Price Salience and Product Choice

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PRELIMINARY AND INCOMPLETE

Abstract

We study the effect of price salience on product choice along two dimensions: whether a good is purchased and, conditional on purchase, the kind of good purchased. Consistent with our theoretical predictions, we find that making the full purchase price salient to consumers reduces both the quality and quantity of goods purchased. The effect of salience on quality is approximately half the size of the effect on quantity.

Textbook models of consumer choice assume that economic agents are fully aware of fees and taxes. Consumption decisions are therefore based on true final prices. As a consequence, any change in the final prices of goods, due to a change in base prices, fees, or tax rates, results in the same change in consumer choices. Recent influential work, however, has challenged this assumption. Chetty, Looney, and Kroft (2009) document that tax salience profoundly affects consumers' decisions to purchase personal care goods in grocery stores. Finkelstein (2009) finds local governments exploit salience limitations to raise fees on toll roads. In this paper, we employ a large-scale

field experiment to show that the effect of price salience on what consumers purchase can be just as important as the effect on whether they purchase.

Consider the example of a percentage fee levied on all the goods. Price salience affects the consumer along two margins. First, increasing the salience of the fee makes all goods appear more expensive, resulting in a higher probability that the consumer chooses not to buy any good. Second, because a percentage fee amounts to a larger fee level for more expensive goods, salience changes the perceived price-quality tradeoff for the goods in the consumer's choice set. As a result, higher salience may encourage the consumer to substitute towards cheaper goods. The contribution of our paper is to offer a more complete analysis of the effect of price salience on consumers' choices by quantifying the importance of both margins.[1]

We begin our analysis with a simple model that illustrates the impact of price salience on consumption choices. The model demonstrates that if prices are made more salient—i.e. fees are listed upfront—then consumers are not only less likely to purchase any good, but conditional on purchasing, they purchase lower quality goods.

We take these predictions to data generated from a large-scale field experiment conducted in 2015 by a StubHub.com. the leading online secondary ticket marketplace. The marketplace experimented with employing an "All-in Pricing" (AIP) strategy, where the site shows consumers the final price from the get-go (their very first viewing of a ticket). This final price includes all ticket fees and taxes. This user experience contrasts sharply with the traditional internet layout, where fees (e.g. shipping and handling) are shown only after consumers have selected a particular product and proceeded to the checkout page.

StubHub randomly selected 50% of users to see an AIP experience, while the other 50% only saw the fee-inclusive price only at the final stage of their purchase, called "Price Display Optimization" (PDO). This experiment provides exogenous variation in fee salience in a setting where we can collect detailed data on the actual choice sets faced, each signal of purchase intent (e.g. product selection and clicks towards checkout) and final purchase choices. These rich data allow us to infer the effect of salience on both the extensive and intensive margins of product choice. Our empirical results bear

[1]In the working paper of Chetty, Looney, and Kroft (2007), they note that the revenue effect is bigger than the quantity effect, which is potentially due to consumers switching to lower priced items. Unfortunately, their data is insufficient to investigate that possibility further.

out the model's predictions: price obfuscation distorts both the quality and quantity. The intensive margin accounts for approximately one-third of the increase in revenue raised from fees.

Analysis of the Clickstreatm data suggests that PDO plays on consumer myopia. AIP users are more likely to exit before exploring any ticket, while PDO users differentially exit at checkout, when they first see the fee. Further, PDO users go back to examine other listings more often than their AIP counterparts. They are more likely to go back multiple times, which suggests PDO makes it price comparisons difficult. PDO affects experienced users, although on a smaller scale, which is consistent with consumers facing optimization costs, even when they anticipate a fee.

We also examine whether salience is more or less pronounced for big-ticket items. If consumers employ heuristics, they may ignore proportional fees for the sort of low-cost items studied in the existing literature (such as drug store beauty aids) but carefully consider those same fees when levied on relatively costly products ($300 playoff tickets). Understanding when and where salience looms large is crucial to crafting both government tax policy and firm pricing strategies.

Finally, we present evidence on price salience from a supplementary experiment at StubHub. This second experiment randomized at the event, rather than cookie, level, which suffers from a separate set of vulnerabilities. Reassuringly, the results are broadly consistent with our 2015 findings.

