ESSAYS ON CONSUMER BEHAVIOR AND DEMAND ANALYSIS

A Dissertation

by

XIAOYUAN WANG

Submitted to the Office of Graduate and Professional Studies of
Texas A&M University
in partial fulfillment of the requirements for the degree of

DOCTOR OF PHILOSOPHY

Chair of Committee,	Steven Wiggins
Co-Chair of Committee,	Alexander L. Brown
Committee Members,	Steven L. Puller
	Stephanie Houghton
	Venkatesh Shankar
Head of Department,	Tim Gronberg

August 2014

Major Subject: Economics

Copyright 2014 Xiaoyuan Wang

ABSTRACT

The thesis consists of two loosely related essays. Both are motivated by consumers' behavior regularities in different market environments. My goal is to show evidence of behavioral biases among decision makers and the consequences of those behavioral effects. Given each market's environment, I found evidence that consumers tend to deviate from what conventional theories dictate and the deviation may affect welfare analysis.

The first market is a non-durable experience good market. Using empirical scanner data, we show evidence that consumers' switching rates among brands are higher than what brand characteristics and consumer heterogeneity can explain. The over-switching behavior may be consistent with consumers' brand satiation. As a result, the consumers may benefit more from a market with more variety. We provide a structural model of the satiation behavior and use the model to demonstrate the model prediction as well as the welfare effect. The second market is a laboratory sequential search market where sellers are allowed to use exploding offers. We show evidence that buyers may be affected by non-monetary incentives, which result in a higher rejection rate for the exploding offers. After accounting for the above mentioned "exploding offer aversion", sellers' optimal strategies may be shifted. As a result, sellers tend to use lower price as well as non-exploding offers more often.

DEDICATION

To my parents, Weiqiang and Zhengping.

ACKNOWLEDGEMENTS

I am most grateful to the members of my committee: Dr. Steven Wiggins, Dr. Alexander L. Brown, Dr. Steven Puller, Dr. Stephanie Houghton and Dr. Venkatesh Shankar, who are willing to provide countless time and effort in advising me and who are willing to tolerate my imperfection and to forgive my mistakes and stubbornness. I benefit greatly from talking and working with them and the dissertation cannot be done without this dissertation committee.

I am also grateful to the experimental group of the department of economics. The faculty members(Dr. Alexander L. Brown, Dr. Catherine Eckel and Dr. John B. Van Huyck) and students in the experimental group offered me extremely valuable advice.

I would like to acknowledge and thank the Department of Economics and the Private Enterprise Research Center of Texas A&M University for supporting my research and providing me opportunities to present my work.

TABLE OF CONTENTS

LIST OF FIGURES

FIGURE Page

LIST OF TABLES

1. INTRODUCTION: THE BACKGROUND AND THE IMPORTANCE OF RESEARCH

1.1 Introduction

Modeling consumer behavior has received much attention recently since more individual data has been made available and since conventional behavioral assumptions cannot well explain individual behavior within markets. The bias caused by inaccurate behavioral assumptions may significantly affect demand analysis and thus further jeopardize welfare analysis.

As a result, much effort has been devoted to incorporating credible behavioral assumptions and improving demand analysis. Depending on specific market, those behavior assumptions includes not only conventional economic behavior assumptions, but also bounded rationality and irrational behaviors .

This dissertation provides evidence of two behavioral effects in different market settings. In Chapter 2, we show that consumers, especially in a non-durable experience good market, may be subjected to a brand satiation effect when consuming the same brand for a while. In order to credibly identify this effect, we utilize detailed individual level scanner data sets (for testing and controlling for heterogeneity in estimation) in a non-durable experience good market. We build a parsimonious non-linear mixed logit model with the assumption of satiation threshold and show that the model can be better interpreted compared with a linear state dependence bench mark model. A counter-factual experiment is conducted to show its welfare effects: less choices leads to extra welfare loss to consumers. In addition, from firms' perspective, we provide a prediction model to reduce firms' cost and improve the matching quality when using direct marketing strategies.

In Chapter 3, in a sequential search market, we show that consumers may care about sellers' intentions during bilateral bargaining and thus reject the "unfair" offer–a take-it-or-leave-it offer–more during the search. Since it is almost impossible to obtain (bargaining and strategy choice) data, in order to identify possible social preference of buyers, we build a laboratory search market where sellers are allowed to use either a normal offer or a take-or-leave-it offer–we compare human consumers with simulated consumers who only care about monetary payoff. Comparing with theoretical optimal play with the actual play, we calculate the rejection rate and the welfare loss. In addition, we use a modified logit quantal response equilibrium model to describe the new equilibrium strategy. The results may provide insights for policy makers to better evaluate the welfare change and may also help firms to make marketing decisions.

The two behavior effects are well founded in behavioral literature. The intertemporal satiation effect is related to the well established marginal utility diminishing assumption. However, few research has pointed out that this effect may encourage brand switching and standard discrete choice models don't allow intertemporal satiation. The tendency to reject unfair offers ("exploding offer aversion") is loosely related to a set of "ultimatum games" in behavioral economics. Ultimatum game is originally designed to demonstrate the possibilities of social preferences, especially the fairness concern. However, few research has considered a general market environment and incorporated this effect. We show that without considering those effects, demand estimation as well as welfare analysis may be biased.

1.2 The Demand Side of a Market: Why do We Care?

Demand analysis is important components for multiple fields. Modern empirical industrial organization is mostly concerned with market performance and welfare effects in markets with imperfect competition. For empirical industrial organization researchers, in order to achieve accurate second stage welfare analysis, it is important to have accurate estimation and/or prediction of the demand before and after a policy intervention. Although a common demand system (e.g. Berry, Levinsohn & Pakes (1995)) is able to capture flexible substitution patterns and consumer heterogeneity cross different consumers. However, it is arbitrage when we hope to consider past dependence or other inter-temporal effects. Our first study (Chapter 2) proposes a parsimonious demand model that has flexibility in interpreting both state dependence and satiation behavior using a threshold parameter.

Demand side itself may be of great interest for studies on consumers' preference and decision making. An extensive literature on demand estimation is motivated by laboratory evidence on reference points preference, limited depth of reasoning, social preference and other well established behavioral effects. Applying those behavioral assumptions, we can investigate how those behavioral effects perform in a more general and less controlled environment. Our second study (Chapter 3) offers a simulated sequential search market environment where sellers can choose different price and offer strategies (a normal offer or a take-it-or-leave-it offer).

From firms' perspective, our analysis may provide marketing researchers insights for firms' optimal marketing strategies. Having a deeper understanding of consumers' diversity needs and consumers' social preference may help firms improve response rates and avoid inefficient competitions.

1.3 Consumer Behavior and Demand Analysis: The Goal

We define consumer behavior broadly. Structural demand analysis usually starts with assumptions of consumer behavior. From a standard Economics point of view, most studies assume consumers are rational and their values are consistent with statistical expected values. By specifying sources of uncertainty and unobserved component (by researchers), we are likely to derive desirable function forms for estimation in the field. However, consumers may care more than monetary payoff. It is well documented, in Behavioral Economics literature, that consumers may be subjected to irrational motivations and bounded rationality. The broader welfare impacts of those behavioral effects, however, are not well studied. One difficulty of modeling new behavioral components is that the identification of those models are not guaranteed due to (other) unobserved factors including consumer heterogeneity. The goal of this dissertation is to demonstrate the evidence of two specific behavioral effects and the importance of considering them in demand estimation and further welfare analysis.

2. CONSUMERS' BRAND DIVERSITY SEEKING BEHAVIOR

2.1 Introduction

Consumers may be subjected to satiation effects: after a certain level of consumption, they may tend to switch to other brands or products. If this fact is significant, brand diversity will have a deeper impact on consumers' welfare, because consumers' choice will not converge to their favorite choice. This paper focuses on how repeated consumption or exposure will affect brand choice in a frequently purchased food market (yogurt). The switching behavior in this market is not likely to be driven only by variation of price or other product-specific characteristics, nor can it be well explained by traditional learning models. A portion of switching behavior may be due to consistent efforts to avoid further satiation. Is it true that consumers switch due to the "satiation effects" and search for diversity? We empirically investigate this question and use structural models to identify the satiation effects.

There are challenges to study brand satiation. First, satiation is an unobserved phenomenon. In a general market, consumers' experiences and consumption are also difficult to observe and record. Moreover, consumers may avoid satiation by changing the consumption occasion, consumption time, or consumption order. By switching within one brand, consumers also achieve consumption diversity. To identify significant brand satiation, this paper studies a frequently purchased experience food (Yogurt) market. Yogurt products are treated as a necessary and healthy nutrition source by many households. Over the past several decades, the categories of yogurt product have been expanding with more and more flavors and sub-brands. Although a yogurt product won't expire until two to three weeks after purchases,large numbers of yogurt products are sold in small packages of one, two or four. In the actual data set we use, a significant number of consumers have strong back and forth switching patterns among different brands. This research is motivated by those data patterns.

Another major challenge is the existence of multiple serially correlated unobserved effects in markets. The previous literature focuses more on whether consumers have inertia and (if so,) why consumers have inertia. For example, consumers are subjected to significant switching cost and time consuming learning process. Moreover, in behavioral economics literature and psychology literature, the power of habit formation has been acknowledged and emphasized. Habitual decision making, rather than conscious decision making, leads to consumers' "structural state dependence"–even when consumers are relatively experienced or aware of multiple choice alternatives. Few papers consider how the state dependence term enters into the utility function and why so. Little literature looks for other possible serially correlated unobservables as the individual data is "contaminated" by the inertia behavior.[1] With relatively rich reduced form evidence of diversity seeking, we introduce a model with a behavioral assumption on an individual's satiation point in hope of explaining why consumers switch (frequently) and to identify the satiation effect).

Finally, heterogeneity needs to be considered: different individuals (households) may have different preferences; moreover, a given individual's preference may change over time (e.g. due to satiation). After using random coefficient models to flexibly control for cross section heterogeneity, we isolate the within individual heterogeneity which is due to satiation.

[1]Large efforts have been spent on distinguishing real and fake inertia, based on Heckman (1981), without considering other sources of the unwanted serial correlation.

The topic is interesting and important for both economics and marketing studies:If a proportion of consumers cares about diversity, then they benefit from a market with sufficient variety. If consumers' switching behavior is due to a satiation effect[2], then consumers may demonstrate back-and-forth switching behavior. Consequently, adding diversity will bring additional welfare gains; they will not only come from the consumers who prefer the new choice, but also from the rest of the population who don't like it as much, but can use it to avoid further satiation. Firms have incentives to use multi-brand strategies with brand-level, image-based advertising to achieve greater producer surplus while making sure that consumers are not over-consuming beyond their satiation limit. Therefore, firms want to better target consumers. From a marketing perspective two implications are important: first, we conjecture that the effectiveness of advertising is related to satiation behavior; second, by collecting consumers' personal purchasing information, profit maximizing firms can better target consumers and advertise on new/ substitute brands to those with high probability of being satiated.

Previously (individual level) discrete choice models in consumer behavior studies explain consumers' switching behavior as the result of variation in observable characteristics or an idiosyncratic shock. A popular specification of these models, in addition, will allow some measures of brand loyalty or other switching cost based control (e.g. lag choices) to additively enter into the utility function. The implicit assumptions of this type of setting include: first, Lancaster (1966) the products or brands under study can be decomposed into pieces of (parallel) characteristics (and consumers are aware of them). Second, although consumers' types may vary within the population, an individual's parameters are stable, indicating

[2]The paper defines "satiation" in a broad way: it may be due to consumption satiation, brand image satiation, or excessive exposure to marketing campaigns.

that consumers' taste and willingness to pay are stable across time. Third, the state dependence term is arbitrary: for example, one can just use the choice in the last period. These assumptions are well founded and easy to implement. However, the assumptions can be restrictive in many applications. In the nondurable experience food market, consumers may be significantly affected by the diminishing marginal utility rule (across periods), leading to a need for diversity over different periods. We mainly explore the nonlinear effect of satiation on consumer purchasing behavior.

To the author's knowledge, starting from Erdem and Keane (1996), the literature incorporated a nonlinear product quality signal into utility with Bayesian learning rules (and a forward looking assumption). The structural model offers another explanation of consumers' choice persistence and switching; information and risk seeking can explain extra switching behavior by the fact that unknown information (larger posterior variance) may bring utility flow to consumers. The model can explain frequent switches as tryouts at the beginning of the shopping trips, especially for those inexperienced brands. However, as those more reduced form work, the structural models imply that, in the end, consumers tend to "converge" to their favorite alternatives when their perception error goes down. Moreover, this convergence might not be able to explain the switching pattern among already experienced products/brands. Similar papers involve Ackerberg (2003), Crawford and Shum (2005), Erdem et al. (2008).

In my data from yogurt market, consumers' purchasing sequences at the brand level are not converging[3]. Instead, continued switching back and forth suggests that other unobservables have significant impacts. Specifically, in the yogurt market, consumers make choice frequently and consumers have relatively small

[3]We provide evidence that consumers are brand choosing in data section.

search costs and a flat learning curve. We observe frequent brand switches and "switching-back" in this market.A fraction of the switching behaviors cannot be well explained by conventional reasons, such as a change in relative price, coupons or in-store advertisement. Meanwhile, these "extra" switching patterns are consistent with a satiation story –consumers switch away because of accumulation of distaste and they will switch back after the effect "washes out" or "recovers" (See Figures 2.1,2.2 for intuition; notice that persistent consumers also switch to outside goods.). However, since the consumers have heterogeneous taste and state persistence (over time), it is hard to recover the satiation pattern from aggregate data analysis. In other words, the satiation effect is likely to be a non-constant, non-random unobservable that varies across time and across individuals.

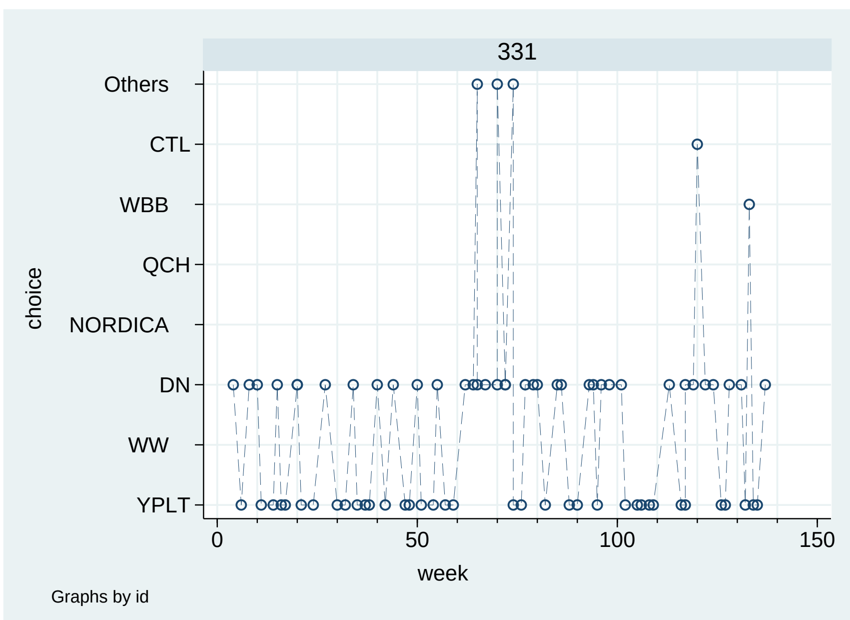


Figure 2.1: Switching Pattern for Consumer A

Another strand of research use forward looking behavior to explain consumers'

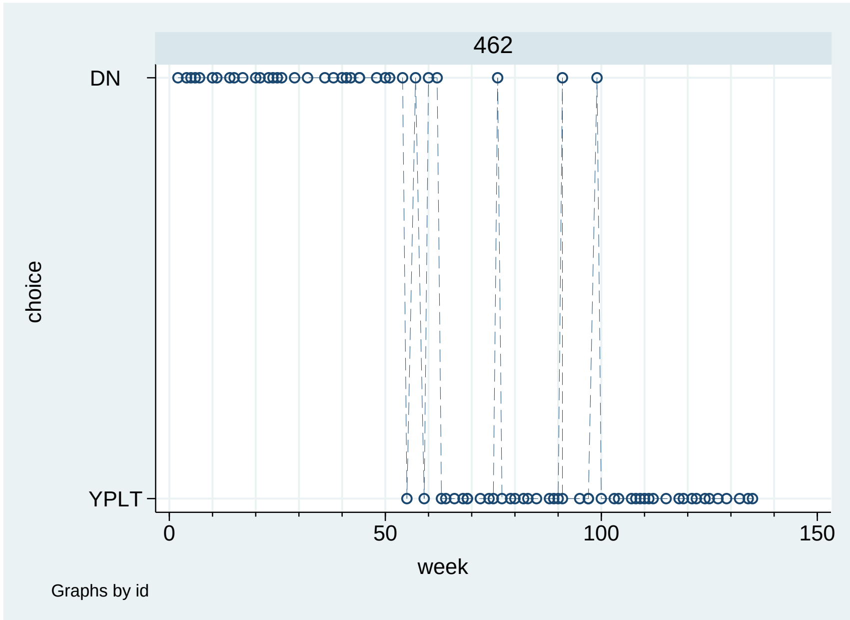


Figure 2.2: Switching Pattern for Consumer B

diversity-seeking behaviors. The underlying assumption is that consumers switch or stop purchasing since the decision to stay with the choice leads to a future disutility. Hartmann (2006) estimates a model with longer lags of previous choices additively entering into utility function, and calculate the consumers' recovery time. Ribeiro (2010) extends it to a differentiated market with frequently chosen products. In contrast, my paper only makes an assumption about a specific satiation rule and we avoid making directly assumptions on outside goods which may be hard to verify. In the yogurt data set we use, the shortening strings of consecutive brand choice may support a satiation story. (Table 2.1 lists selected utility specifications for comparison.)

