	11287.95	9895.11
	total costs	20498.92	21716.29	20308.95
	transport costs	4013.48	4428.334	4413.841

5. Conclusion

We designed an experiment using the theoretical basis provided by F&T and a previous experiment by BDP. In contrast to BDP, we can confirm the positive first-period price effect of behavior-based pricing over uniform pricing, validating an additional comparative static result from F&T's model. We find that, in the case of behavior-based pricing, second-period prices are driven upwards when participants play the first period themselves – but not when both periods are disjointed and played by different participants. This also contrasts with the findings of M&V, who observed significantly larger-than-predicted prices when participants play a disjoint second period against computerized competitors. While our study does not require direct policy recommendations, it questions the circumstances that necessitate policy recommendations drawn from experimental studies, and to what extent. Separating the decisions of the first and second period reveals particular volatility within the chosen strategies. Going forward, this insight can be helpful in the fundamental design of experiments. For multi-period experiments, separating the individual stages may be necessary to reveal conclusively whether participants play according to predictions.

Furthermore, when volatility is anticipated, welfare measures should be chosen carefully. In the case of behavior-based pricing experiments, we have shown that transport costs are a welfare measure that is robust to confounding factors. Some pertinent questions remain and could be investigated further in future research. It remains unclear precisely how first-period prices drive second-period prices up in the behavior-based pricing cases in BDP and our experiment. It is possible that prices are interpreted as signals and change beliefs toward second-period behavior. Another possibility is that first-period prices have an anchoring effect; this could be resolved by showing either first-period prices of past experiments (along with the first-period cutoffs) or irrelevant numbers of the same magnitude (that serve as anchors for participants) in a follow-up experiment. Moreover, we cannot explain why participants in BDP's Case 1 chose lower prices in the second period. They may not have understood that, because consumers have independent preferences, the two resulting markets can be treated as two separate markets. Again, this question could likely be answered by separating the confounding factors and conducting an experiment in which participants are confronted with two independent markets in the second period.

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