The next section presents a simple model of price salience and derives empirical implications. Section 3 discusses the experiment run at a secondary ticket market platform as well as the data used in the analysis. Section 4 provides results. Section 5 contains evidence on mechanisms. Robustness checks based on the second experiment are presented in section 6. Section 7 concludes.

2 A Model of Consumer Choice with Limited Fee Salience

The firm cares ultimately about the effect of AIP on revenue per cookie. Our experiment design allows us to estimate this revenue effect simply as the difference in average revenue across the treatment (PDO) and control (AIP)

groups

$$\frac{\partial E[R_i]}{\partial T_i} = E[R_i|T_i = 1] - E[R_i|T_i = 0]$$

where T_i is an indicator for treatment and R_i is revenue per cookie. However, this net change in revenue subsumes two separate effects: one on price and one on quantity. Let Q_i be an indicator for whether consumer i purchases any product and P_i is the price of the product that i purchases. We decompose revenue using conditional probability as:

$$E[R_i] = E[P_i|Q_i = 1] \cdot E[Q_i].$$

So that the change in revenue from treatment is

$$\frac{\partial E[R_i]}{\partial T_i} = \underbrace{\frac{\partial E[P_i|Q_i = 1]}{\partial T_i}}_{\text{Price Effect}} \cdot E[Q_i] + \underbrace{\frac{\partial E[Q_i]}{\partial T_i}}_{\text{Quantity Effect}} \cdot E[P_i|Q_i = 1].$$

The standard discrete choice model from Industrial Organization provides predictions about the signs of these two effects. Let the utility consumer i gets from product j be:

$$u_{ij} = v_j - \alpha \cdot p_j \cdot \theta(T_i) + \epsilon_{ij}$$

where v_j is the mean utility of product j, p_j is its final price, α is the shadow value of money, $\theta(T_i)$ captures price salience, and T_i indicates treatment. Under the standard logit assumptions on ϵ_{ij}, the probability consumer i purchases good j is:

$$q_{ij} = \frac{\exp\{v_j - \alpha p_j \cdot \theta(T_i)\}}{1 + \sum_{k \in J} \exp\{v_k - \alpha p_k \cdot \theta(T_i)\}}$$

2.1 Quantity Effect

The parametric model predicts that treatment should increase the likelihood of purchase.

$$\begin{aligned}\frac{\partial E[Q_i]}{\partial T_i} &= \frac{\partial \left[\frac{\sum_{k \in J} \exp\{v_k - \alpha p_k \cdot \theta(T_i)\}}{1 + \sum_{k \in J} \exp\{v_k - \alpha p_k \cdot \theta(T_i)\}} \right]}{\partial T_i} \\ &= -\alpha \cdot \frac{\partial \theta(T_i)}{\partial T_i} \cdot (1 - E[Q_i]) \cdot E[R_i] > 0\end{aligned}$$

The magnitude of the quantity effect is increasing in price sensitivity α

Rather than estimate the individual components that comprise the quantity effect, we estimate the quantity effect directly using the sample moments analogous to the population counterparts. Since suppliers cannot price discriminate between treated and control users, we need not worry that the two groups face different prices.

$$\text{Quantity Effect} = E[Q_i|T_i = 1] - E[Q_i|T_i = 0]$$

Importantly, we need not assume a functional form for $\frac{\partial\theta(T_i)}{\partial T_i}$ nor lean on the extreme value assumption to estimate the quantity effect. Randomization permits us to test the model's sign prediction. As an example, if price obfuscation generates a 'disgust' factor, wherein adding fees at the end upsets consumers, then our estimated quantity effect would be negative, leading us to reject the standard price salience model.