Consumers' preferences in the market are likely to be heterogeneous. There is an extensive literature dealing with both cross individual heterogeneity and positive state dependence effects. Keane (1997) allows not only random coeffi-

Table 2.1: Comparison of Utility Specifications

Utility Specification	Rationale	Paper
$U_{ijt} = C_{ij} + \alpha_i P_{jt} + \gamma_{1i}\mathcal{I}(y_{ijt-1} = 1) + [\gamma_{2i}\mathcal{I}(y_{ijt-1} = y_{ijt-2} = 1) + ... + \gamma_{t'i}\mathcal{I}(y_{ijt-1} = y_{ijt-2} = ... = y_{ijt-t'} = 1)] + \epsilon_{ijt}$	With flexible controls for "heterogeneity", a positive γ indicates a "structural" state dependence.	DHR(2010)
$U_{ijt} = C_{ij} + \alpha_i P_{jt} + \gamma_i(\sum_{\tau}^{t-1} y_{ij\tau}) + \epsilon_{ijt}$	Using the summation of previous choices to represent state dependence effects	DHR(2010)
$U_{ijt} = C_{ij} + \alpha_i P_{jt} + \gamma_i \frac{1}{\sum_{\tau}^{t-1} y_{ij\tau}+1} + \epsilon_{ijt}$	Allowing a nonlinear curve of previous choices: consumers gradually learn the true brand experience value	EK(1996)
$U_{i0t} = f(y_i^{t-1}, \epsilon_{i0t})$ $U_{ijt} = C_{ij} + \alpha_i P_{jt} + \gamma_{1i}\mathcal{I}(y_{ijt-1} = 1) + \epsilon_{ijt}$	Waiting generates more utility after continue purchasing of the same brand (for long time).	R(2011)
$U_{ijt} = C_{ij} + f(y_{ij}^{t-1}, \gamma) \cdot S_{ijt-1} + \alpha_i P_{jt} + \epsilon_{ijt}$, where S is a satiation function which may take value smaller than 1 if "cumulative consumption" is large	When a consumer's "cumulative consumption" for brand j reaches a threshold, she cannot derive the original utility.	This paper

[1] y_i^t represents history of choices for all brands at each period.
[2] y_{ijt} is 1 if household i chooses brand j at period t.
[3] Cumulative consumption is defined in Section 2.3

cients over observed attributes and state dependence effects, but a flexible error term which depends on unobserved attributes as well. Estimation results (using the method of simulated moments) support a true state dependence. Hierarchical Bayesian approaches have also been widely used to control for heterogeneity. Seetharaman et al. (1999) use a Hierarchical Bayesian approach to study state dependence effects. They allow the coefficients to be normally distributed and vary with household-specific characteristics and category-dependent variables. Moreover, they also define the wear-out effect which depends on the time the household has stayed in a certain brand-category since the last purchase. Sufficient controls show state dependence effects remain positive within the range of observed periods. Dub et al. (2010) uses a finite mixture of normal distributions to capture the cross sectional (non-normal) heterogeneity and obtain similar state dependence results. Compared with the categories they use, yogurt may be more frequently purchased and the high switching frequency suggests within individual heterogeneity as well. We use a random coefficient model to account for cross sectional heterogeneity while structurally modeling a satiation effect.

This paper uses two sets of data. The first data sets are Nielsen data sets from 1986 to 1988. Using the similar data sets, Ackerberg (2001) considers different advertising effects on one newly introduced product "Yoplait150". We process the data at the brand level in order to explore how consumers will switch among them. In my work, it is also important to provide a relatively precise brand price index. The data set is not perfect: Ackerberg mentioned the missing price problem and manufacturer coupon users. There are also other data problems related to my study: First, each purchasing history is recorded at household level, we assume household preference is consistent within all members of the household or they do not shuffle to make purchasing decisions.[4] Second, the data set does not have direct information about availability of the products; we provide evidence to rule out product availability issue. Moreover, consumption is not observed directly. The second data sets are IRI data sets from 2001 to 2003. The extra benefit from the data is that we can control for more product features including store displays and advertisement. Yet, with expanding products within each brand, the satiation effects are likely to be weakened. We compare our results in both data sets. Although we worry less about stockpiling behavior in the yogurt market (due to storage cost and expiration date), without knowing the exact date of consumption it is hard to directly conclude that the satiation effect is due to the consumption. Therefore the work focuses on the switching/satiation effects without arguing the channel behind. Possible explanations include consumption satiation, image value satiation, characteristics satiation, etc. We assume households consume yogurt with relatively smooth speed. The structural model is estimated using Maximum Simulated Likelihood (MSL) methods.

[4]We calculate the switching pattern of single member households and half of them involve switches that may not be explained by price, promotion and advertising.

We applied MSL methods on a set of linear and nonlinear mixed logit models. Mixed logit models have been very popular in the literature, mainly due to their flexibility as well as tractability (with explicit closed form solution). Consider Brownstone and Train (1998), Calfee et al. (2001), McFadden and Train (2000) for applications of mixed logit models. Both MSL and Hierarchical Bayesian (HB) methods have been found to be suitable for random coefficient models (Rossi et al. (2005), Train (2009)). Similar HB treatment can be found in Athey and Imbens (2007). MSL methods are more flexible and easier to implement when dealing with dynamics and nonlinear utility functions; therefore we use it to estimate the structural model. The gap between the two approaches is shrinking (Revelt and Train (2000)), for example, both approaches can be used to estimate reliable individual-level parameters. The choice of two approaches is mostly based on implementation convenience.

The results of the satiation model shows that all specification reports finite satiation thresholds. In one specification in the ERIM data sets, the satiation threshold is significantly smaller than 7 consecutive purchases. After controlling for advertisement and displays, IRI data sets show that the mean satiation threshold is significantly smaller than 4 consecutive purchases. Based on 100 re-samples of markets of 127 households using the satiation model and real data, the simulated market frequency in most markets is closer to that in the real data, compare with a linear model. The satiation point is robust to changes in function form. We offer a counter-factual experiment using IRI data set that consumers are subjected to extra welfare loss after removing 2 brands from the market. Using the IRI data sets, we include an example of targeting individual consumers. We show that conditional on an individual household's previous purchasing history, she prefers private brands and has a shorter satiation threshold.

The paper is structured as follows. Section 2 introduces the dataset. Section 3 focuses on the structural model and identification. Section 4 provides estimation results and discussion. Section 5 summarizes and concludes.

2.2 Data

Two sets of data have been used for descriptive evidence. Both data sets consists of household-level panel data of supermarket purchasing records in yogurt section. The first data sets (ERIM data sets)[5] were collected by A.C. Nielsen during 1986 to 1988 in a mid-sized city, Sioux Falls, South Dakota; the second data sets (IRI data sets,Bronnenberg et al. (2008)) were collected by Information Resources, Inc during 2001 to 2003 in in Eau Claire, Wisconsin and Pittsfield, Massachusetts. In this section, we will use households who have more than 20 shopping trips (within the three year period) to show their switching behavior. 467 households in the ERIM data sets and 3081 households in the IRI data sets meet this criterion. In order to structurally model and estimate consumers' (weekly) choice decision, 127 households in ERIM (Year 1987) and 181 households in IRI (Year 2003) have been randomly selected (from the consumers with high purchasing frequency) and used in further analysis.

We assume households make brand choice decisions at each shopping trip. The yogurt markets in the ERIM data sets contain 21 brands in total[6] and over 400 sub-brand products. Seven major brands[7] in Sioux Falls had taken 97% of the market share. These major brands come with relatively rich price information, while we define a composite good which consists of all the rest yogurt products.

[5]http://research.chicagobooth.edu/marketing/databases/erim/index.aspx
[6]2 other brands have very few entries and thus are omitted.
[7]YPLT (YOPLAIT), WW (WEIGHT WATCHER), DN (DANNON), NORDICA, QCH, WBB, CTL

The IRI data sets contain 89 different brands and much more sub-brand products. We define the market at firm level: 10 major brands [8] and private brands take 96.5% of the total market share, where private brands include all store owned brands.

The data sets support our assumption: consumers in both data set are likely to be brand choosing. By looking at consumers' choices at each shopping trip in the ERIM data sets, we see that out of 20,881 choice situations, only 1,620 (7.8%) involve multiple brands in one shopping trip. The more recent IRI data sets report higher (14.2%) mixed choices; yet only 1.6% shopping occasions involve more than 2 different brands. On individual household level, more than half of them (63.2% for the ERIM data sets and 72.9% for the IRI data sets) have fewer than 2 multiple brands choice within about 3 years and about 93% of the households (in both data sets) have fewer than 10 choice occasions with multiple brands selected. Thus consumers not only care about the flavor and ingredient of a yogurt product, but also it appears that they appreciate the brand experience (texture, special feature, package, etc.)from each brand and/or they may have different feelings about the brands due to the company's advertising, public relation and news (brand image). Consumers are assumed to be aware of all major choice alternatives at each shopping trip if they are available. For multiple brands in a shopping trip, we will use the most heavily chosen brand.

The brand price index used in calculation is the store level weekly average price per six ounces of all major sub-products under that brand given a fixed time. We achieve the price index information using different methods for different data sets. For the ERIM data sets, real transaction data has to be used to calculate price

[8]COLOMBO, BREYERS, DANNON, KEMPS, OLD HOME, STONYFIELD FARM, WELLS DAIRY, YOFARM and YOPLAIT.

Table 2.2: Summary Statistics 1: Sioux Falls

No.	Brand	Price[1]	Std. Dev.	Min	Max	Scoupon[2]	Mcoupon[3]
1	YPLT	0.57	0.09	0.25	0.69	48	802
2	WW	0.45	0.038	0.29	0.52	1	168
3	DN	0.44	0.071	0.19	0.66	2	278
4	NORDICA	0.38	0.068	0.23	0.5	392	15
5	QCH	0.27	0.043	0.15	0.37	0	0
6	WBB	0.28	0.051	0.14	0.37	0	10
7	CTL	0.26	0.028	0.12	0.5	1	24
8	Others	-	-	-	-	0	8

[1] Price is average transaction price per 6 ounce of yogurt.

[2,3] Scoupon is store coupon and Mcoupon is the recorded manufacturer coupon.

Table 2.3: Summary Statistics 1: Eau Claire & Pittsfield

Brand	Price[1]	Std. Dev.	Min	Max	Display[2]	Advertisement[3]
COLOMBO	0.57	0.103	0.25	0.82	0.36	1.43
BREYERS	0.54	0.105	0.20	0.85	0.22	1.08
DANNON	0.72	0.096	0.29	1.75	0.58	2.40
KEMPS	0.33	0.110	0.09	1.46	0.23	0.48
OLD HOME	0.56	0.059	0.34	1.03	0.71	0.46
STONYFIELD FARM	0.77	0.135	0.30	1.68	0.11	0.95
WELLS DAIRY	0.66	0.132	0.30	1.12	0.33	0.52
YOFARM	0.73	0.136	0.23	1.68	0.63	1.74
YOPLAIT	0.77	0.108	0.28	1.28	0.52	1.88
PRIVATE	0.42	0.080	0.18	1.42	0.42	2.22

[1] Price is average transaction price per 6 ounce of yogurt.

[2] Display: the average of the total displays (minor or major) each week

[3] Advertisement: the average of the total advertisements (including coupons and large ads) each week

indices of other alternatives that a household did not choose. When there is no price information, we approximate the price index using the product in the closest store and the closest week [9]. Store coupons are factored into the price. Table 2.2 provides summary statistics for the brand price index with coupon information. From the table, "Global Brands" including YOPLAIT, WEIGHT WATCHER and DANNON are with relatively higher price and larger standard deviation. We also notice that about 14% of YPLT shopping trips, 10% WW, and 8% DN involved manufacturer coupons and 7% NORDICA purchases involved store coupons. We don't have information on the coupon usage for alternatives. Meanwhile, for the IRI data sets, we have detailed store level data which gives us more accurate information on prices and other marketing strategies. In addition, the IRI data also contains information on private brands–the brands owned by stores. However, most brand contains more sub products, resulting in larger noise in brand price index (Table 2.3). Therefore, both data sets are not perfect. By combining evidence from both data sets, we hope to provide a more comprehensive view of the diversity seeking behavior.

Table 2.4 and 2.5 offer a summary of the switching behavior in both data sets. For example, from the Sioux Falls data set, 8,785 out of 20,881 total shopping trips involve a purchase that is different from the following brand choice. Yoplait and Weight Watcher's products have the lowest switching rate-indicating loyalty-while local brands witness higher switching rates. To further investigate the source of these switches, we consider changes in relative prices and marketing strategies. We define relative price as the price of a certain brand choice at each period with respect to the rest brands at the same period. If the choice at period t is different from the choice at $t+1$, but the relative price of choice at period t is not increasing

[9]Missing price problem has been also discussed in Ackerberg (2001)

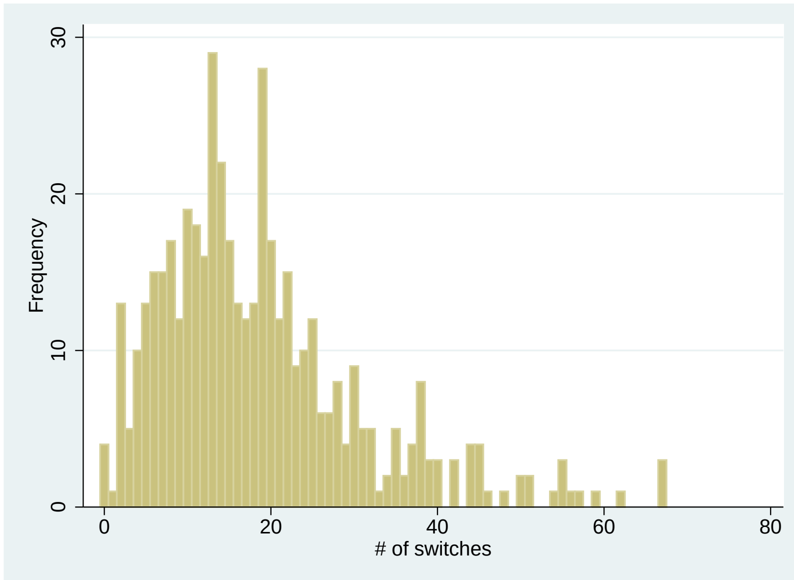


Figure 2.3: Switching Frequency: Sioux Falls

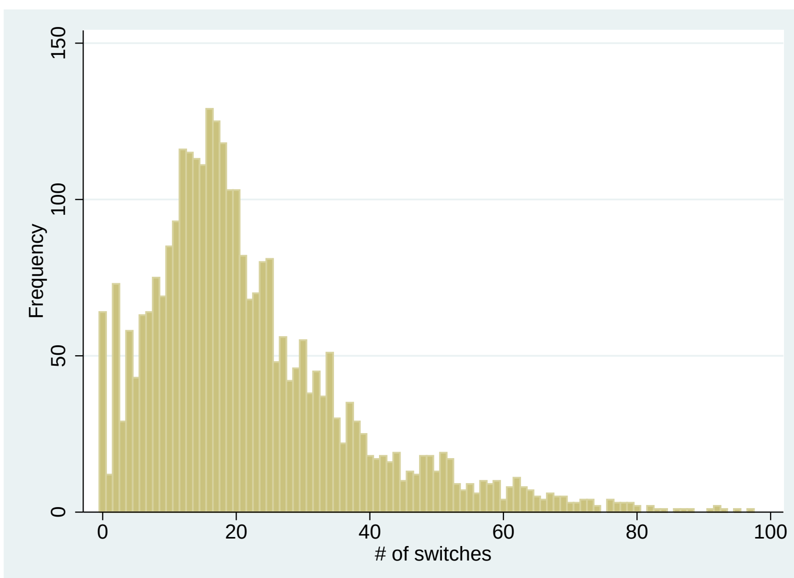


Figure 2.4: Switching Frequency: Eau Claire & Pittsfield

and the relative price of choice at period $t + 1$ is not decreasing, then the switch cannot be explained by price. Similarly, if a brand switch between period t and period $t + 1$ is not due to a coupon for the target brand at period t or a coupon for the original brand at period t, then the switch cannot be explained by coupons. The sample suggests that even accounting for relative price changes and marketing strategy changes, about 10% of the switches remain unexplained. Although we observe several extremely persistent consumers, the switching behavior is not rare across most individuals. For each individual, the average number of shopping trips is approximately 45 and average number of switches (Figure 2.3) is 19 (standard error: 0.61). Given that other product characteristics are relatively stable; this evidence is in favor of a taste variation explanation. Moreover, the global brands Yoplait, Weight Watcher and Dannon have larger market shares and lower switching rate, which supports a brand loyalty explanation. However, those brands seem to have a higher percentage of unexplained switches. To further rule out the brand switches due to the periodic product availability, we also search for unexplained switches only among products that are recorded in the dataset during all the weeks. The results in Table 2.4 show that there are still significant number of unexplained switches. In the IRI data sets, we have a better measure of advertisement and display: after conditioning on the two measure, Table 2.5 shows that, on average, 8.49% of the switches cannot be explained by observed characteristics. This measure is relatively conservative since it is completely possible that the switches due to satiation coincide with an advertisement or a promotion period or the products chosen are not subjected to the change of advertisement or display. Figure 2.4 shows the individual level switching rate.

The unexplained switches may be attributed to unobserved characteristic, which is hard to identify even holding all observed characteristics constant. Exam-

Table 2.4: Summary Statistics 2: Sioux Falls

Brand	Choice[1]	Brand Switches[2]		Unexplained[3]		Availability[4]	
YPLT	5710	1821	31.89%	214	11.75%	170	9.34%
WW	1565	460	29.39%	73	15.87%	56	12.17%
DN	3505	1442	41.14%	161	11.17%	120	8.32%
NORDICA	3888	1603	41.23%	102	6.36%	79	4.93%
QCH	1220	655	53.69%	21	3.21%	7	1.07%
WBB	1517	968	63.81%	76	7.85%	4	-
CTL	2546	1201	47.17%	75	6.24%	51	4.25%
Others	930	635	68.28%	49	7.72%	21	3.31%
(Total)	20881	8785	42.07%	771	8.78%	508	5.78%

[1] ”Choice” describes the market share of the brands

[2] A ”Brand Switch” is defined as the number of times consumers switch away from the certain brand

[3] An ”unexplained” switch means both brands are available in store for both periods and the switch is not due to the following reasons: a, discount of the target brand; b, price increasing of the original brand;c, relative price increase. Coupon or advertising conditions are exactly the same.