2.2 Price Effect

The model also predicts that treatment increases the expected purchase price (conditional on purchase).

$$\begin{aligned}\frac{\partial E[P_i|Q_i = 1]}{\partial T_i} &= -\alpha \cdot \frac{\partial\theta(T_i)}{\partial T_i}\Big(E[P_i^2|Q_i = 1] - E[P_i|Q_i = 1]^2\Big) \\ &= -\alpha \cdot \frac{\partial\theta(T_i)}{\partial T_i} \cdot Var(P_i|Q_i = 1) > 0\end{aligned}$$

The intuition underlying this result is simple: in a logit model, the conditional variance of price is high when there are several goods of almost equal total utility (taking into account price). When a proportional fee is hidden, the utility of the more expensive goods increases disproportionately.[2] Again, we can test this implication directly by comparing the average purchase price in the treatment and control groups:

$$\text{Price Effect} = E[P_i|T_i = 1] - E[P_i|T_i = 0]$$

Ex ante, it is unclear whether average prices should rise among treated compared to control purchasers. So long as perceived prices are weakly less than

[2]There is no such price effect, for example in a log-log demand specification.

final prices, then there are two components to the price effect: (1) more consumers will purchase at least one ticket and (2) consumers will purchase more expensive tickets than they would otherwise. (1) may actually depress average ticket prices in the treatment group if marginal consumers buy the cheapest tickets. Our simple discrete choice model ignores consumer heterogeneity, so there is no change in the identity of the marginal consumer.

3 Experimental Design

We examine an experiment in price salience on StubHub, a platform for secondary market ticket sales. Prior to 2015, the platform showed all fees upfront to consumers, so that the initial price that the consumer saw was the final checkout price. The platform refers to this as All-in Pricing (AIP). In 2015, the firm ran an experiment during the final two weeks in August (August 19th - 31st). Treated consumers were shown ticket prices without the additional fees; these fees were only added at the checkout page, much like taxes added at the register of a grocery store.[3] The platform refers to this as Price Display Optimization (PDO). The platform employs a non-linear fee structure: the buyer fee is 15% of the ticket price plus shipping and handling, if applicable. The platform also charges seller fees which peak at 15%.

The experimental condition was assigned at the cookie-level, where 50% of site visitors were assigned to the treatment (PDO) group at their first touch of an event page. On the event page, users are shown a list of tickets. Consumers assigned to the AIP experience (the control group) are shown conspicuous onsite announcements confirming that the prices they saw upfront were inclusive of all charges and fees. On the other hand, users in the test group are shown only the base price. Once users select a ticket, they are taken to a ticket details page, where they can log in to purchase the ticket. Once logged in, they review the purchase. It is at this point where the control group are shown the total price (ticket cost plus fees and shipping charges). Users then can proceed to checkout.

In total, the experiment included a few million visitors who frequented the site over ten days. To check randomization, we test whether we can reject a 50% treatment assignment probability. Results are presented in table 1. While the odds of assignment to the treatment group are 50.11% in the full

[3]Other ticket platforms, including Ticketmaster, employ a similar pricing scheme, where fees are only included at the final stage of the transaction.

sample, the scale of the experiment allows us to reject the null hypothesis of a 50% assignment probability at the 5% level. Upon closer scrutiny, we discovered two glitches in the randomization: first, all users who logged in during the first 30 minutes of the experiment were assigned to the treatment group, and second, users on a particular browser-operating system combination were also skewed to the treatment group. Once we eliminate these two groups, we can no longer reject a 50% assignment at the 1% level.[4] We therefore exclude these users in our main analysis. Although the probability of treatment remains slightly higher, the difference is economically insignificant.

Table 1: Treatment Assignment

Sample	% in Niether PDO nor AIP	% Site in Sample	% PDO	T-statistic
Full	0.78	100	50.11	4.28
Time Restriction	0.78	99.82	50.09	3.41
Time & Browser Restriction	0.82	66.12	50.06	1.99

As a robustness check, we test whether treatment and control users share similar observable characteristics. Unfortunately, since treatment was assigned before users are required to log-in, the set of observables is fairly limited. As an example, even if a user has visited the site before, we do not know their purchase history if they never log into the site during the experiment and they have also cleared their cookies. However, we are able to measure site visits since the last cookie-reset, which we use to measure experience. Table 2 shows that the two groups have almost identical experience levels. Treatment and control users also visit the site at similar hours-of-the-day, and are equally likely to be mac users. We devote the remainder of the paper to a detailed analysis of the experiment.

4 Effect of Salience on Revenue

Theory indicates that obfuscation should encourage marginal consumers to switch from buying nothing to buying something and also encourage con-

[4] Or at the 5% level in a one-sided test against the null that the treatment assignment is $> 50\%$.

Table 2: Covariate Balance

	% Difference	T-statistic
Experience	0.01	0.02
Hour	-0.08	-1.6
Mac User	0.16	0.01

sumers to switch from purchasing lower to higher quality tickets. Table 3 shows the composite effect on revenue of the price salience treatment. Cookies in the treatment group, where price is shrouded, spend 21% more than those assigned to the control group. We show revenue effects for the session (same-day) and over the entire experiment (10 days).

Unfortunately, quantifying salience is difficult so it is hard to compare this effect to the Chetty, Looney and Kroft (2009) benchmark. (While the change in user experience in the StubHub experiment is similar in spirit to their experiment adding fees to supermarket shelf prices, it is hard to measure how closely they align.) They find that obfuscating a 7.35% tax leads to an XX% revenue increase. In our setting, obfuscating a 17% fee leads to a 21% revenue boost. [5] We explore reasons the effect might be larger on StubHub below.

4.1 Quantity Effect of Salience

We next examine the quantity impact separately. The third row of table 3 shows that price obfuscation increased the transaction rate over the full course of the experiment. We find that consumers in the control group are 13% less likely to purchase a ticket during a visit. Fees average roughly 10% of ticket prices, suggesting a salience elasticity of 1.2, which is similar to the elasticity of 1.1 found in Chetty, Loony & Kroft. The 10-day elasticity is 1.4, suggesting that the long-run effects of salience may be even larger. In Section 5.1, we expand this further by looking at the rate that users engage with each phase of the purchase funnel.

[5] Katy Osborn. September 1, 2015. "Why StubHub is tacking on ticket fees again." *The Wall Street Journal."*

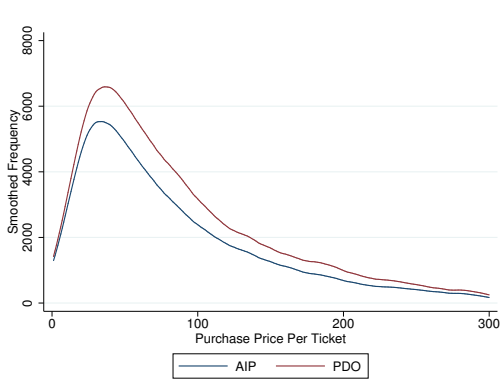
Table 3: Effect of Salience on Purchasing

	PDO vs AIP % Difference	
	Baseline	Conditional on Purchasing
Cookie 10-day Revenue	20.64	5.42
	(1.38)	(1.03)
Propensity to Purchase at Least Once	14.10	_
	(0.09)	
# Transactions within 10 Days	13.24	-0.90
	(0.88)	(0.37)
Cookie Session Revenue	18.96	5.61
	(1.27)	(0.96)
Cookie Session Propensity to Purchase	12.43	_
	(0.002)	
Cookie-Session # Transactions	11.76	-0.66
	(0.54)	(0.25)

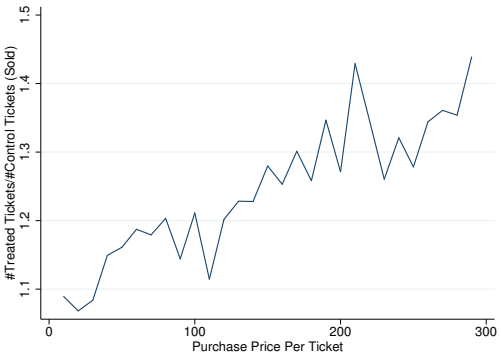
4.2 Price Effect of Salience

Table 3 compares differences in control and treatment group behavior conditional on a purchase. This comparison allows us to assess the price effect: control group users spend 5.42% more than their treatment counterparts. We interpret this as an upgrade effect, where shrouding fees leads consumers to buy higher quality tickets than they would otherwise purchase. While this amount is smaller than the quantity effect but still economically meaningful. We see this magnitude of response with both on a per-transaction and a per-user comparison. Interestingly, control group users purchase a lower total quantity. While this response margin is outside of the discrete choice model, it hints at the second effect of price obfuscation: a change in the marginal consumer. The marginal consumer, attracted by seemingly lower prices, may be more price-sensitive and therefore in the market for fewer tickets.