[4] The availability adjustment is for sub-categories (with only last 3 digits different in UPC code) that exist in all weeks.

Table 2.5: Summary Statistics 2: Eau Claire & Pittsfield

	Choice[1]	Brand Switches[2]		Unexplained[3,4]	
COLOMBO	13299	7288	54.80%	533	7.31%
BREYERS	5802	3702	63.81%	337	9.10%
DANNON	32912	14713	44.70%	1228	8.35%
KEMPS	6904	3593	52.04%	291	8.10%
OLD HOME	5538	2781	50.22%	281	10.10%
STONYFIELD FARM	5832	2751	47.17%	239	8.69%
WELLS DAIRY	3474	1404	40.41%	197	14.03%
YOFARM	3503	2100	59.95%	269	12.81%
YOPLAIT	42222	14378	34.05%	1167	8.12%
PRIVATE	10283	5312	51.66%	385	7.25%
(Total)	129769	58022	44.71%	4927	8.49%

[1] “Choice” describes the total purchase occasions with the brand

[2] A “Brand Switch” is defined as the number of times consumer switch away from a certain brand

[3] An “unexplained” switch means both brands are available in store for both periods and the switch is not due to the following reasons: a, discount of the target brand; b, price increasing of the original brand;c, relative price increase. Coupon or advertising conditions are exactly the same.

[4] 1098 out of 3081 households have at least one unexplained switch.

ples include brand learning, brand satiation or indifference. We provide evidence that part of the purchasing patterns may favor a brand satiation explanation. First, we show that a significant number of consumers tend to consistently switching around two or three products (frequent switches followed by quick switch-back). For example, according to Table 2.6 in Sioux Falls, there are in total 2524 immediate switch-backs after one period. More complicated switch back-and-forth patterns are common to the dataset–especially when considering the fact that the total number of switches is only 8785. With the results in Table 2.4, it shows that around 29% of the total switches involve immediate switching back to the original brand the consumer purchased previously. Generally, random behavior or ignorance won't cause this strong back and forth pattern. For example, without state dependence, a consumer may be indifferent with two brands: A and B (she never chooses other brands). With equal probability she will make random draws from the two. The probability of immediate switch back ("A-B-A" or "B-A-B") is 25%; with more choice alternatives or state dependence effects, there may be fewer immediate switch-backs. This type of switching pattern persists in the sample: brand learning won't explain all the data pattern, since they imply convergence to the favorite choice. For example, still using the Sioux Falls data set, in 1986 the total switching back-and-forth patterns within three shopping trips is 817 times and in 1987, the number (for the same set of households) becomes 948. For the IRI data sets we use, we also observe switch back behavior for each brand (Table 2.7): the switch back rate is about 27.5% which is also higher than the probability of flipping an even coin.

Second, we investigate the patterns in purchasing length for individual households. We count the number of consecutive shopping trips with the same brand involved and find that length of consumers' purchasing string is diminishing given

Table 2.6: Switch-Back Pattern: Sioux Falls

Brand	$A?A$	$A??A$	$A*A*A$	$A?A?A?A$
YPLT	583	250	202	24
WW	144	65	45	1
DN	412	201	143	7
NORDICA	579	257	218	18
QCH	132	73	36	2
WBB	207	111	70	4
CTL	356	196	128	4
Others	111	83	54	1
(total)	2524	1236	896	61

[1] "?" represents any brand not equal to A
[2] "$*$" indicates any combination of other brands with length less than 2. e.g. *ABABBA* or *ABABA*
[3] $A?A$ is a row(or string) of choice starting with A, diverge to other brand for one period, and return to A again

Table 2.7: Switch-Back Pattern: Eau Claire & Pittsfield

	COLOMBO	BREYERS	DANNON	KEMPS	OLD HOME	
Switches	7288	3702	14713	3593	2781	
$A?A$	1729	533	4390	930	607	
$A*A*A$	770	182	1753	377	228	
	STYFD FM	WELLS DAIRY	YOFARM	YOPLAIT	PRIVATE	(Total)
Switches	2751	1404	2100	14378	5312	58022
$A?A$	607	373	380	5172	1318	16039
$A*A*A$	222	129	123	1894	484	6162

[1] "?" represents any brand not equal to A
[2] "$*$" indicates any combination of other brands with length less than 2. e.g. ABABBA or ABABA
[3] $A?A$ is a row(or string) of choice starting with A, diverge to other brand for one period, and return to A again

an initial long length. Table 2.8 and Table 2.9 illustrate the point using ERIM data sets. Without considering the heterogeneity, Table 2.8 indicates that: 1. Given a relatively long initial length, the second length of the string is diminishing; 2.The longer the initial length is, the stronger the diminishing effect at the first switch-back. These facts suggest that at least a portion of consumers are not randomly switching among different brands. The high average initial lengths in columns one, four and seven are evidence for consumers' inertia and the quick diminishing of the purchasing length may further suggest diversity-seeking attempts. We further provide Table 2.9 to show the links between gaps. Table 2.9 indicates an increasing length of waiting trips before consumers' switching back to their original brand. Learning models may not be able to generate similar patterns (at the later periods).

When considering heterogeneity, one may not be able to draw quick and clear conclusion. A state-dependence model with heterogeneity may generate a shortening strings as illustrated above. For example, the data pattern may be generated by eight types of consumers with each type preferring one yogurt brand. However, a further diminishing in length of second choice strings and third choice strings in Table 2.8 may be generated by satiation behavior. Moreover, with only a positive state-dependence coefficient, the data evidence from Table 2.8 and Table 2.9 are very difficult to compromise with Table 2.6 which shows that there are a large number of frequently switching back-and-forth actions for each brand. Intuitively, for each individual consumer, if one observes both positive state dependence and immediate switch-backs, the possible explanation involves a brand satiation process.

Table 2.10 provides similar tables in Eau Claire & Pittsfield. On average, the initial length is even longer compared with ERIM data sets. The fact indicates a stronger state dependence effect. However, returning consumers tend to purchase much less of the same yogurt, suggesting a counter effect may exist to offset the state dependence behavior. The expanding gaps also suggests that households are less likely to switch back after relatively large amount of consumption of the same brand.

Table 2.8: Average Length of Row(string): Sioux Falls

	first string length>=2			first string length>=3			first string length>=4		
	string1[1]	string2	string3	string1	string2	string3	string1	string2	string3
YPLT	4.43	1.89	2.02	6.63	2.70	3.21	8.21	3.93	4.79
WW	6.25	2.43	2.13	8.02	2.83	2.33	11.00	3.72	2.32
DN	4.42	2.26	2.14	6.57	3.01	2.14	9.24	3.64	2.49
NORDICA	3.37	1.33	1.29	4.99	2.05	1.89	6.47	1.80	2.02
QCH	3.63	1.95	1.33	5.28	2.56	1.52	6.00	2.79	1.32
WBB	2.86	1.14	0.98	4.78	1.56	1.56	5.90	2.20	1.90
CTL	3.71	1.57	1.48	5.13	2.01	2.26	6.70	1.98	2.95
Others	3.20	0.89	0.60	4.00	0.80	0.80	5.10	1.10	0.70

[1] A "string" indicate a set of consecutive shopping trips with the same brand for each individual.
[2] The reason to condition on a long length of initial string, is to create an "initial condition", where presumably consumers have a large interest in the brand (or consumers simply have a larger loyalty value on the brand.)

In sum, there are a significant number of switches and switch-backs that cannot be explained by observed characteristics. The purchasing pattern suggests that, in addition to the state dependence effect, consumers may also be subjected to a negative effect after consecutive within-brand consumption. Admittedly, Some households in the data are consistent in brand choice. For those consistent household, although they switch less within yogurt market, some also stop/ switch to outside good constantly. In the next section, we propose a model with heterogeneous types and heterogeneous switching threshold such that the consistent type consumers can also be captured.

Table 2.9: Average Length of the Gap: Sioux Falls

	Average Length		Gap expanding?		
	gap1[1,2]	gap2	gap1<gap2	gap1≤gap2	N
Brand 1	1.28	2.75	30	65	71
Brand 2	1.39	3.28	11	26	28
Brand 3	1.42	2.26	17	51	65
Brand 4	1.48	2.60	24	41	50
Brand 5	1.38	4.10	7	19	21
Brand 6	1.23	4.62	7	12	13
Brand 7	1.57	2.61	20	39	46
Brand 8	1.14	6.71	3	7	7

[1] Gap1 represents the number of trips with other brands between string1 and string2; gap2 is between string2 and string3. The table is calculated under the condition that initial length is equal to 3, and it shows that 80% to 90% percent of time, the gap1 is less or equal than the gap2.

[2] We have restricted *gap* <= 5 weeks. Without this restriction the effects still exist, yet are weakened.

Table 2.10: Average Length of Row(String): Eau Claire & Pittsfield

	first string length>=3					
	String1[1]	String2	String3	Gap1[2]	Gap2	N[3]
COLOMBO	7.06	2.98	2.94	2.30	3.07	230
BREYERS	6.82	2.25	2.69	3.28	4.42	67
DANNON	6.92	2.84	2.79	2.59	2.73	717
KEMPS	7.21	3.31	2.61	2.42	3.13	149
OLD HOME	7.24	2.84	2.58	2.31	2.77	100
STONYFIELD FARM	7.92	3.54	3.41	2.61	2.96	113
WELLS DAIRY	6.00	3.47	2.84	2.18	2.89	57
YOFARM	6.51	2.49	2.37	2.51	3.93	57
YOPLAIT	7.42	3.44	3.04	2.08	2.77	1049
PRIVATE	7.60	3.58	3.15	2.09	2.60	196

[1] A "string" indicate a set of consecutive shopping trips with the same brand for each individual.

[2] A "gap" indicate a set of consecutive shopping trips of other brands between 2 strings.

[3] N represents number of observations.

2.3 Structural Models of Consumers' Satiation Effects

According to the descriptive evidence above, we argue that in this market consumers care about diversity, and thus by forming a structural model of consumer behavior that incorporates this feature, one may be able to revise pricing/advertising policy, predict future switching/market share and conduct welfare evaluation.

We model the consumers' distaste effect using a satiation threshold. The consumers are assumed to make a purchasing decision every week; they choose from available inside goods (major brands and one combination of others in the yogurt market) and one outside choice. A switch is defined by either a switch to other yogurt brands or the outside choice. In the data section, the time dimension variable is shopping trip(s); to facilitate accumulation of previous shopping trips, we use weeks instead. This data structure has been used by Erdem and Keane (1996). In addition, we also need to assume consumers don't store yogurt and consume within each week. This assumption is likely to be true since yogurt products have a relatively short life and a high storage cost. Households also tend to purchase yogurt products in small packages.

An individual consumer i's, during week t, has the following utility specification for choice j:

$$U_{ijt} = C_{ij} + \alpha_i(w_i - P_{jt}) + \delta_{ijt} + \epsilon_{ijt}, \tag{2.1}$$

where w_i denotes a consumer's income; C_{ij} is a brand dummy for household i and brand j. P_{jt} is choice j's price and δ_{ijt} represents the experience quality received by consumer i at week t. In previous literature, state dependence models use the following δ_{ijt}:

$$\delta_{ijt} = \gamma_i f(y_{ij}^{t-1})$$

where γ_i is the individual-specific state dependence parameter. $f(\cdot)$ is a function of past choices or states; y_{ijt} is a dummy variable indicating purchases of brand j at period t (y_{ij}^t represents the vector $\{y_{ij1}, y_{ij2}, ..., y_{ijt}\}$). For example, $f(\cdot)$ can be an index function with unit value if y_{ijt-1} is equal to one, or a sum of previous consecutive choices of the same brand ($\sum_{\tau}^{t-1} \mathcal{I}(y_{ij\tau} = y_{ij\tau+1} = ... = y_{ijt-1} = 1)$). The former specification suggests that if the choice j is chosen last period, a consumer's utility will be shifted by a constant γ_i. The case of $\gamma_i > 0$ may be viewed as "structural state dependence"; however, the case $\gamma_i < 0$ may not be well interpreted. The later specification implies that consecutive purchases generate linearly cumulative state dependence effects. The more a consumer purchases a certain brand, the more she is likely to stay in her choice. Learning models assume nonlinear impacts on a utility function. For example, if one assumes the true experience value of each brand follows a normal distribution, the $f(\cdot)$ function may have the following form: $f(\cdot) = \frac{1}{\sum_{\tau}^{t-1} y_{ij\tau}+1}$. When $\gamma_i < 0$, it can be seen that frequent consumption leads to convergence to the true brand value.

The estimation of the first two models confirms a positive state dependence effect in the market. However, the models offer little intuition about the negative draws of the state dependence coefficient γ_i, nor can they offer explanations for non-random switching behavior. The nonlinear model allows a decreasing state dependence effect for consecutive shopping periods. Yet the model contains a convergence state for each brand where brand preference is stable. We consider a model to incorporate satiation by assuming consumers have an upper bound "tolerance" of the brand. If consumers' cumulative consumption B_{ijt} on brand approaches or "hits" the critical value $\bar{B}_i$, she may no longer be able to derive the original experience value from the brand. The closer the level B_{ijt} to the upper bound $\bar{B}$, the higher the probability that consumers will trigger the switch.

To keep the analysis simple, cumulative consumption of brand j is defined as a summation of previous consecutive shopping trips,

$$B_{ijt} = \sum_{\tau}^{t-1} \mathcal{I}(y_{ij\tau} = y_{ij\tau+1} = ... = y_{ijt-1} = 1)$$

This specification implies that as long as a consumer stops shopping for one period, the satiation effect will go away. Other possible specifications for B_{ijt} may incorporate time discounting and purchase quantity. Those specifications usually require more parameters and creates more nonlinearity. This is especially true for a discount rate parameter: a higher discount rate and a higher satiation point may have similar effects so that the identification become less clear. Therefore we focus on a simple cumulation rule while discussions and an estimation of alternative models will be provided later.[10]

Adding a satiation component, the δ function is defined below:

$$\begin{aligned}
\delta_{ijt} &= \gamma f(y_{ij}^{t-1}) \cdot s(y_{ij}^{t-1}) \\
f(y_{ij}^{t-1}) &= \sum_{\tau}^{t-1} \mathcal{I}(y_{ij\tau} = y_{ij\tau+1} = ... = y_{ijt-1} = 1) \\
s(y_{ij}^{t-1}) &= \begin{cases} 1 & \text{if } B_{ijt} \leq \bar{B}_i + \eta_{ijt} \\ 0 & \text{if } B_{ijt} > \bar{B}_i + \eta_{ijt} \end{cases} \\
\gamma &> 0
\end{aligned}$$

[10] A previous version of the paper consider the following accumulation rule:

(1) $B_{ijt} = \lambda B_{ijt-1} + y_{ijt-1}$
(2) $B_{ijt} = B_{ijt-1} + y_{ijt-1} + \eta_{ijt-1}$ ...$\eta_{ijt} \sim \mathrm{N}(0,\sigma_\eta)$
(3) $B_{ijt} = \lambda B_{ijt-1} + Q_{ijt-1}$ ...Q represents quantity

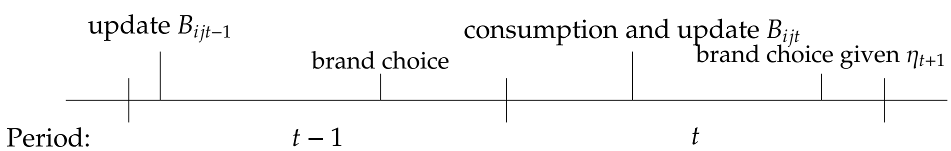
$$E(\delta_{ijt}) = \gamma f(y_{ij}^{t-1}) \cdot \Phi((\bar{B} - B_{ijt})/\sigma_\eta) \tag{2.2}$$

Again $f(\cdot)$ captures state dependence, while the satiation function $s(\cdot)$ takes value zero or one depending on a consumer's consumption level. First of all, γ is interpreted as a positive state dependence parameter and it captures the habitual reinforcement from each consecutive purchase in the past. γ is a positive value; alternatively, γ can be drawn from a positive distribution to allow heterogeneity. Second, a smooth probability function is used to generate satiation effects. If the cumulative consumption is smaller, the state dependence effects are stronger; in contrast, if it surpasses the "satiation point", the state dependence effects may be small. Third, the positive satiation point $\bar{B}_i$ is assumed to vary for each individual. We assume it follows a log-normal distribution.

As a result, a consumer has to face the following trade-off at each shopping trip: she may choose to stick to the original choice, however she will have the risk that the experience quality value reaches her satiation point; alternatively, she may choose to switch to her secondary choice–in that case she may be less satisfied if she would have received larger experience value from the original choice. Her decisions are likely to depend on her satiation point. If she is with a low satiation point (less than one), then she cannot derive original utility from a brand after one purchase. In previous literature, this type of consumers may be captured by a negative state dependence coefficient.

The model allows extra uncertainty (for both consumers and researchers), since consumer i is not sure about η_{ijt} at period t. This assumption is plausible because purchase occasions usually are different from consumption occasions. When making purchase choices, a consumer has to plan ahead. The assumption is also not the same as those in forward-looking models; purchases and actions can be viewed as two sub-phases within a period. We list the implicit timing rule in Figure 2.5. At period $t-1$, individual i will update her consumption level B_{ijt-1} from consumption and then decide which brand to choose and how much she would like to consume next. At period t, she will consume the products and receive B_{ijt} according to the cumulation rule, where the η_{ijt} is realized. Based on new B_{ijt}, the consumer will decide her brand choice and consumption level. The assumption on η_{ijt} may have a significant impact on the satiation point, since it determines the shape of the satiation function. With a normal distribution, we allow the consumption level B_{ijt} to surpass the satiation point $\bar{B}_i$.