Figure 1: Transaction Per Ticket Price Distribution



(a) Kernel Smoothed Histogram



(b) Ratio of Treated to Control Purchase Counts

We next consider the heterogeneity of response by price range. Theory suggests that treated users should be more likely to purchase any ticket, but in particular, more likely to purchase an expensive ticket. Figure 1a shows the overlapping test and control distributions (kernel smoothed) of ticket prices for all purchased tickets with prices less than $300 during the experiment. There is a surprising consistency in response across all price points. But it is not completely uniform, the second pane of Figure 1b.

Table 4: Relative Purchase Probability by Ticket Price

Ticket Price	Relative Purchase Probability by PDO versus AIP Users
< $20	1.02
$20 - $100	1.13
$100 - $200	1.23
$200+	1.27

5 Behavioral Mechanisms

5.1 Myopia

We leverage StubHub's detailed data to better understand why fee salience affects consumers so greatly. First, we examine consumer myopia using web-browsing behavior. If consumers do not anticipate fees, then they should be more likely to exit when the fee first appears. For consumers who are nearly indifferent between purchasing at the base ticket price, the fee makes the outside option their utility-maximizing choice. Importantly, this theory has an implication about where (in the purchase funnel) treatment and control users should differentially exit.

To buy a ticket, a user goes down the StubHub purchase funnel on the website: (1) the event page, which contains a seat map and a sidebar with top ticket results, sorted by price in ascending order; (2) once a consumer clicks on a ticket, the ticket details page[6]; (3) checkout page; (4) purchase confirmation.[7] PDO users are shown lower prices than their control peers until stage (3), when they are shown the final price, inclusive of fees. If consumers are ignorant of fees, there should be a larger drop-off between stages (1) and (2) for the AIP group, since they see higher prices initially. But there should be a larger drop-off between stages (3) and (4) for the PDO group. If the former is smaller than the latter, then PDO increases quantity sold.

Table 5 shows the absolute and relative rate of AIP and PDO user arrivals at each step in this process. Consistent with myopia, PDO users are 16% more likely to select tickets (transition from stage 1 to 2) than users in the AIP group. The difference is statistically significant at the 1% level and economically large. In contrast, the drop off rate at the final stage – purchase – is much large for PDO users: 30%. Interestingly, the difference in drop off rates between stages 2 and 3 is also statistically significant (although smaller in magnitude than the others). We hypothesize that this difference results from selection; the users who differentially attrit due to price salience are more price sensitive.

Table 6 examines the quality response at each step in the purchase funnel.

[6] the log-in page (optional; bypassed if the consumer is already logged into his account)

[7] Of course, many searches are non-linear (Nosko and Tadelis), where consumers examine multiple event pages. PDO users might even return to the search stage (1) once they see the additional fees leveed at stage (4).

The average price of tickets under consideration declines at each step in the funnel. AIP experience prices are lower than their PDO counterparts, but the difference generally narrows as users move closer to purchase. At the point where fees are revealed, the gap is 7% compared to an initial difference of 19%. PDO users, who see no fees, are more likely to contemplate expensive tickets. When fees are revealed, more of the (surprised) PDO users exit than the AIP users who see no change in their expected outlay.

One important question, from both the firm and policy perspective, is whether consumers learn about the fees over time. As an example, consumers could be entirely myopic in their ticket selection each time they visit the site. In this case, websites stand to gain substantially by shrouding fees. This contrasts to a model where consumers anticipate a fee, but do not know the exact level. Once a consumer makes a purchase, she updates her priors on future StubHub fees and does not make the same 'mistake' twice. To examine learning, we repeat our principle analysis (Table 3) separately by user experience. If consumers are forward-looking, then those with experience should not react to obfuscation.

To measure experience, we calculate the number of visits each cookie has made to StubHub.com. A 2006 ComScore study finds that 31% of users clear their cookies within 30 days, so we interpret this as a short-term measure of experience. Unfortunately, we cannot exploit information about logged-in users (such as number of past transactions), since log-in is a potential response to our treatment. Users who see lower prices initially may be more likely to log in to the website, since it is a prerequisite to purchase. Importantly, however, our mesure captures the most recent interactions with StubHub, which are likely to be the most relevant for a users' knowledge of the site.