Figure 2.5: Timing



The proposed model allows a probabilistic determination rule which depends on cumulative consumption and the thresholds. In addition, The model allows consumers to adjust their experience value according to its position relative to the satiation point. Figure 2.6 show the expected value of $C_{ij} + \delta_{ijt}$ at each cumulative consumption level conditional on different thresholds $\bar{B}$ and σ_η. The solid line in the figure represents the experience value flow when the base utility $C = 5$, incremental rate $\gamma = 0.4$, consumption error $\sigma_\eta = 1$ and satiation point $\bar{B} = 2$. The simulated results consist of an increasing interval and a decreasing interval: the former part is largely determined by γ and σ_η; the later part (linearly) depends on $\bar{B}$ and nonlinearly depends on σ_η. The peak of the curve can be interpreted as the satiation point (in expectation); this value can be different from $\bar{B}$, depending on consumption error σ_η. A high value of σ_η delays satiation; however, it also lower the highest possible experience value.

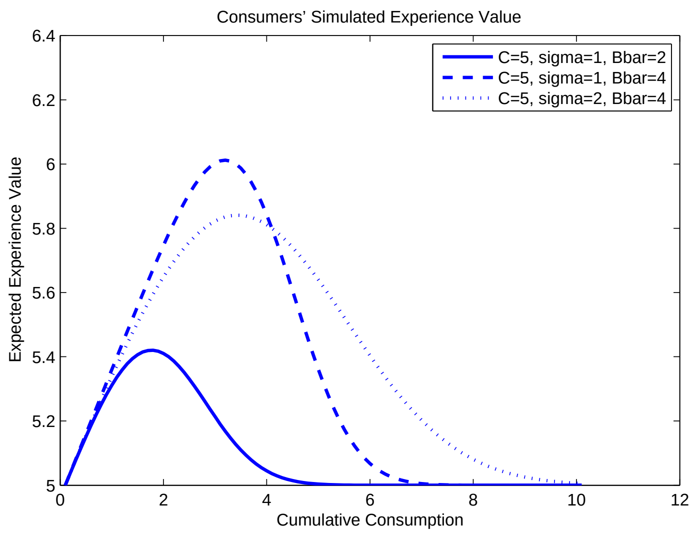


Figure 2.6: Simulated Data

The nonlinear model further implies that consumers may achieve the highest utility of one brand by keeping a constant cumulative consumption level. Speeding up or slowing down consumption may both have a negative effect on experience value. Factors that induce unstable consumption may lower consumers' brand experience and reduce the probability of staying in a certain brand. A temporary brand promotion may lead consumers to over-consume, and thus encourage switching. The structural form also provides a different welfare implication–if satiation points are low and choices are limited, consumers are likely to be subjected to welfare loss after quick satiation.

2.3.1 *Estimation of the Threshold Model*

A consumer's expected utility can be written as:

$$E(U_{ijt}|\theta_i) = C_{ij} + E(\delta_{ijt}|y_{ij}^{t-1}) + \alpha_i P_{jt} + \epsilon_{ijt} \tag{2.3}$$

where $E(\delta_{ijt}|y_{ij}^{t-1})$ is defined in Equation 2.2. Assuming that ϵ_{ijt} follows an extreme value distribution, satiation point $\bar{B}_i$ follows a log-normal distribution and all the random coefficients except satiation point follow normal distributions, the probability of consumer i purchasing brand j at shopping trip t can be written as:

$$\bar{\theta} \equiv \left\{\alpha, \{C_j\}_j, ln(\bar{B})\right\}$$
$$\sigma_\theta \equiv \left\{\sigma_\alpha, \{\sigma_{C_j}\}_j, \sigma_{ln(\bar{B})}\right\}$$
$$\theta_i \sim N(\bar{\theta}, \sigma_\theta)$$
$$P(y_{ijt} = 1|\theta_i, \gamma) = \int \frac{exp(E(U_{ijt}|\theta_i, \gamma))}{\sum_k exp(E(U_{ikt}|\theta_i, \gamma))} dF(\theta_i|\bar{\theta}_i, \sigma_\theta)$$

Since the model has random coefficients, there is no analytical solution. Yet one can use simulation based methods to integrate out the distribution of the random coefficients. In practice, we use MSL to estimate the above model. The numerical integration is over the random coefficients. In practice we use year 1987 data for estimation. For each iteration, the program will calculate B_{ijt} and then calculate the expected experience value. The simulated probability for person i is:

$$\check{P}(y_{ijt} = 1|\theta_i, \gamma) = \frac{exp(E(U_{ijt}(\theta_i^r, \gamma)))}{\sum_k exp(E(U_{ikt}(\theta_i^r, \gamma)))}$$
$$\check{P}(y_i = 1|\theta_i, \gamma) = \frac{1}{R}\sum_{r=1}^{R} \check{P}(y_{i1}, y_{i2}, ..., y_{it})$$
$$= \frac{1}{R}\sum_{r=1}^{R}\prod_t \sum_{j=1} \mathcal{I}(y_{ijt} = 1)\frac{exp(E(U_{ijt}(\theta_i^r, \gamma)))}{\sum_k exp(E(U_{ikt}(\theta_i^r, \gamma)))}$$

R represents the number of the simulated draws–we use 1000 independent simulated draws for each of the random parameters and maximize the simulated log-likelihood function:

$$SLL = \sum_i log \sum_{r=1}^{R}\prod_t \sum_j (y_{ijt}\check{P}(y_{ijt} = 1|\theta_i, \gamma))$$

2.3.2 Identification

The model's key parameters, namely C_j, σ_{C_j} and $\bar{B}$, need to be identified. Consumers without switching history won't help in identifying $\bar{B}$. However, consumers who systematically switch back-and-forth(conditional on the promotion and price effects) will help distinguish $\bar{B}$, since the lower the $\bar{B}_i$ is, the more frequently a consumer will switch. Variation of purchasing length within each individual will be explained by σ_η. There is a significant number of switches and switch-backs in the data set as demonstrated in Section 2.

C_{ij} is the constant base experience value one can achieve for each period. The variation in market share will be used to identify mean value of C_{ij}; The deviation of C_{ij} from C_j is determined by the difference in share for each individual. α_i

is identified by the asymmetric substitution effect of brand j (i.e. after a price decrease, the obtained market share is asymmetric and it draws more market share from the products with similar price.). To see the difference between market share (which is largely determined by C_{ij}) and $\bar{B}_i$, consider two choice patterns of different consumers, "*A*?*A*?*A*?*A*?..." and "*AA*??*AA*??" ("A" may be any brand.); conditional on constant characteristics, they have the same market share for A, while the second sequence has a higher $\bar{B}$. [11]

2.4 Estimation Results

We estimate the model using individual household and store level data in 2003 IRI data sets; the working sample is the 25% random draw of the households with at least 20 shopping trips. 181 individual households are selected in to the sample. [12]

We first list the estimation results of linear models in Table 2.11. The households' utility function consists of a brand fixed effect, price and marketing effects and a one-period state dependence effects. All components additively and linearly enter into the utility function. According to the estimation results, the price coefficient is negative and significantly (p-value< 0.001) different from zero. Consumers prefer national brands, especially YOPLAIT and DANNON. The estimated mean brand fixed effect is significantly better than the mean of the outside good (p-value < 0.001). Moreover, the standard deviation of those two brand fixed effects are also relatively smaller compared with other brand fixed effects. The parameter γ implies that if an average consumer purchase a brand last period, her utility will

[11] Without the satiation parameter, if majority of the consumers follow the first choice pattern(*A*?*A*?*A*?*A*?...), the state dependence parameter will be negative, which cannot be well interpreted.

[12] In the Appendix, we list a variety of estimations using different data sets or using different selection rule.

increase by 0.52 on average. Equivalently, a consumer is indifferent about a 14 cents price increase if she has purchased the item last period.

However the linear models report a large standard deviation for γ_i even after we account for other marketing variables. Those negative draws don't have a clear interpretation. In the brand satiation model, we interpret this phenomenon as consumers reaching a threshold. Estimation of the threshold may be informative: first, it offers a more clear view of the trade-off between state dependence and satiation effect. For example, previously, researchers were unsure about the number of periods to be included in the model; with a satiation limit, it is possible to estimate the time when a state dependence effect will disappear. Second, we are able to explore a form of within-individual heterogeneity: even with similar brand fixed effects, it is still possible that different households have different switching behavior and the average shopping trips can be different. Third, it may also have different welfare implications as well as marketing applications, since the model implies that the high utility flow cannot sustain forever.

Table 2.12 list the estimation results from satiation models. The mean of most brand fixed effects are similar compared with those in the linear model–only the fixed effect of Dannon is not significantly different from 0; the price coefficient and the effect of other market variables all have similar signs. Consumers' state dependence now depends on the δ function which consists of three different parameters: $\gamma_i, \bar{B}_i$ and σ. The satiation point $\bar{B}_i$ and the inertia effect γ_i are drawn from log-normal distributions; therefore, $ln(\bar{B}_i)$ and γ_i follow normal distributions. A significant positive $ln(\bar{B}_i)$ suggests that $\bar{B}_i$ is greater than one shopping trips; a significant negative $ln(\gamma_i)$ indicates that γ_i is between zero and one. According to the estimated δ function, if a consumer with median satiation threshold (2.23) purchases a brand last period, in current period the state dependence effect is

Table 2.11: Estimation Result 1: Eau Claire & Pittsfield

	Linear Model				
	Brand Fixed Effects			Other Coefficents	
	A	sqrt(D)		A	sqrt(D)
COLOMBO	-1.089^{***}	2.359^{***}	Price	-3.683^{***}	0.056
	(0.251)	(0.181)		(0.279)	(0.072)
BREYERS	-1.851^{***}	1.705^{***}	γ	0.524^{***}	0.330^{***}
	(0.235)	(0.127)		(0.043)	(0.075)
DANNON	0.633^{**}	1.163^{***}	Display	1.083^{***}	1.615^{***}
	(0.211)	(0.078)		(0.177)	(0.157)
KEMPS	-3.540^{***}	2.969^{***}	AD	0.491^{***}	0.986^{***}
	(0.423)	(0.287)		(0.120)	(0.113)
OLD HOME	-1.203^{***}	1.802^{***}	LL	12542.9	
	(0.305)	(0.194)			
STONYFIELD	-1.020^{***}	1.338^{***}	AIC	25145.8	
	(0.281)	(0.104)			
WELLS DAIRY	-1.263^{***}	2.464^{***}	BIC	25241.755	
	(0.285)	(0.200)			
YOFARM	-3.063^{***}	2.790^{***}			
	(0.372)	(0.203)			
YOPLAIT	0.817^{***}	1.203^{***}			
	(0.226)	(0.063)			
PRIVATE	-2.166^{***}	2.015^{***}			
	(0.235)	(0.120)			
OTHERS	-2.135^{***}	1.440^{***}			
	(0.273)	(0.114)			

[1] The utility of the outside good is normalized to zero.

0.40. Equivalently, she is willing to take an extra 9 cents and remains her utility the same as previous period. Similarly, with the satiation threshold $\bar{B} = 3$, a consumer's state dependence effect after initial purchase is 0.44. The satiation effect becomes stronger with consecutive purchase: for example, an median household with mean satiation threshold has an increasing state dependence effect until the second consecutive purchase. However, the model also indicates that the median household is likely to be fully satiated after five consecutive trips. Figure 2.7 demonstrate the relation between the experience value of the first five brands and consecutive shopping trips for a median household in the sample. In addition, we draw the 90% confidence interval of the whole δ function: the satiation threshold is bounded between one and three consecutive shopping trips; and the household is likely to be fully satiated within two to seven consecutive shopping trips.

Table 2.12: Estimation Result 2: Eau Claire & Pittsfield

	NonLinear Model				
	Brand Fixed Effects			Other Coefficients	
	A	sqrt(D)		A	sqrt(D)
COLOMBO	-0.475^{***} (0.196)	1.898^{***} (0.105)	Price	-4.442^{***} (0.282)	0.815^{***} (0.073)
BREYERS	-1.193^{***} (0.207)	1.576^{***} (0.097)	$\ln(\gamma)$	-0.800^{***} (0.093)	0.173^{***} (0.072)
DANNON	1.277^{***} (0.214)	1.282^{***} (0.080)	$\ln(\bar{B})$	0.801^{***} (0.137)	1.114^{***} (0.079)
KEMPS	-1.978^{***} (0.236)	2.279^{***} (0.160)	Display	1.558^{***} (0.166)	0.349^{***} (0.051)
OLD HOME	-0.728^{**} (0.262)	1.447^{***} (0.118)	AD	0.386^{**} (0.113)	1.411^{***} (0.086)
STONYFIELD	-0.403 (0.283)	1.582^{***} (0.117)	σ	1.003^{*} (0.411)	
WELLS DAIRY	-1.213^{***} (0.357)	3.029^{***} (0.297)	LL	12446.500	
YOFARM	-2.318^{***} (0.313)	2.336^{***} (0.162)	AIC	24959	
YOPLAIT	1.641^{***} (0.228)	1.204^{***} (0.060)	BIC	25064.550	
PRIVATE	-1.496^{***} (0.204)	2.194^{***} (0.120)			
OTHERS	-1.871^{***} (0.264)	1.752^{***} (0.133)			

$\bar{B}$ and γ are assumed to have a log-normal distribution since satiation threshold should be positive.
The utility of the outside good is normalized to zero.

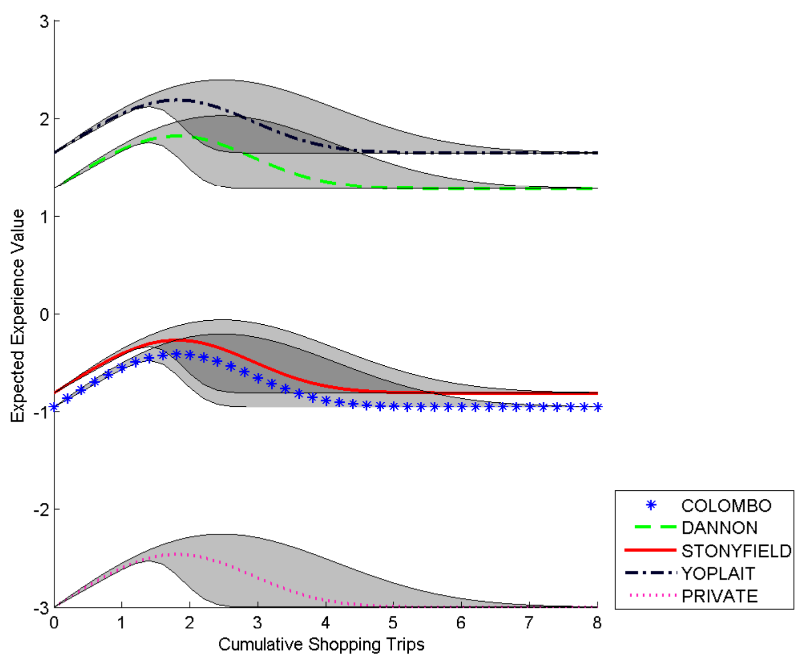


Figure 2.7: Estimated Delta Flow: Eau Claire & Pittsfield

The nonlinear model assumes that before satiation, consumers are subjected to state dependence effects such that the more she purchases, the higher her loyalty will be. However, with a satiation threshold, the consumer (household) may not be able to maintain the state dependence forever, this is unlike a linear model which explains switching behavior by idiosyncratic shocks. The new model allows us to interpret previously unexplained switches and negative state dependence coefficients as due to a satiation effect. At certain periods after consecutive purchases of the same brands, a consumer may be more likely to switch. Compared with the linear model, the satiation model significantly improves the goodness of fitting in terms of both AIC and BIC.

2.4.1 Heterogeneity and Individual Household Prediction

To better illustrate that the satiation model can flexibly control for the within-household heterogeneity and to better illustrate that the satiation model may predict switching behavior, we plot the parameters of individual households who have a high number of shopping trips of certain yogurt brand. The method of individual parameter approximation we use is suggested by Train (2009). One may calculate the distribution of coefficients given a certain sequence of observed choices; the conditional distribution will carry more information for each individual household and thus can be used to predict behavior of a certain type of consumers.

First denote $h_i(\theta_i|y, x, b)$ the pdf of the individual household who chooses a sequence of choice y under the observed characteristics x, where b represents the true hyper parameters that generate the random coefficient distribution. Denote $f(\theta_i|b)$ the estimated distribution of random coefficient θ_i. The true distribution of

θ_i does not depend on choice results, while $h(\cdot)$ does. According to the Bayes rule,

$$h(\theta_i|y_i, x_i, b) = \frac{P(y_i|x_i, \theta_i)f(\theta_i|b)}{P(y_i|x_i, b)}$$
$$= \frac{P(y_i|x_i, \theta_i)f(\theta_i|b)}{\int P(y_i|x_i, \theta_i)f(\theta_i|b)d\theta_i}$$

For individual i, we also can calculate $p(y_{ijT+1}|x_{iT+1}, \theta_i)$, i.e. the probability that individual chooses brand j next period. By using the consumers' purchasing information, we integrate out θ_i using $h(\theta_i|y_i, x_i, b)$:

$$P(y_{ijT+1}|x_{iT+1}, y_i^T, x_i^T, b) = \int P_{ijT+1}(y_{ijT+1}|x_{iT+1}, \theta_i)h(\theta_i|y_i^T, x_i^T, b)d\theta_i$$
$$= \frac{\int P_{ijT+1}(y_{ijT+1}|x_{iT+1}, \theta_i)P(y_i^T|x_i^T, \theta_i)f(\theta_i|b)d\theta_i}{\int P(y_i^T|x_i^T, \theta_i)f(\theta_i|b)d\theta_i}$$

The above probability can be simulated by taking draws (θ_i^r) from the random coefficients and calculating $\check{P}(y_{iT+1}|x_i, y_i^T, \theta_i^r)$.

Using an individual purchasing record of 2003 in the IRI data sets and using the estimation result from Table 2.12, we plot individual households' updated distribution and compare it with the sample distribution. In the Figure 2.9 and 2.8, the blue curves represent sample distribution according to estimation result in previous section (specification 2 with extra controls). The red curves is from an individual household's conditional density function for the brand fixed effect of the private brand ($h(C_i|y^i, x^i, \tilde{\theta}_i)$, where $\tilde{\theta}_i$ is a vector of all parameters except C_i) and the satiation threshold ($h(\bar{B}_i|y^i, x^i, \tilde{\theta}_i)$, where $\tilde{\theta}_i$ is a vector of all random coefficients.). [13] Figure 2.8 shows 4 households with the highest number of shopping trips involving private brands ("C" represents private brands.) in the IRI data sets. Although the four households all strongly prefer private brands, they show heterogeneous

[13]We plot the pdf curves within 2 standard deviations of the unconditional mean of each θ_i.

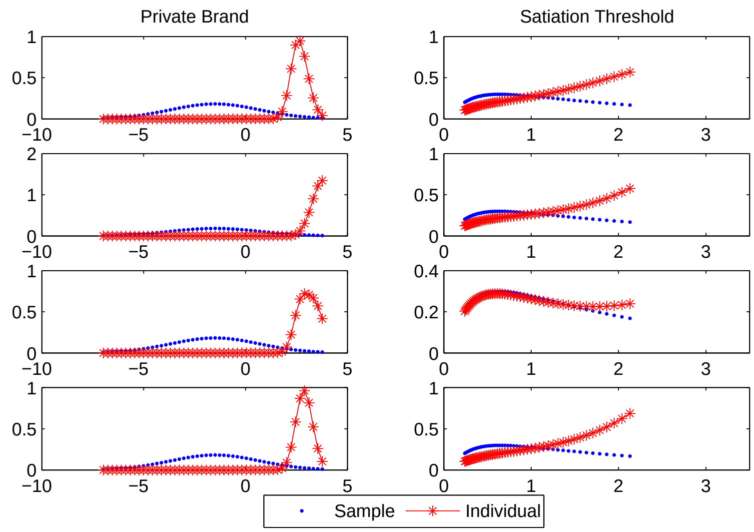


Figure 2.8: Individual Households who Purchase Private Brand Frequently

satiation parameters; intuitively the satiation parameters identify their switching behavior which is unexplained by changes of observable characteristics . Figure 2.9 shows 4 households with high number of shopping trips involving Yoplait ("C" represents Yoplait.)in the IRI data sets. With a stronger brand fixed effect, the first household is still subjected to a smaller satiation threshold compared with the sample mean, indicating frequent unexplained switching behavior.

By estimating the satiation threshold, it is possible to predict consumers' switching behavior at the individual level. As a result, with extra information on satiation thresholds, firms may be able to adjust promotion and (direct) advertising strategy accordingly. With firms focusing on brand diversity, consumers may also benefit from a larger choice set and less irrelevant marketing campaigns.

2.4.2 Diversity Preference and Welfare Implications

We illustrate the welfare implication using a counter-factual experiment. Consider a world where we drop Yoplait from the market: those consumers who prefer

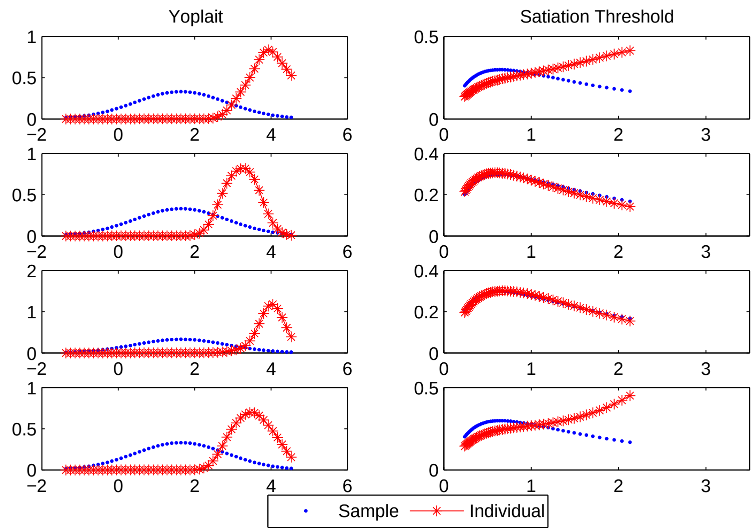


Figure 2.9: Individual Households who Purchase Private Brand Frequently

Yoplait will be affected for sure; in addition, consumers who don't prefer Yoplait may also be affected when Yoplait is the second best choice.

We generate 100 markets of 181 households making brand choice over 50 weeks using the satiation model and calculate the total utility (TU_0) for the consumers who don't prefer Yoplait yogurt most. We have two treatments (TU_1 and TU_2): in the first treatment, we drop the brand Yoplait and the households are subjected to only positive state dependence effects; in the second treatment, after dropping Yoplait, households make brand choice under the satiation preference. We compare the difference in the change of the total utility between the treatments. In Figure 2.10, the dashed curve represents a kernel density plot of the change of the utility ($\frac{TU_1 - TU_0}{TU_0}$) under only state dependence effects; the solid curve is under satiation preference ($\frac{TU_2 - TU_0}{TU_0}$). When Yoplait is removed from the choice set, consumers who prefer other brands instead of Yoplait are significantly affected under the satiation preference: the mean welfare loss is 3.69%. Yet a conventional state dependence model suggests little welfare loss. Intuitively, if consumers are likely to be satiated, alternative choices are required to "restore" their preference. As a result, consumers generally benefit from a larger choice set.

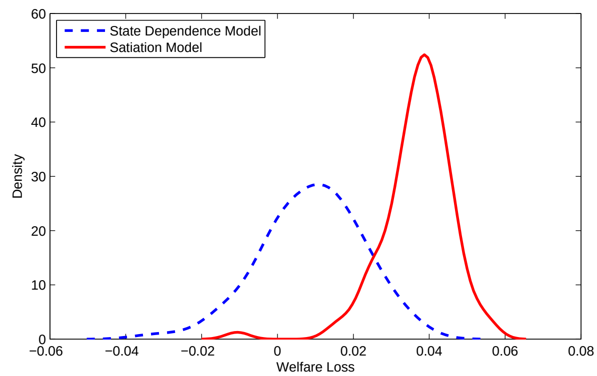


Figure 2.10: Welfare Loss for Households who Prefer Other than Yoplait

2.4.3 Extension and Limitation

The proposed satiation model provides better interpretation (of the negative state dependence and of the length of history to be included in the model) and prediction (of a switching probability), compared with a linear model. Meanwhile, it requires extra assumptions and those assumptions may be weakened or removed in the future studies. The first assumption is the zero carry-over rate assumption. According to the model, if a consumer stops purchasing, all her previous history is forgone. It may be more realistic to allowing a cumulation of discounted consumptions. However, including a discount parameter may cause identification issues with the satiation threshold, since a high satiation point and a high discount rate both lead to longer state dependence, even though they change at different rates. Moreover, different people may have different discounting rate–by using a universal one, the interpretation of satiation threshold becomes less clear.

The model also assumes an identical threshold for all available choices. However, allowing brand specific satiation points also comes with an identification problem: for each household, usually only a few alternatives will be frequently purchased. For the rest of the brands, the experience value should remain constant. With a longer period and a larger sample, it is possible to use a selection function to locate the choices that are frequently chosen and to allow different satiation points for each of them.

The data sets offer limited information on firms' marketing strategies. For example, in the ERIM data sets, complete information on promotions and advertising displays are available only for the purchased items. For the rest of the items, the data are recorded only at specific times. In the IRI data sets, although we have rich information on advertisement and displays. Yet we have to deal with a much larger choice set, where collapsing on brand/ firm level will create significant noise. With a more detailed data set and a simple choice structure, it would be possible to reach a higher credibility and may help investigate future research topics. For example, it may be possible to look at the effects of satiation on consumers' responsiveness to marketing strategies. With a consecutive purchases, the advertising displays become less effective. We observe a decreasing (positive)correlation between purchasing behavior and advertisement at different lengths of the cumulative consumption in the ERIM data sets.

Although we focus on demand-side estimation, satiation behavior, also creates firm-side problems including firms' optimal pricing behavior and other marketing strategies. Those problems are beyond the scope of this paper.

2.5 Conclusion

In this paper, we propose a model where consumers' switching behaviors are not only due to the variation of brand characteristics, but due to intertemporal brand satiation as well. One possible explanation is that in a frequently purchasing/non-durable, differentiated good market, consumers' consumption has cumulative effects over time: they have high experience value at the beginning state; yet consumers' satiation effects may dominate state dependence effects at high cumulative consumption levels; consumers' loyalty will recover as consumers switch away to other brands or stop consuming the product. we use a structural model to test the the hypothesis of satiation preference. Since the consumption is not observed, we work with shopping trips and specify that consumers will switch when the cumulative purchasing is close to an upper threshold. The estimation results suggest that consumers show large heterogeneity in satiation point and after consecutive purchases, an average household will be subjected to a negative satation effect. The simulated market frequency is closer to the real one than in a linear model. We conclude that some of the consumers in the sample are subjected to satiation effects.

The satiation model improves upon previous models in the following ways: first, a satiation model explains negative state dependence effects using a satiation threshold. Linear models simply treat a negative state dependence coefficient as a result of heterogeneity; however it is not clear why the previous choices for certain consumers lead to switching at the next period, given that all other factors remain the same. In my model, the repurchase probability goes down due to the threshold. Second, the satiation model suggests a way to treat purchasing history. For a linear model, a researcher has to debate the choices of lags for the state dependence terms. The satiation model allows a nonlinear experience value curve: the peak of the curve indicates the highest state dependence effect and only before the peak, the state dependence effect dominates the satiation effect such that those periods reflect the optimal length of the state dependence lags for each household.

Third, the proposed model can be used to predict households' switching behavior. Previous models only explain switching using independent random draws. With assumption in satiation threshold, a household closer to the threshold is more likely to switch to alternative choices. This information can be useful in today's business practice–since it may improve the effectiveness of marketing strategies. As a result, the waste of resources may be reduced by better targeting satiated consumers. Moreover, households' welfare may be improved if they are provided with right alternatives when satiated.

Finally, under the assumption of satiation, a more diversified market is preferred. The model helps explain the expanding categories in differentiated goods markets, especially the nondurable food market. With a simulation experiment, We showed that after dropping a brand in the market, the consumers who don't prefer those two brands are still subjected to significant welfare loss. This result may be consistent with the development of the yogurt industry where more sub-brands and flavors have been provided.

Admittedly, there are alternative ways to model the (inter-temporal) satiation effects, especially after incorporating more and more market elements and behavioral assumptions. With the satiation effects being modeled, firms' marketing strategies may be reconsidered and market equilibrium may be altered–those facts may lead to promising research topics and field tests in the future.

3. BUYERS' RESPONSE AGAINST EXPLODING OFFERS

3.1 Introduction

An exploding offer is a method that a seller uses to encourage a quick decision by refusing to sell to a customer unless she buys immediately.The offer strategy is widely used in a job market where an applicant has to accept or reject an offer within a very short period of time. Exploding offers have been also seen in other sequential search markets including apartment renting market, vehicle selling market, etc. An exploding offer can be written down as a formal offer, yet it can also be informal and oral. Sellers tend to use this offer type since it provides a discrimination tool to extract extra surplus from high value consumers. However, anecdotally exploding offers create inequality contexts with higher price and limited decision time which may result in not only a low efficient match in the market, but lower profits as well. The paper focuses on inequality contexts and explores if inequality aversion will make an exploding offer less effective in the equilibrium.

Previous studies about exploding offers focus more on matching market especially in a job search or a recruiting market. In these contexts, an exploding offer is defined as the offer that requires individuals to respond in a short period of time before they can search for alternative options. These studies show that exploding offers lower the matching quality. The result is likely to extend to a more general market environment with price offers; however, the market phenomenon becomes less documented. On one hand, the offer can be given in a very informal way [1]; on the other hand, firms don't have incentive to record or release exploding offer to

[1] For example, by simply saying "we have another customer interested in the item and will come tomorrow..." is likely to force a buyer to make a quick decision.

public. Moreover, those similar markets offer more durable products or long term services, and receive certain amount of new demand at each period, which makes information less transparent and traceable at individual consumer level. Those issues from demand and supply sides may explain why empirical studies with respect to this topic are relatively sparse. It is not clear how effective an exploding offer is in a general marketing environment.

In this paper, we adopt experimental methods and use an abstract lab search market to demonstrate that with rational buyers, sellers tend to choose exploding offers with higher price; however with human buyers and under the control environment, the market equilibrium is shifted to lowest price and exploding offer. We test unobserved behavioral components and provide evidence that 1. buyers over-reject exploding offers; 2. sellers are less willing to use exploding offers. These findings are important since previously in a lab search market, we observe buyers with bounded rationality or risk aversion are less likely to search the market, while in our setting, buyers consistently reject and search the second sellers' offer.

3.2 Literature Review

One strand of recent literature involves using experimental methods to test the effects of exploding offers in a labor market where the quality of matching is the research interests. For example, in Niederle and Roth (2009)'s setting, a firm can hire one applicant and an applicant can choose one firm. Each firm has a fixed quality which is known to all firms and all applicants whereas the qualities of applicants are revealed over time. Each of a match firm and applicant's payoff depends on the quality of his/her match. They found that markets with exploding offers, together with binding acceptances create early and dispersed transactions.

In the same environment, when they restricted subjects to use only open offers, or to allow applicants to renege on early acceptances, late and thick transactions were observed. Tang et al. (2009) studied exploding offers by introducing the Ultimatum Deadline Game. A proposer makes an offer and gives a deadline to a responder to accept a proposal. If the offer is accepted, the responder gets a payoff X. A better offer that pays a responder $Y > X$ is uncertain, and the timing of its arrival is stochastic. Since the conditional probability of the better offer arriving drops over time, the proposer prefers a short to a long deadline. On the other hand, if the responder accepts an offer, he sacrifices a more favorable choice when the deadline is short than when it is long. Proposers in their studies tended to set too short deadlines, and their offers were frequently rejected.

A more recent paper, Lau et al. (2011) started looking at impact of responders' other-regarding preference on exploding offers. To be specific, they investigated hiring situations where a proposer chooses between an exploding or extended offer. A responder can discover a better alternative offer only if a proposer chooses an extended offer. If the offer is accepted, the responder can alter the proposer's payoff. Many responders in the experiment chose a negative reciprocation after they accept exploding offers which made a large proportion of proposers with exploding offers worse off. They argued that participants may have overlooked negative impact from choosing exploding offers. The paper models labor input as a reciprocating stage, while we are interested in a general market with endogenous price.

Another strand of studies propose theories and derive equilibrium conditions for different selling strategies. Lippman and Mamer (2012) analyzed a market where a buyer seeks to purchase an asset from a seller who has a finite time T to sell. In their model, the buyer can be either an exploding or a permanent offer.

They investigated when the exploding offer is a good strategy to use. However, in their setting, buyers will choose exploding offers or regular ones and sellers will decide whether to accept. The valuation is exogenously given by the i.i.d. draws from a known distribution.

Our paper uses the setting close to the one from Armstrong and Zhou (2012) where we want to model exploding offers in a general search market. Armstrong and Zhou (2012) analyzed a market with sequential consumer search where multiple firms choose whether to use exploding or free recall offers and set prices accordingly. Moreover, they also investigated a buy-now discount offer (which offers a lower price for an immediate purchase). They showed, using a game-theoretic model, that in some cases, firms have an incentive to use these techniques. Using these strategies reduces the quality of the match between consumers and products since they need to buy more quickly; moreover, these offers also raise market prices on average. Compared with Armstrong and Zhou, we consider a discrete strategy, discrete valuation case where the sellers' game can be viewed as a 6 by 6 normal form game. We focus on equilibrium changes due to potentially both sides' non-monetary incentives.

3.3 Analytical Framework

In this section we analyze an experimental search market of two sellers where buyer visits each of them sequentially in a random order. Each seller sells an item which has independent value from the same ex ante value distribution for a buyer: $V^i_k \in \{V^i_1, V^i_2, ..., V^i_K\}$ (where $i = 1, 2$ represents sellers and $k = 1, 2, ..., K$ represents possible value) with probability $\lambda_1 \equiv prob(V_1), \lambda_2 \equiv prob(V_2), ..., \lambda_3 \equiv p(V_K)$. The step of the game is as follows:

1. Each seller sets a price from a possible price range: $P^i \in \{P^i_1, P^i_2, ..., P^i_L\}$ and

chooses an offer type as either an exploding or a free recall offer.

2. The nature selects which seller the buyer will visit first (S^1).[2]

3. The buyer observes the price of each seller (P^1 and P^2) and the value of the item of the first seller he visits (V_l^1).

4. The buyer chooses whether to accept the first offer or to visit S^2. If he[3] chooses to accept, the transaction is occurred and the game is ended; otherwise, continue to the next step.

5. The buyer visits S^2 and observes the value of the item (V_l^2).

6. The buyer chooses whether to accept or reject the offer from S^2. If he accepts, the transaction is occurred and the game is ended. If he rejects and the first offer was an exploding offer, no transaction is occurred and the game is ended. If he rejects and the first offer was a free recall offer, continue to the next step.

7. The buyer chooses whether to accept or reject the offer from S^2 (if it is a free recall offer).

Each player's payoff is determined after the game is ended. If there is no transaction, all players receive zero payoff. If there is a transaction, the buyer receives a payoff equals to the value of the item he bought, that seller receives a payoff equals to the price he chose, and the other seller receives zero payoff.

3.3.1 Buyer's Best Response

We will assume from now on that the objective of the buyer is to maximize his expected payoff. Since an offer type of the second seller has no effect on the buyer

[2]Let call the first seller S^1 and the other seller S^2.

[3]We will assume female sellers and a male buyer.

strategy, we only need to consider two cases; (1) the first offer is a free recall offer and (2) the first offer is an exploding offer.

If the first offer is a free recall offer, visiting S^2 does not prevent the buyer from revisiting and accepting the offer from S^2, so the buyer will always search.[4] After visiting both sellers, the buyer would choose an option that provides him the highest payoff from three possible options which are accepting the first offer ($V_k^1 - P^1$), accepting the second offer ($V_l^2 - P^2$), and rejecting both offers (zero payoff).

If the first offer is an exploding offer, the buyer would compare between the payoff from accepting the first offer and the expected payoff from rejecting the offer. The payoff from accepting the first offer is the difference between the value and the price of the first offer or $\Pi^1 = V_l^1 - P^1$ while the expected payoff from visiting S_2 is[5]

$$E(\Pi^2) = \sum_{l=1}^{K} \lambda_j^* \max(0, V_l^2 - P^2)$$

The buyer would accept the first offer if $\Pi^1 < E(\Pi^2)$ and reject otherwise.[6]

3.3.2 Sellers' Strategies

In this market, each seller needs to choose a price and an offer type before knowing whether a buyer would visit her first or not. There are three cases we need to consider; both sellers use exploding offers, both sellers use free recall offers, and sellers use different strategies.