Table 5: Purchase Funnel Rates

	Relative to Initial Page				Relative to Prior Page			
	AIP	PDO	Difference	% Difference	AIP	PDO	Difference	% Difference
Event Page	100	100	–	–	–	–	–	–
Ticket Details	62.92	66.93	4.00	0.06	62.92	66.93	4.00	0.06
	(0.21)	(0.21)	(0.3)		(0.21)	(0.21)	(0.3)	
Start Checkout	13.72	21.45	7.73	0.56				
	(0.15)	(0.18)	(0.23)					
Review & Submit	10.04	15.66	5.61	0.56	15.96	23.40	7.43	0.47
	(0.13)	(0.16)	(0.21)		(0.2)	(0.23)	(0.3)	
Purchase	6.00	6.78	0.79	0.13	59.71	43.32	-16.39	-0.27
	(0.1)	(0.11)	(0.15)		(0.68)	(0.55)	(0.87)	

Table 6: Per Ticket Price Along the Purchase Funnel

	PDO	AIP	Difference	% Difference
Event Page	\$1.00	\$0.84	\$0.16	19%
			(4.68)	
Ticket Details	\$0.86	\$0.78	\$0.08	10%
			(7.60)	
Start Checkout	\$0.77	\$0.75	\$0.02	3%
			(14.28)	
Review & Submit	\$0.56	\$0.52	\$0.04	7%
			(5.34)	
Purchase	\$0.42	\$0.39	\$0.03	7%
			(0.58)	

Notes: Average price of each touch point using that tickets price at time of touch. Standard errors in parentheses.

We hypothesize that frequent StubHub users ought to be aware of fees and therefore less sensitive to price salience (and the treatment). Table 7 shows that the treatment effect is smaller for cookies with at least 20 site visits: the revenue effect is 15% compared to 21%. These results suggest that salience effects ought to be most important in markets where consumers purchase infrequently (for example, real estate or automobile markets). However, price obfuscation still generates substantial revenue, which indicates only limited consumer learning – even experienced users seem to be caught off-guard by fees.

Table 7: Salience by User Experience

	% Difference		
	New User	Low Experience	High Experience
Cookie 10-day Revenue	21.52	21.80	15.09
	(0.02)	(0.02)	(0.04)
Propensity to Purchase at Least Once	15.33	13.68	10.19
	(0.007)	(0.01)	(0.02)
# Transactions within 10 Days	14.33	13.53	8.81
	(0.01)	(0.01)	(0.03)
% Sample	67%	27%	6%

5.2 Search Frictions

Obfuscating fees may lead consumers – particularly first-time visitors – to spend more on the platform than they would otherwise if they don't anticipate fees. When fees are revealed, PDO consumers are already at check-out with their tickets. They must choose to go back to the event page if they wish to re-optimize and purchase other seats. Table 8 shows the average number of tickets viewed for PDO and AIP users. PDO cookies are 56% more likely to view multiple ticket listing compared to their AIP counterparts. Table 9 shows that PDO users view cheaper tickets upon their return (6 percentage points lower). In contrast, AIP users (who are less likely to return) go back for relatively more expensive tickets. PDO users are twice as likely to

Table 8: Average Number of Tickets Viewed

# of Tickets	PDO	AIP
1	75%	84%
2	16%	12%
3	5%	3%
4	2%	1%
5+	2%	1%

view 3 or more listings than their AIP counterparts. Viewing more than

two tickets suggests the effects of price obfuscation extend beyond an initial confusion about fees. PDO consumers who return to the event page choose tickets already having seen fees, but they must calculate the StubHub fee for each ticket they consider to compare total prices. If this calculation cost is high, consumers might choose to go down the funnel multiple times, so that StubHub reveals the final price, rather than compute the fees themselves. Obfuscation as a search friction is consistent with our findings on experienced customers, who ought to anticipate fees but might still bear a higher search cost when they are hidden. This evidence is consistent with Ellison and Ellison (2009), who find that firms endogenously create such frictions to soften price competition.