---

[4] In some cases, it is not neccessary for the buyer to search. For example, if he receives the highest possible value from the distribution and $P^1 \leq P^2$. In which case, searching provides no additional benefit for him. However, there is also no harm for him, so we assume for simplicity that the buyer will always visit the second seller if the first offer was a free recall offer.

[5] If a value of the item from the second seller is higher than the price, the buyer would accept the offer and gain $V_l^2 - P^2$; however, if $V_l^2 < P^2$), he would reject the offer and earn zero payoff. So, for each value l of the second item, the buyer would earn the greater between 0 and $V_l^2 - P^2$. The expected payoff is calculated from the sum of each of the multiplication of $\max(0, V_l^2 - P^2)$ and its probability as shown above.

[6] If $\Pi^1 = E(\Pi^2)$, we assume that the buyer will search with probability $\frac{1}{2}$.

First, consider a case where both sellers use exploding offers. Let consider seller i with a price P^i, who gets matched with seller j with a price P^j. There are two possible situations with equal probability:

1. A buyer visits seller i first. The buyer will accept the offer if the difference between his valuation of the first item and its price is greater than the expected payoff from the second offer; i.e., $V_k^i - P^i > E(\Pi^j) = \sum_{l=1}^{K} \lambda_l{}^* \max(0, V_l^j - P^j)$ and reject otherwise. The probability that he will accept the offer is

$$\text{Prob(accept } i_{11}) = \sum_{k=1}^{K} \lambda_k{}^* D_k$$

   where $D_k = 1$ if $V_k^i - P^i > E(\Pi^j)$ and $= 0$ otherwise.

2. A buyer visits seller j first. Similar to the first case, the buyer will accept the offer from j with probability $\sum_{l=1}^{K} p_l{}^* C_l$ where $C_l = 1$ if $V_l^j - P^j > E(\Pi^i) = \sum_{k=1}^{K} \lambda_k{}^* \max(0, V_k^i - P^i)$ and $= 0$ otherwise. If the buyer reject the offer from j, he will visit i. Upon visiting i, he will accept the offer as long as his value is above P^i or with probability $\sum_{k=1}^{K} \lambda_k{}^* B_k$ where $B_k = 1$ if $V_k^i > P^i$ and $= 0$ otherwise. So, the probability that the buyer will purchase from seller i is

$$\text{Prob(accept } i_{12}) = (1 - \sum_{l=1}^{K} \lambda_l{}^* C_l)^* \sum_{k=1}^{K} \lambda_k{}^* B_k$$

   Therefore, seller i's expected payoff is $P^{i*}[\frac{1}{2}\text{Prob(accept } i_{11}) + \frac{1}{2}\text{Prob(accept } i_{12})]$.

Second, consider a case where both sellers use free recall offers. Again, consider seller i with price P^i who gets matched with seller j with price P^j. An order of visiting has no effect here because a buyer always searches in this scenario.

Therefore, the buyer will purchase his item as long as (1) $V^i_k - P^i > V^j_l - P^j$ and (2) $V^i_k - P^i > 0$. A probability that the buyer will purchase from her is

$$\text{Prob(accept } i_2) = \sum_{k=1}^{K} \sum_{l=1}^{K} \lambda_k \lambda_l {}^* A_{kl}$$

where $A_{kl} = 1$ if $V^i_k - P^i > V^j_l - P^j$ and $V^i_k - P^i > 0$ and $= 0$ otherwise. Therefore, his expected payoff is $P_i{}^*$Prob(accept i_2).

Last, consider a case where one seller uses an exploding offer and another seller uses a free recall offer. Since an offer type of the second seller has no effect on the buyer' strategy, we can use the expected payoffs from the previous cases. If seller i uses an exploding offer while seller j uses a free recall offer, seller i's expected payoff is $P_i{}^*[\frac{1}{2}$Prob(accept i_{11})$+\frac{1}{2}$Prob(accept i_2)$]$.[7] If seller i uses a free recall offer while seller j uses an exploding offer, seller i's expected payoff is $P_i{}^*[\frac{1}{2}$Prob(accept i_2)$+\frac{1}{2}$Prob(accept i_{12})$]$.[8]

3.3.3 *Sequential Search Market in the Lab*

We have shown how to calculate payoffs in this game above. For any sets of values $V^i_k \in \{V^i_1, V^i_2, ..., V^i_K\}$, probability $\lambda_1, ..., \lambda_K$, and prices $P^i \in \{P^i_1, P^i_2, ..., P^i_L\}$, we can calculate payoffs for any combinations of strategies for each seller. Because we are interested in a case where the Nash Equilibrium is for both sellers to use exploding offers, we choose parameters for our experimental market as follows:

$V \in \{10, 25, 40, 55, 65, 70\}$

$\lambda(10) = \lambda(25) = \lambda(40) = \lambda(55) = 0.125$ while $\lambda(65) = \lambda(70) = 0.25$

[7]The case where the buyer visits i first is equivalent to the case where both sellers use exploding offers and the case where the buyer visits j first is equivalent to the case where both sellers use free recall offers.

[8]The case where the buyer visits i first is equivalent to the case where both sellers use free recall offers and the case where the buyer visits j first is equivalent to the case where both sellers use exploding offers.

$P \in \{25, 30, 35\}$

In this case, there exists a unique equilibrium in which both sellers in the market choose an exploding offer with the highest price of 35. In this equilibrium, a buyer would accept the first offer only if his value for the first item is either 65 or 70 and reject all other values. If the first offer was rejected, the second offer would be accepted as long as his value for the second item is above 35 (40, 55, 65, 70). All other combinations of choices cannot be established as Nash Equilibrium and we provide expected payoffs for all decisions in Table 3.1.

Table 3.1: Payoff Matrix

	E25	E30	E35	F25	F30	F35
E25	11.91	13.28	13.28	**15.04**	15.82	16.21
E30	11.72	13.59	15	13.36	**17.58**	18.52
E35	**13.67**	**13.67**	<u>**15.86**</u>	14.49	15.59	**20.51**
F25	9.18	12.7	13.48	12.3	15.23	16.41
F30	9.14	10.08	13.83	10.78	14.06	17.34
F35	10.12	10.66	11.76	10.94	12.58	16.41

3.4 Experimental Design

Two treatments were conducted. In the baseline (computer buyers treatment), human sellers were matched against computer buyers programmed to play an optimal strategy. In the treatment (human buyers treatment), human sellers were matched against human buyers. One cohort consisted of eight sellers (for both treatments) and sixteen buyers (only for human buyers treatment). In each period, four markets were randomly formed in each cohort. Each market in the baseline consisted of two sellers and twenty-four computer buyers while each market in the treatment consisted of two sellers and four human buyers who made six independent decisions each. Twenty periods were played in all sessions and the role of each participant was fixed for the entire session. In the game, half of buyers visited one seller first and the other half visited the other seller first.

A sequence of values of items were randomly generated and were the same for every cohort in every session in both treatments. In addition, we used the same random matching in every cohort.[9] Using human buyers in the treatment was the only difference from the baseline.

The insructions were both shown on screen and read aloud to insure the game was common information among the participants. After the instructions, the participants answered a quiz, in multiple choices form, to establish that they understood how to play the game. Each participant needed to answer all questions correctly before the game started.

Each seller in both treatments got paid based on one randomly selected period. The earnings were determined by the price chosen in that period multiplied by the quantity sold and the conversion rate was one point for four cents. Each buyer in the human buyers treatment got paid based on one random decision in one random period. The earnings were calculated from the difference between the value and the price of that particular item purchsed or zero if no purchase was made. The conversion rate for a buyer was two points for a dollar. In addition, a five dollar show up fee was added to the total earnings for each participant.

Four cohorts in two sessions in the baseline and three cohorts in the treatment were conducted. All 104 participants were Texas A&M University undergraduate students recruited campus wide using ORSEE, see Greiner (2004).

The experiment was programmed and conducted with the software z-Tree, see

[9] If in one cohort, participant i was matched with participant j in period n; in all other cohorts, participant i would be matched with participant j in period n as well.

Fishchbacher (2007). The experiment was conducted in the Economic Research Laboratory at Texas A&M University, which has 36 networked participant stations, in April and October 2013. A five dollar show up fee plus their earnings in the session were paid to the participants in private and in cash. On average participant earned about $18 for a session that lasted about 80 minutes.

After the decision making portion of the session was completed and while they waited for their earnings to be calculated, participants filled out a questionnaire which consisted of demographics information, a risk preference test, see Eckel and Grossman (2008), and a cognitive reflection test, see Frederick (2005).

3.5 Result and Data Analysis

Result 1 *Sellers play different strategies against computer and human buyers. Sellers offer lower prices and choose to use exploding offers less often against human buyers. Both tendencies persist, if not intensify, over the course of the experiment.*

We first compare sellers' decisions in a computer buyer condition (CB) with those in a human buyer condition (HB). Table 3.2 provides a summary of all seller decisions across both treatments. Over all periods, sellers used exploding offers more often (67.96% in CB vs. 54.58% in HB) and offered lower prices (30.36 in CB vs. 26.95 in HB). Pooling these values at the subject level and comparing across condition, a rank sum test confirms that these values are significantly different ($p < 0.035$ and $p < 0.001$, respectively).

Table 3.2 also shows the frequency that each combination of strategy and price was used over 20 periods. The modal response (32%) in the CB treatment was the equilibrium strategy, an exploding offer with a price of 35. Less than 5% in the HB treatment used this strategy. The modal response in the HB treatment was an exploding offer with a price of 25 (used by 34% of subjects), only about 11% in the

Table 3.2: Summary Table of Sellers' Decisions

Buyer type	Observations	Average Price	Exploding Offers	25E	30E	35E	25F	30F	35F
	640	30.36	435	71	157	207	110	75	20
computer	100.00%	(0.16)[1]	67.96%	11.09%	24.53%	32.34%	17.19%	11.72%	3.13%
	480	26.95	262	165	75	22	164	40	14
human	100.00%	(0.14)	54.58%	34.38%	15.62%	4.58%	34.17%	8.33%	2.92%

[1] Standard error is given for average price rather than percent value.

CB treatment used this offer.

We can also observe the dynamics of subject decisions. Over the twenty periods in the experiment, both the sellers in the CB and HB treatments increased their use of exploding offers (Figure 3.1). The percentage of sellers who used an exploding offer in the CB is higher than in the HB in most periods. In the last 5 periods, about 76% of sellers in CB session used an exploding offer, while only about 65% of sellers in HB session used an exploding offer. A joint test of the period dummy variables suggested that the average exploding offer usage was significantly different between two treatments ($p \approx 0.010$). Yet a linear trend test showed that the increase rates for both session were similar ($p \approx 0.476$).

Selling pricing dynamics are quite different (Figure 3.2). In the first 2 periods, average prices across condition are nearly identical. After that, they diverge. While sellers in CB remained at higher price level (if not increased), in HB, they quickly dropped the price (p-values for linear trend coefficients were 0.176 and 0.000, respectively). In the last 5 periods, seller prices were on average 30.49 in the CB condition and 26.65 in the HB condition.

Result 2 *When given an exploding offer, buyers reject the offer (search for the second seller's item) more often than profit-maximizing play dictates. This tendency holds over all prices and valuations and persists throughout the experiment.*

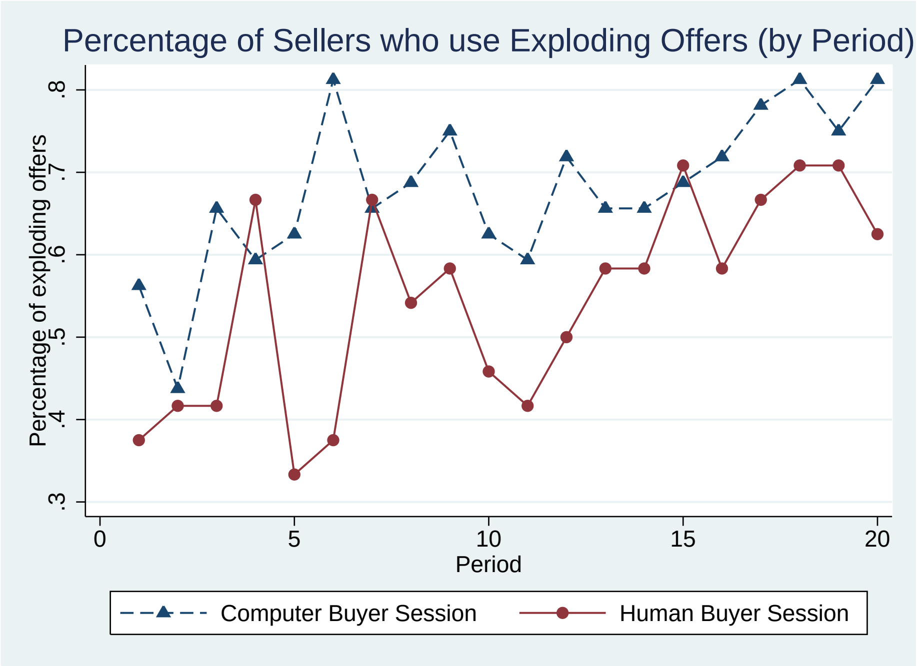


Figure 3.1: Sellers' Offers

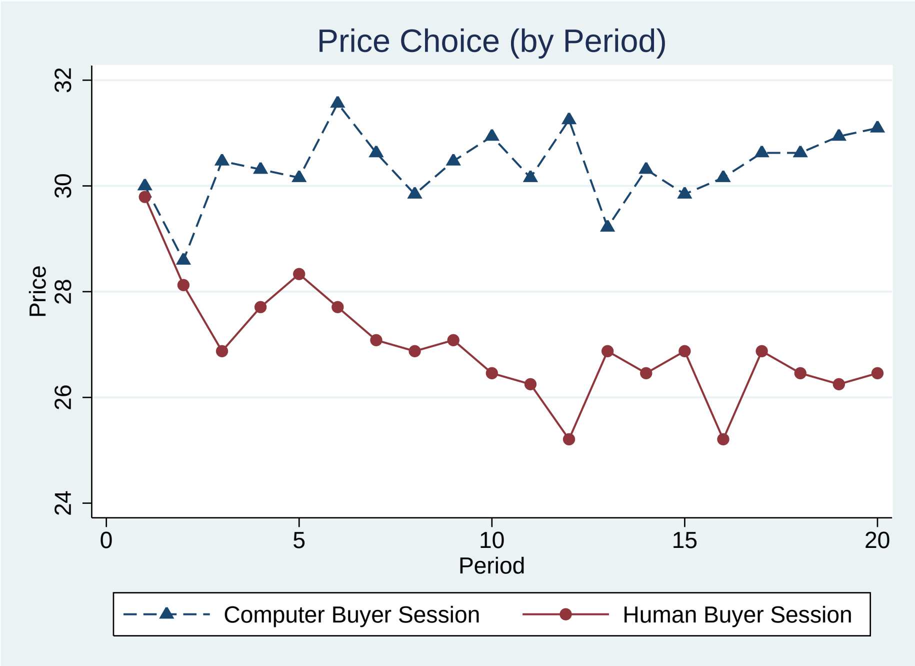


Figure 3.2: Sellers' Prices

Table 3.3: Summary Table of Buyers' Decisions

	1st offer is exploding		1st offer is free-recall		Overall	
	Actual	Optimal play	Actual	Optimal play	Actual	Optimal play
Accepts 1st offer, immediately	1618 51.46%	1860 59.16%	539 20.68%	689 26.43%	2157 37.51%	2549 44.32%
Searches for 2nd offer	1526 48.54%	1284 40.83%	2068 79.32%	1918[2] 73.57%	3594 62.49%	3202 55.68%
Accepts 2nd offer	1131 35.97%	712(+189)[1] 22.65%(+6.01%)	1085 41.62%	1018(+241) 28.92%(+9.24%)	2216 38.53%	1730(+430) 30.08%(+7.48%)
Recalls 1st offer	-	-	794 30.46%	536(+243) 20.56%(+9.32%)	794 13.81%	536(+243) 9.32%(+4.23%)
Accepts neither offer	395 12.56%	383(+189) 12.18%(+6.01%)	189 7.25%	86(+89) 3.30%(3.41%)	676 11.75%	469(+278) 8.15%(4.83%)
Total offers	3144	3144	2607	2607	5751	5751

[1] Numbers in the brackets represent indifference conditions for optimal play. The subjects can receive the same net value or the subjects may receive a best offer with 0 net value. Therefore, we provide a conservative measure and its upper bound.
[2] We assume that consumers search only when the current value is strictly smaller than the difference between the highest value 70 and the other seller's price. Therefore, this measure is also a lower bound. There are 498 indifference cases.

Buyers made 6 purchase attempts in each period over 20 periods. Pooling the results from 3 sessions of 16 buyers each we have a total of 5760 ($6 \times 20 \times 16 \times 3$) purchase attempts. Table 3.3 provides summary data on all of these choices.[10] In 3144 of these purchase attempts buyers encountered an exploding offer on the first item they searched. Optimal play (based on price of the items and buyer valuation of the first item) dictates that buyers should have accepted this first offer in 1860 (59.16%) instances; instead buyers accepted in only 1618 instances (51.46%), a difference that is statistically significant ($p < 0.001$). The net result was that buyers accepted the second offer, the only offer that remained, far more often than optimal strategy dictates. Buyers accepted the second offer 1131 (35.97%) times after an exploding offer, far higher than the 712–901 (22.65–28.66%) times[11] they would

[10] Due to a computer glitch 9 buying attempts were unable to be recorded. These affected four different buyers over two periods in one session. Given the small number of observations lost compared to the total number in the sample, we cannot envision how this loss of data would affect any results.

[11] This number varies depending on whether optimal buyers would have bought the second item if the net gain from doing so was zero (when value=price).

have if they followed optimal strategy. The calculated loss of such deviation is about 1.08 per item, a value that is significantly different from 0 ($p < 0.001$).

It should be noted that buyers also displayed a tendency to search for a second offer more often than "optimal" with free-recall offers, though these cases are very different than with exploding offers. In general, buyers with a free-recall offer should search for the second offer unless they get the highest value at a price less than or equal to the second offer. In those cases, it is unnecessary for buyers to search—the first offer is optimal—but searching produces no economic loss as buyers may recall their first offer. Buyers with free-recall offers ultimately chose the right item—the one with the highest net gain—86.74% of the time.[12]

The tendency for buyers to turn down exploding offers more often than optimal play was not isolated to a specific valuation or seller price pair. Figure 3.3 illustrates optimal response (dashed line) and actual response (solid line) in terms of rejection rate for buyers over different valuations for the first item when the seller uses an exploding offer. For instance when a buyer has a value higher than 55, in most instances optimal play would be to accept the offer. In the experiment, however, buyers showed a significant amount of rejection under these high values. Separating the data by seller-price pairs (i.e., the price the first seller makes with an exploding offer and the price the second seller offers), the over-rejection patterns remain under all price pairs (Figure 3.4).

Buyers persistently over-rejected exploding offers over the course of the experiment. Figure 3.5 plots the rejection rate from optimal play and buyer rejection rate. In every period, the actual rejection rate is greater than or equal to the rate predicted by optimal play. Both a parametric t-test and non-parametric rank sum

[12] In the remainder of these choices buyers mistakenly chose the item they valued most, ignoring price, rather than focusing on net gain.

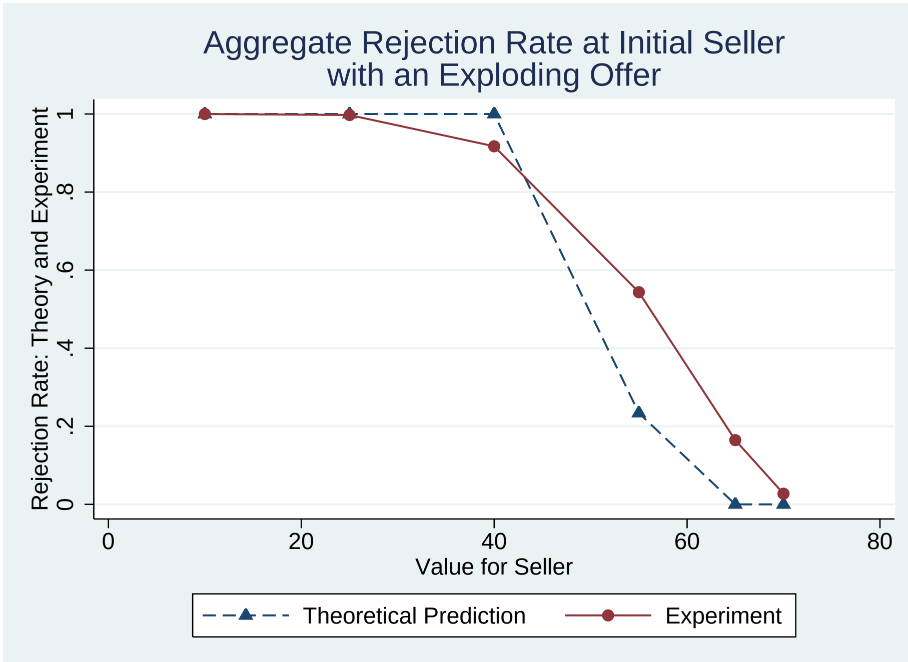


Figure 3.3: Rejection Rate

test, collapsed to subject, suggest the rejection rate with human buyers is higher than optimal ($p < 0.001$).

Result 3 *Because of their increased propensity to reject exploding offers, human buyers present different incentives to sellers than computers following optimal strategy. In addition to the standard equilibrium found when buyers play the theoretically optimal strategy, the sellers' pricing game with the payoffs created by human buyers contains a second equilibrium where sellers both make exploding offers at the lowest price. The quantal response equilibrium shows this second equilibrium is the convergent equilibrium.*

Result 2 demonstrates that human buyers act significantly different than computer buyers programmed to follow optimal play. As one might expect, this presents different expected payoffs for the two sellers depending on whether they face human or computer buyers. Table 3.4 presents a comparison of payoffs de-

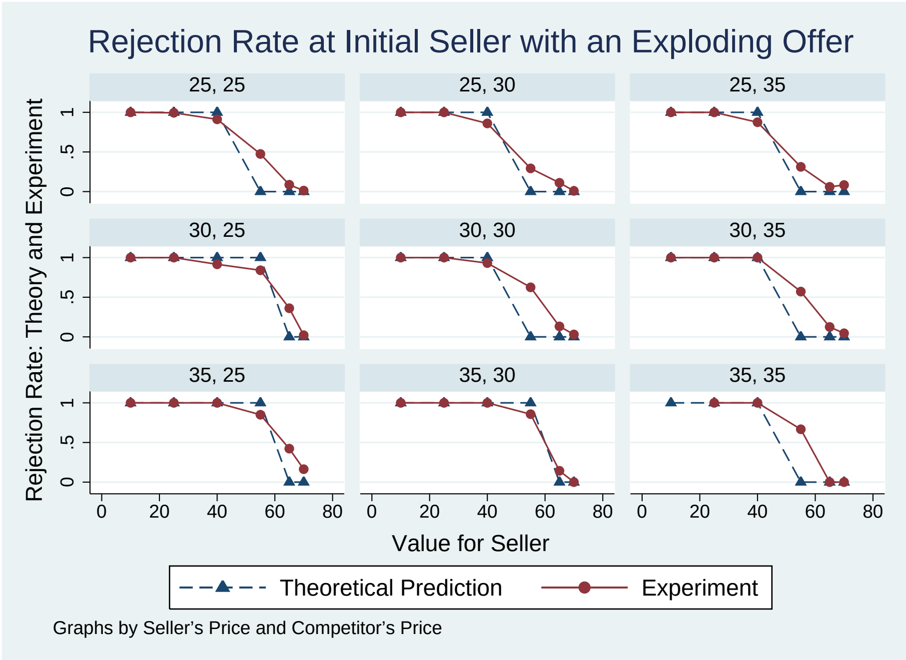


Figure 3.4: Aggregate Rejection Rate

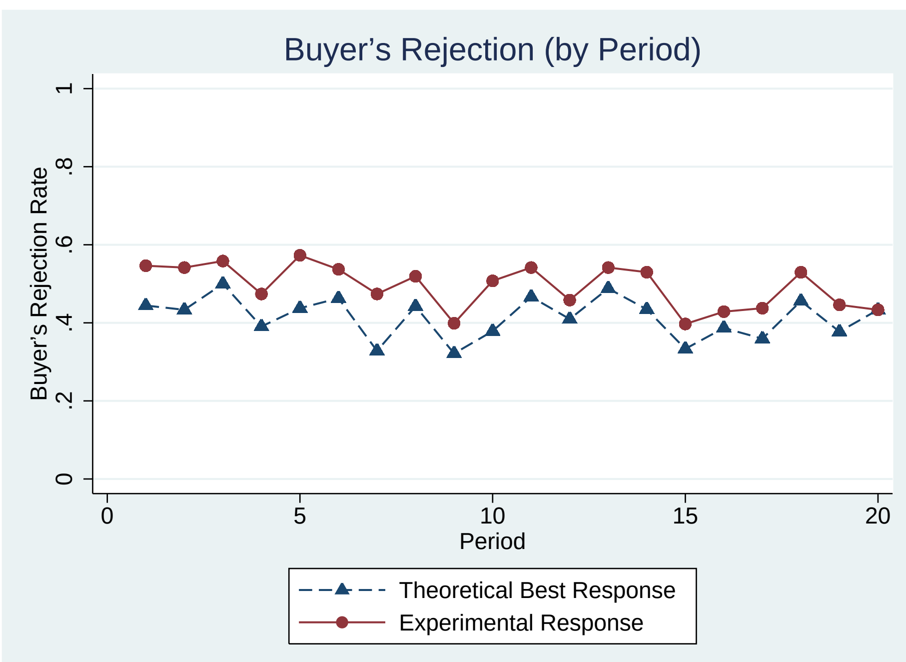


Figure 3.5: Buyers' Response

pending on whether the two sellers in the game face human or computer buyers. The human buyer payoffs are constructed using the buyer choice distributions in our sample. They capture the fact that an average buyer will over-reject exploding offers. Payoff values are determined by a simulation where 20,000 "human" buyers receive the offers of two sellers in random order. The payoffs for strategies that involve exploding offers are generally lower with human buyers than the theoretical prediction. This difference creates a second, pure-strategy, symmetric equilibrium where both players offer the lowest price as an exploding offer ($(25, E)$, $(25, E)$) in addition to the pure-strategy, symmetric equilibrium of both players playing the highest price with an exploding offer ($(35, E)$, $(35, E)$). The latter strategy pair is the only pure-strategy, symmetric equilibrium that exists in theory or against computers buyers who play the theoretically optimal strategy.

There are two points about the game with simulated human buyers that require more explanation. First, it is difficult to understand the intuition that buyers rejecting exploding offers more often than optimal leads to the creation of a new equilibrium where exploding offers will still be used. To consider this possibility, note that if sellers pick equal prices with different types of offers, the seller with the exploding offer does much better. However, lowering prices against an exploding offer can lead to higher payoffs in some cases. Sellers may find it effective to offer an exploding offer with a lower price to "pay" the reluctant buyer to accept an exploding offer.

Second, the existence of two pure-strategy, symmetric equilibria brings up the issue of equilibrium selection. It is desirable to be able to focus on one equilibrium and there are many techniques to do so. One popular technique, the quantal response model (QRE) (McKelvey and Palfrey (1995)), shows that the lower priced equilibrium ($(25, E)$, $(25, E)$) is the "convergent equilibrium."

Table 3.4: Simulated Payoff Matrix

Theoretical						
25, E	11.909	13.271	13.271	13.674	15.059	15.641
30, E	11.721	13.563	14.949	12.887	16.409	18.071
35, E	13.675	13.675	**15.824**	14.200	15.035	19.143
25, F	10.016	12.740	13.309	11.781	14.528	15.679
30, F	9.650	11.291	14.312	10.816	14.137	17.434
35, F	10.486	11.258	13.173	11.012	12.618	16.493
Simulated Human Buyers[1]						
	25, E	30, E	35, E	25, F	30, F	35, F
25, E	**11.730**	13.694	14.901	12.571	14.647	15.595
30, E	10.880	13.105	14.401	11.759	14.475	16.601
35, E	10.812	13.566	**15.513**	11.510	13.624	17.839
25, F	10.940	13.575	14.985	11.781	14.528	15.679
30, F	9.937	12.767	15.234	10.816	14.137	17.434
35, F	10.313	12.561	14.167	11.012	12.618	16.493

[1] The "human buyer" payoff matrix is calculated like the theoretically optimal matrix, except that the observed rejection rate of exploding offers is used rather than the theoretical optimum.

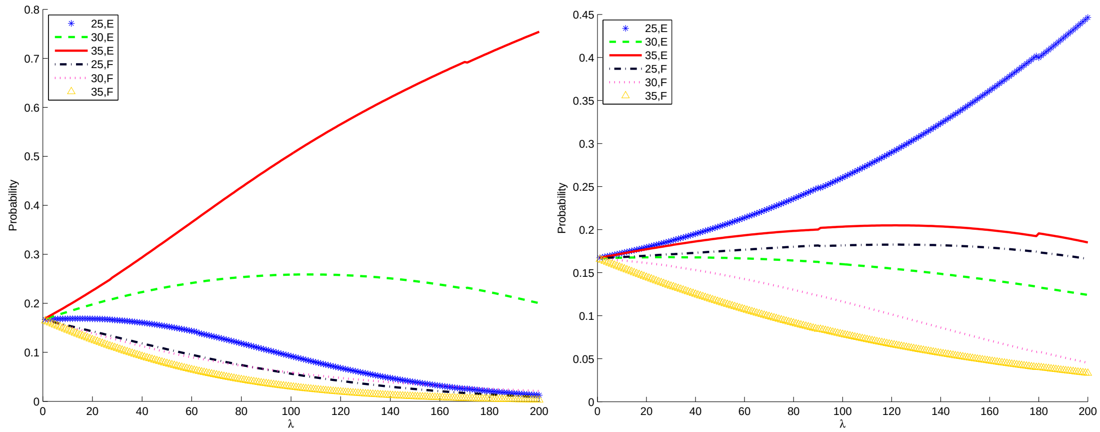
To model the quantal response equilibrium, we define the expected payoff of using strategy s_i when playing with computer buyers as:

$$u_i(s_i) = \lambda \left[\sum_{-i} u\left(s_i, s_{-i}\right) \pi_{-i}\left(s_{-i}\right) \right] + \epsilon_{s_i}, \tag{3.1}$$

where $u(s_i, s_{-i})$ represents the expected payoff when the seller uses s_i and the other seller uses s_{-i}. We assume that ϵ's follow type-1 extreme value distributions. Letting $\sigma_i(u_i, u_{-i}) = prob_i(u_i, u_{-i})$, a quantal response equilibrium for the game with both sellers is any $\pi \in \Delta$ such that

$$\pi_i(s_i) = \sigma_i\left(u_i\left(\pi_{-i}\left(s_{-i}\right)\right), u_{-i}\left(\pi_i\left(s_i\right)\right)\right), \text{ for } i, -i \text{ and all } s.$$

Figure 3.6: QRE in HB and CB sessions with different λ



(a) CB sessions

(b) HB sessions

Figure 3.6 illustrates the prevalence of different seller strategies under the quantal response equilibrium model in the human and computer buyer sessions. The payoffs given in table 3.4 are directly used as sellers' payoffs for playing different strategies. In the computer session, exploding offers lead to consistently better payoffs than free-recall offers given the computer buyers' optimized play. In the human session, however, buyers consistently over-rejected exploding offers. Modifying seller payoffs to account for this over-rejection creates a new game, one where both sellers making an exploding offer with price 25 becomes an additional Nash Equilibrium. Figure 3.6(b) shows that the QRE model selects this equilibrium as the convergent equilibrium.

Result 4 *In both conditions, sellers demonstrate a reluctance to play strategies that involve the use of exploding offers. The tendency persists against human buyers, but dissipates against computer buyers who play optimal strategy. This analysis controls for the differential expected payoffs of both strategies in the human and computer buying session.*

The quantal response model provides a baseline utility framework for sellers (see equation 3.1). In order to determine whether sellers have any preferences toward exploding offers not captured in the model, we introduce a new term δ that is included in sellers' utility only if they make an exploding offer. If δ is negative (positive), than sellers are reluctant (overeager) to use exploding offers; they derive additional negative (positive) utility from making them. If δ is zero, sellers do not have a systematic bias in their use of exploding offers. As the use of exploding offers varies between sessions and also within session by period (see Figure 3.1), we introduce four terms to capture the dynamics and session effects of exploding offers. The terms δ_{H0}, δ_{HT} represent the delta term in the first and last periods of the human buyer session, respectively; the terms δ_{C0}, and δ_{CT} represent the delta term in the first and last periods of the computer buyer session, respectively. All other periods are convex combinations of their respective sessions' two terms. Similar terms are constructed for λ in the QRE model: λ_{H0}, λ_{HT}, λ_{C0}, and λ_{CT}. Equation (3.2) provides this utility model for subject i in period t.

$$u_{it}\left(s_{it}\right) = \left(\frac{20-p}{19}u_{X0}\left(s_{it}\right) + \frac{p-1}{19}u_{XT}\left(s_{it}\right)\right) \tag{3.2}$$

$X \in \{C, H\}$ represents two treatments.

where

$$u_{C0}\left(s_{it}\right) = \lambda_{C0}\left(\sum_{-i}\hat{u}\left(s_{it}, s_{-i}\right)\pi_{-i}\left(s_{-i}\right) + \delta_{CO}\mathcal{I}(\text{exploding offer})\right)$$

$$u_{CT}\left(s_{it}\right) = \lambda_{CT}\left(\sum_{-i}\hat{u}\left(s_{it}, s_{-i}\right)\pi_{-i}\left(s_{-i}\right) + \delta_{CT}\mathcal{I}(\text{exploding offer})\right)$$

$$u_{H0}\left(s_{it}\right) = \lambda_{H0}\left(\sum_{-i}\hat{u}\left(s_{it}, s_{-i}\right)\pi_{-i}\left(s_{-i}\right) + \delta_{H0}\mathcal{I}(\text{exploding offer})\right)$$

$$u_{HT}\left(s_{it}\right) = \lambda_{HT}\left(\sum_{-i}\hat{u}\left(s_{it}, s_{-i}\right)\pi_{-i}\left(s_{-i}\right) + \delta_{HT}\mathcal{I}(\text{exploding offer})\right)$$

Table 3.5: Estimation Result

	Computer Session	Human Session
λ_{X0}	0.964***	1.427***
	(0.149)	(0.205)
λ_{XT}	0.748***	3.272***
	(0.139)	(0.212)
δ_{X0}	−2.017***	−1.106***
	(0.202)	(0.232)
δ_{XT}	−0.595	−1.442***
	(0.308)	(0.269)
LL	-1036.710	-710.265

[1] $X \in \{C, H\}$ represents computer buyer treatment or human buyer treatment.

Table 3.5 provides parameter estimates for this model. Initially, in both the human and computer conditions sellers were reluctant to use exploding offers. Both coefficients, δ_{CO} and δ_{HO}, are significantly less than 0 ($p < 0.001$). By period 20, however, sellers' reluctance to use exploding offers on human buyers persists (δ_{HT} is significantly less than 0, $p < 0.001$), but sellers show no reluctance to use exploding offers on computer buyers (δ_{CT} is not significantly less than 0, $p \approx 0.054$). The terms of this "exploding offer aversion" are economically significant. Literally interpreting the coefficients suggests that sellers experienced a disutility equivalent to \$1.10–\$1.40 in possible earnings the use of exploding offers against human buyers.[13] Full analysis of both buyer and seller earning are found in the next result.