Table 9: Average Price of Tickets Viewed
Relative to AIP Initial Selections

PDO		AIP	
Initial Checkout	Follow-up Actions	Initial Checkout	Follow-up Actions
8%	1%	0%	2%

5.3 Endowment Effect

Finally, we investigate whether PDO creates attachment bias. In a seminal paper, Khaneman and Tversky (1979) suggest that consumers value objects differently when they feel ownership over the good. In this case, consumers who don't anticipate fees may put tickets in their "cart" and be loathe to part with these tickets later, even when fees are revealed. By hiding fees, the platform changes the consumer's utility function at the purchase juncture.

The endowment effect logic works as follows: PDO users don't anticipate fees. Once they see fees, some decide to go back. Who decides to return given that search is costly? The folks who are most price sensitive. These consumers should choose relatively cheaper seats than the average AIP cookie. But the seats they do choose are actually more expensive than the average AIP price. 9 shows that returning PDO users interact with 2% more expensive tickets AIP users. This suggests that the PDO folks who go back put a higher premium on quality, consistent with an endowment affect.

6 A second experiment: randomization at the event-level

In the 2015 experiment, feel salience was randomized across cookies. Treatment and control users had the same StubHub experience, but for the addition of fees in the latter's search results. In a second experiment at StubHub, fee salience was randomized at the event level. Randomization at the event level presents distinct challenges, but offers a nice robustness check for the 2015 experiment.

The uniqueness of StubHub inventory threatens the independence assumption for the 2015, but not the 2012, experiment. Suppose that price obfuscation merely accelerates, but does not actually alter, the consumer's purchase decision. In this example, treatment users will tend to buy first in the 2015 experiment. If treatment users buy up all the inventory, then control users can no longer purchase a ticket. Comparing purchase probabilities without taking this censorship into account would mistakenly suggest that a positive treatment effect. In other words, treating user A affects user B. Blake and Coey (2014) discuss this challenge on eBay.com. Fortunately, the 2012 experiment does not suffer from the same contamination concern because all tickets for a particular event are share the same treatment status. In the above example, there would be no difference in sales across treated and control games, but only a difference in the timing of purchases.

A second challenge that the 2012 experiment addresses is multi-homing. In the 2015 experiment, we sort users into the treatment or control group the first time they touch the an event page on StubHub during the experiment period. StubHub employs cookies to track users, so that the user remains in the appropriate group through the duration of the trial. However, the cookie does not follow the user if he were to visit StubHub on a second computer or on a mobile device. Instead, the user would be re-randomized into the treatment or control group. Multi-homing is particularly problematic if its incidence depends on initial treatment assignment. As an example, if control users – upon seeing higher initial prices – delay their purchase and revisit StubHub on a second device, then treatment would be artificially correlated with purchasing. In the 2012 experiment, tickets to each event retain their treatment status regardless of the device that consumers employ. If a Red Bulls-Revolution match shows the fee-inclusive price on their personal laptop, it also shows the fee-inclusive price on their work Desktop.

Finally, randomization at the event level provides insight into general equilibrium effects. When StubHub alters the consumer's user experience, it potentially alters sellers' incentives. As an example, if price obfuscation attracts more elastic buyers, then sellers might lower their prices. If these effects are large, then the 2015 experiment does not provide the true counterfactual of interest: what happens on StubHub when price is obfuscated for all users. Instead, the econometrician only observe what happens on StubHub when price is shrouded for 50% of users. The 2012 experiment provides insight into the importance of these GE effects, since a ticket-seller for a particular match faces an entirely PDO or AIP audience, but not a mix of both.

In the 2012 experiment, 33 out of 99 Major League Soccer Games were randomly selected for All-in-Pricing. Prices for tickets to these games included fees, even from the initial event page. For the remaining 66 matches, fees were added only in the final checkout stage of the purchase funnel.

Table 10: 2012 Experiment Resultsl

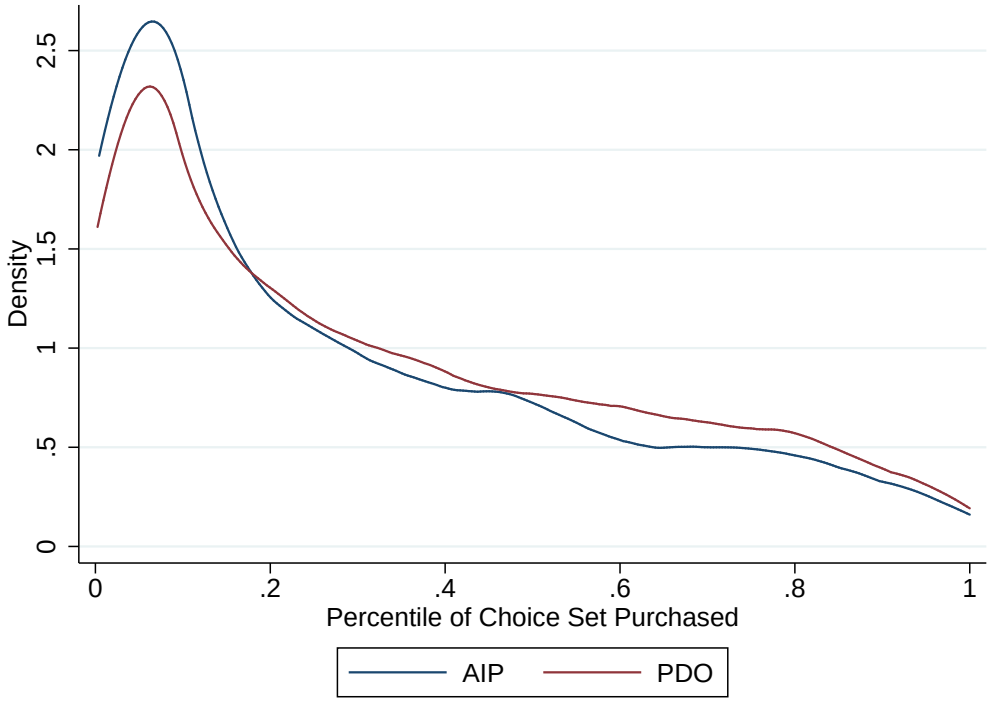
	AIP vs PDO % Difference
Purchase Probability	-0.13
	(0.07)
Percentile of Choice Set Selected	-0.12
	(0.06)

Notes: Standard errors clustered at the event level.

The results from the 2012 MLS experiment, displayed in table 10 , confirm our 2015 findings: fee salience reduces revenue substantially. Consumers are 13% less likely to buy tickets to an All-in-Pricing match (note that fees were approximately 10% in 2012). The difference has a p-value of 0.076, with standard errors clustered at the event-level.

We also examine whether users upgrade to more expensive tickets for PDO games. Unfortunately, tests based on purchase prices are underpowered because of the high sampling variance across matches. To control for the unobserved popularity of each match, we test whether users purchase from the same quantile of price in PDO versus AIP matches. For each transaction, we calculate where the purchase ranks in user's choice set (StubHub's entire inventory at the time of purchase for the match in question). On average,

Figure 2: Percentile of Choice Set Purchased in the 2012 Experiment



consumers buy from a 12% lower quantiles for AIP compared to PDO games. Figure 2 shows the full distribution of purchase quantiles for PDO and AIP matches.

While these results are heartening, we prefer the 2015 experiment for its larger sample size. Experimentation at the event-level suffers from a different kind of contamination bias. The chief concern is that consumers may substitute away from AIP matches (which appear more expensive) to PDO matches. The 2015 experimental design is not vulnerable to this type of contamination. The ability to execute two experimental designs is a crucial advantage of the StubHub setting.

7 Conclusion

In a randomized control trial on StubHub.com, we find that shrouding buyer fees substantially increases total revenue. The control group was shown fee-inclusive prices from the initial search page, while the treatment group was shown base prices until the checkout page. We decompose the impact of obfuscation into a quantity effect and a slightly smaller, but still meaningful, price effect. The latter suggests consumers upgrade to higher quality products when they observe lower prices. We find consumers who are shown fees upfront drop-off early in the purchase funnel, while those shown fees later exit later (only once the site displays total prices). The hazard rates are consistent with consumer myopia.

The effect of salience abates only slightly in a comparison of experienced users. Even users who choose to conduct a second search (after observing the total price for their initial selection) select more expensive goods when fees are less salient. This evidence suggests that obfuscation is not a one-off phenomenon, which becomes irrelevant as consumers learn about the sales environment. To the contrary, it indicates that site design can have a profound impact on consumer behavior.