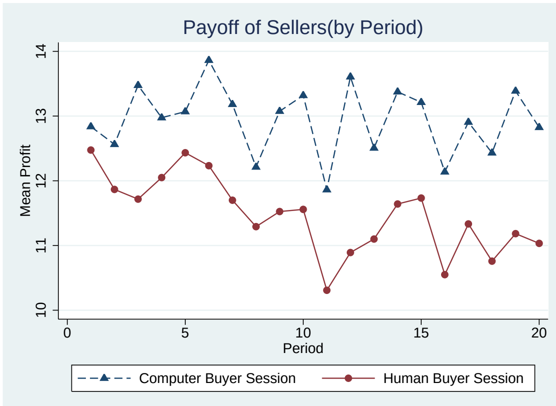
The λ term in the human-buyer condition is generally greater than the corresponding term in the computer-buyer condition. An F-test rejects the joint hypothesis of both $\lambda_{CO} = \lambda_{HO}$ and $\lambda_{CO} = \lambda_{HO}$ ($p < 0.001$). Further, the estimate

[13]This is a tricky point. Sellers are only paid based on one round of twenty so no one decision to avoid an exploding offer has an expected cost of \$1.10–\$1.40. However, the pattern of behavior of *continually* avoiding exploding offers does cost sellers losses of this magnitude.

of λ increases in the human buyer session over the 20 periods (δ_{H0} is significantly greater than δ_{HT}, $p < 0.001$), but if anything the estimate decreases in the computer buyer session. The λ is usually interpreted as the "noisiness" parameter in a QRE model; our estimation results indicate that sellers play more "accurately" with human buyers. This may be due to two facts. First, we used empirical play information in the estimation. The empirical play is determined by seller-buyer interactions. Second, sellers may face less payoff uncertainty when playing with human buyers, given that they rejected high price offers or exploding offers with higher probability.

Result 5 *Sellers in the human-buyer condition earn less than sellers in the computer-buyer condition. Human buyers are better off compared with computer buyers in the computer session. The aggregate surplus of the human session is significantly lower than that of the computer session.*

Result 5 shows the primary difference between human buyers and the optimal play, utilized by computer buyers, is the human buyers' increased tendency to reject exploding offers. This difference in play leads to great differences in earnings. Sellers earn more on average each period with computer buyers ($12.94) than human buyers ($11.47). Both a parametric t-test and non-parametric rank sum test, collapsed to subject level, confirm sellers earn more in the computer buyer session ($p < 0.001$ for both tests). Human buyers earn significantly less on average than optimal strategy given sellers' choice ($16.254 vs. $16.794, $p < 0.001$ for both tests). Meanwhile, human buyers' earnings are significantly improved compared with computer buyers ($16.254 vs. $15.224, $p < 0.001$ for both tests). These results cannot be due to different realizations of buyer valuations; both computer buyers and human buyers received exactly the same draws of a random distribution of



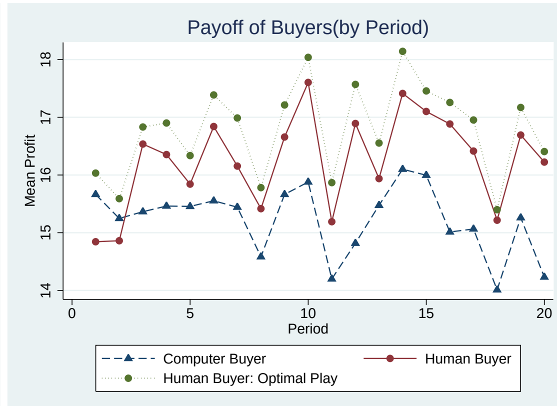


Figure 3.7: Profit Comparison

valuations.

Figures 3.7(a) and (b)—which show the average earnings of sellers and buyers, respectively, in each condition, over the twenty periods of the experiment—demonstrate these differences in payoffs persist. There is evidence to suggest the difference between seller earnings in human- and computer-buyer conditions is actually *increasing* over the course of the experiment. Between the two conditions, the average difference in seller earnings is \$1.172 in periods 1–10; the average difference in seller earnings is \$1.771 in periods 11–20. A difference-in-difference regression reveals this result is significant (\$0.60, $p < 0.001$). Similarly, buyers' profit difference on average is \$1.582 and it is increasing over time ($p = 0.002$). There is also a downward trend in the average profit for computer buyers ($p = 0.029$). [14]

The aggregate market surplus for both buyers and sellers is higher for the computer buyer treatment. Both t-test($p = 0.019$) and rank-sum test ($z = 0.011$) at group level show the difference is statistical significant. In monetary value, the average difference is \$0.44–or 1.6% of the average surplus each period.

[14]The earnings for computer buyers were not recorded at individual level; the difference is significant at group level.

3.6 Conclusion

Charness and Rabin (2002) concludes that subjects may be motivated by reciprocity in addition to distributive differences in their payoff functions. We are interested in the performance of exploding offer strategies in a search market. In this setting, from both sellers' side and buyers' side, an exploding offer can be viewed as an intention based device. Since buyers observe sellers' conducts before making choices, an exploding offer may signal negative intention and lead buyers to negatively reciprocate that even they can be better off without rejecting an exploding offer. For the seller side, sellers simultaneously move in the market, and they may expect that exploding offers may trigger more intense competition. The experiment results support our conjecture.

In our experiment, theory predicts that with only monetary incentives, the equilibrium involves sellers using highest price and exploding offers. Yet controlled experiments with human buyers deviate from this prediction. In the human buyer session, we find evidence that buyers systematically over-reject exploding offers. This fact confirms a negative reciprocity story: buyers choose to deviate from their best response due to the sellers' aggressive strategy choices. On the other hand, sellers hesitated to use exploding offer as competing tools even when exploding offers are optimal.

4. CONCLUSION

In the previous two sections, we demonstrate that without considering the additional behavioral effects, our market/ demand analysis can be different, which leads to distinct policy implications. The findings or models may have potentials to be applied in the field. For example, the model of brand satiation may help firms' direct marketing programs by providing information on consumers who are more likely (and more willing) to switch. The experiments on exploding offers may provide information for policy makers to evaluate the welfare change or at least motivate more investigations in the field. Our papers may also provide insights for theory development. For example, Optimal pricing under diversified preference can be an important research topic.

Our analysis relies on detailed individual level data sets as well as experimental designs. With individual level data sets, we may not only test the core behavioral assumptions of theories, but also build empirical models based on individual behavioral patterns. However, detailed data sets are not panaceas for identification problems. It is possible that consumers' choices are subjected to other unobserved factors. We remain cautious about our conclusions: our source of identification primly comes from consumers' unexplained back-and-forth switches. We define "brand satiation" as a phenomenon rather than a mechanism. With appropriate experimental designs, we achieve higher credibility by controlling for observed characteristics and by randomizing over unobserved characteristics. We interpret the "exploding offer aversion" as a fundamental preference component that is likely to be held in the field.

Similar approaches can be applied to other individual markets to investigate unexplained market phenomenons and test existing theories, especially with better data collecting technologies and experimental tools. We think those empirical studies can contribute to both real world applications and theory developments.

REFERENCES

Daniel A Ackerberg. Empirically Distinguishing Informative and Prestige Effects of Advertising. *RAND Journal of Economics*, 32(2):316–33, Summer 2001.

Daniel A. Ackerberg. Advertising, learning, and consumer choice in experience good markets: an empirical examination. *International Economic Review*, 44(3): 1007–1040, 2003. ISSN 1468-2354. doi: 10.1111/1468-2354.t01-2-00098.

Susan Athey and Guido W. Imbens. Discrete choice models with multiple unobserved choice characteristics. *International Economic Review*, 48(4):1159–1192, 2007. ISSN 1468-2354. doi: 10.1111/j.1468-2354.2007.00458.x.

Bart J. Bronnenberg, Michael W. Kruger, and Carl F. Mela. Database paper-the iri marketing data set. *Marketing Science*, 27(4):745–748, 2008. doi: 10.1287/mksc.1080.0450.

David Brownstone and Kenneth Train. Forecasting New Product Penetration with Flexible Substitution Patterns. *Journal of Econometrics*, 89(1-2):109–129, November 1998.

John Calfee, Clifford Winston, and Randolph Stempski. Econometric Issues in Estimating Consumer Preferences from Stated Preference Data: A Case Study of the Value of Automobile Travel Time. *The Review of Economics and Statistics*, 83(4):699–707, November 2001.

Gregory S. Crawford and Matthew Shum. Uncertainty and learning in pharmaceutical demand. *Econometrica*, 73(4):pp. 1137–1173, 2005. ISSN 00129682.

Jean-Pierre Dub, Gnter J. Hitsch, and Peter E. Rossi. State dependence and alternative explanations for consumer inertia. *The RAND Journal of Economics*, 41(3): 417–445, 2010. ISSN 1756-2171. doi: 10.1111/j.1756-2171.2010.00106.x.

Tlin Erdem and Michael P. Keane. Decision-making under uncertainty: Capturing dynamic brand choice processes in turbulent consumer goods markets. *Marketing Science*, 15(1):1–20, 1996. doi: 10.1287/mksc.15.1.1.

Tlin Erdem, Michael P. Keane, and Baohong Sun. A dynamic model of brand choice when price and advertising signal product quality. *Marketing Science*, 27 (6):1111–1125, 2008. doi: 10.1287/mksc.1080.0362.

Wesley R. Hartmann. Intertemporal effects of consumption and their implications for demand elasticity estimates. *Quantitative Marketing and Economics*, 4(4):325–349, 2006. ISSN 1570-7156. doi: 10.1007/s11129-006-9012-2.

James J Heckman. Heterogeneity and state dependence. pages 91–140, 1981.

Michael P Keane. Modeling heterogeneity and state dependence in consumer choice behavior. *Journal of Business & Economic Statistics*, 15(3):310–327, 1997.

Kelvin J. Lancaster. A New Approach to Consumer Theory. *Journal of Political Economy*, 74:132, 1966.

Daniel McFadden and Kenneth Train. Mixed mnl models for discrete response. *Journal of Applied Econometrics*, 15(5):447–470, 2000. ISSN 1099-1255. doi: 10.1002/1099-1255(200009/10)15:5<447::AID-JAE570>3.0.CO;2-1.

Richard D. McKelvey and Thomas R. Palfrey. Quantal response equilibria for normal form games. *Games and Economic Behavior*, 10(1):6 – 38, 1995. ISSN 0899-8256. doi: http://dx.doi.org/10.1006/game.1995.1023.

David Revelt and Kenneth Train. Customer-specific taste parameters and mixed logit: Households' choice of electricity supplier. *Department of Economics, UCB*, 2000.

Ricardo Ribeiro. Consumer Demand for Variety: Intertemporal Effects of Consumption, Product Switching and Pricing Policies. *MPRA Working Paper*, (25812), August 2010.

Peter E. Rossi, Greg M Allenby, and Robert Edward McCulloch. *Bayesian Statistics and Marketing*. J. Wiley & Sons, 2005.

PB Seetharaman, Andrew Ainslie, and Pradeep K Chintagunta. Investigating household state dependence effects across categories. *Journal of Marketing Research*, pages 488–500, 1999.

Kenneth E. Train. *Discrete Choice Methods with Simulation*. Cambridge University Press, 2nd edition, Autumn 2009.

APPENDIX A

CONSUMERS' BRAND DIVERSITY SEEKING BEHAVIOR

A.1 Brand Price Issue of ERIM Yogurt Data Sets

A.1.1 Introduction

Price information for each product is not perfect. First of all, only transaction price is recorded. Second, each brand may have certain number of sub-brands, and the sub-brands may not be in the market for all 3-year-period. Third, at store level, we don't have products availability information. Also, coupon should be considered.

We want to capture the brand value using a brand price index. The simplest way is to just calculate weekly average price for all the products within that brand, weighted by the sample size at store level. In this case all individual in the dataset will face the same brand price at the same week. The estimation results with this specification have large negative log likelihood value. A more elaborated approach is to search for weekly store level price; the approach was used in the application part of Athey&Imbens(2007). Moreover, they treat missing value as due to the availability issue.

A.1.2 Process Price Information in the ERIM Data Sets

For the potential concerns on price, we offer some more data evidence for your consideration. Table A.1 sum up the store level weighted average price for all purchasing records within that brands, the problem is that the price variation may be only due to the change of market share of certain products (i.e. some low price products leave the market). To rule out the possibility, we list the possible brand categories within a brand with their frequency and average price in Table A.2 and A.3. By category, we mean a group of products that may have similar price. We can see that major brands like Yoplait and Dannon tend to have more sub-categories or sub-brands. Some of those sub-categories did not last for the whole 3 years of the dataset, some of them are newly introduced in the middle of the dataset. To avoid the effect of those products in calculating store level average price, we drop that price information (plus they tend to have much lower purchasing frequency).

In addition, the average price may be problematic if we don't consider the store effects. For some stores the average prices tend to be relatively stable, while the aggregate average price tends to be increasing in the 3 years(with or without consideration of the brand category variation). So we calculate the store level average price using information from main brand categories. Figure A.1 demonstrates the price trend using Yoplait.

Table A.1: Average Price for each Brands (obs:59201)

	1986	1987	1988
brand1	0.5198	0.5478	0.5710
brand2	0.4118	0.4364	0.4507
brand3	0.4145	0.4323	0.4467
brand4	0.3936	0.3271	0.3397
brand5	0.2682	0.2765	0.2759
brand6	0.3398	0.2703	0.2809
brand7	0.2625	0.2562	0.2775
brand8	0.3211	0.3402	0.3492

Table A.2: Information of Brand Sub-categories: ERIM Data Sets

Index	Brand	Possible Sub-category
1	YPLT	YPLT FOB, YPLT BKFST, YPLT 150, YPLT Y-C DST, YPLT ORIGINAL, YPLT CUSTARD
2	WW	WW NF
3	DN	DN FF MP , DN FRSH FLVR, DN HRTY N&R, DN , DN SP, DN XS
4	NORDICA	NORDICA, NORDICA SW, NORDICA LF FOB
5	QCH	QCH, QCH LF, QCH SW
6	WBB	WBB
7	CTL	CTL BR/LF, CTL BR BKFST, CTL BR EURO

Table A.3: Information of Brand Sub-categories 2: ERIM data sets

1.YPLT	Subbrand	Freq	mean price	St.d	note
1	ORIG	8,003	0.607	0.003	
2	FOB	438	0.531	0.001	1st yr
3	CUSTARD	3,079	0.303	0.003	
4	Y-C DST	612	0.543	0.002	1st, 2nd yr
5	BKFST	422	0.674	0.006	1st yr
6	150	880	0.624	0.005	2nd, 3rd yr
3.DN					
1	DN/DN MP	6,876	0.429	0.001	
3	FRSH FLVR	867	0.417	0.003	
4	HRTY N&R	5	0.503	0.008	
5	SP	34	0.512	0.020	1st yr
6	XS	255	0.508	0.006	1st yr,few 2nd
4.NORDICA					
1	None	260	0.246	0.003	2nd, 3rd yr
2	SW	7949	0.342	0.001	
3	LF FOB	5786	0.344	0.001	
5.Q CH					
1	None	1,560	0.276	0.001	
2	QCH LF	2,346	0.266	0.001	
3	QCH SW	134	0.277	0.004	
7. CTL BR					
1	None/LF	7,441	0.263	0.000	
2	N SW	88	0.309	0.004	mostly 1988

[1] The periods of records are listed in the note column.

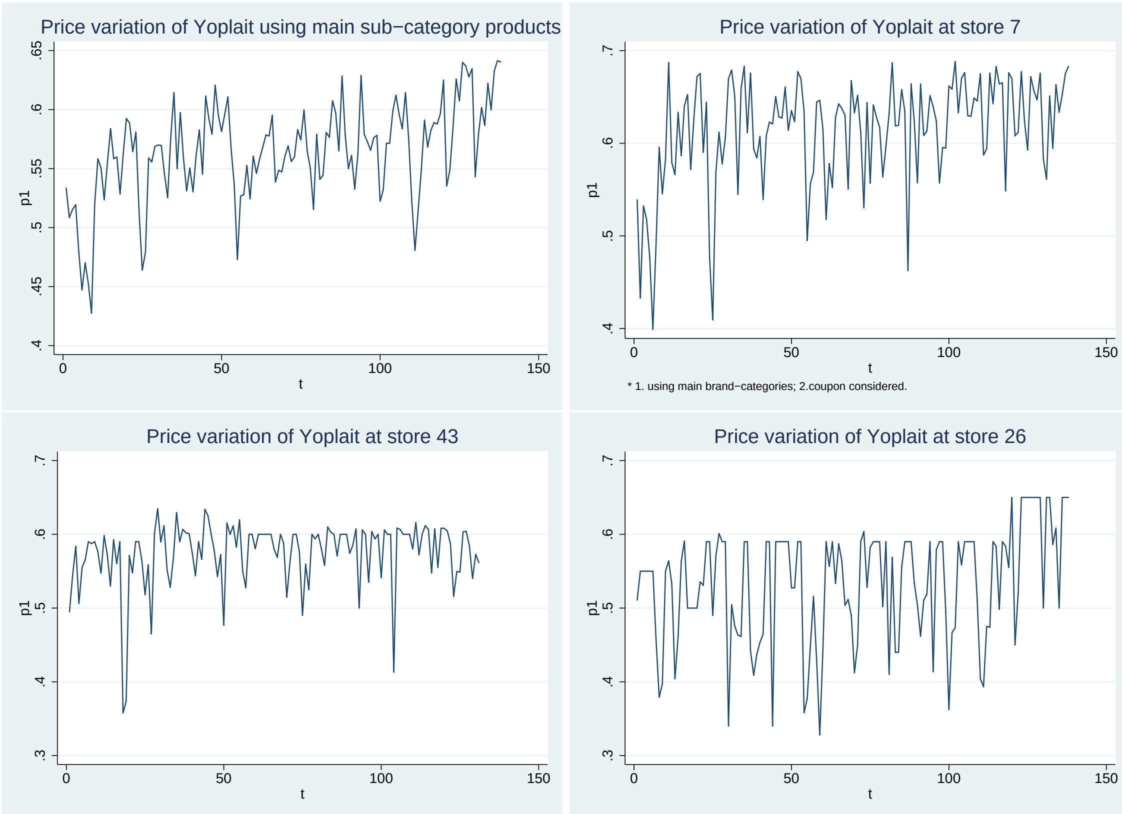


Figure A.1: Price variation

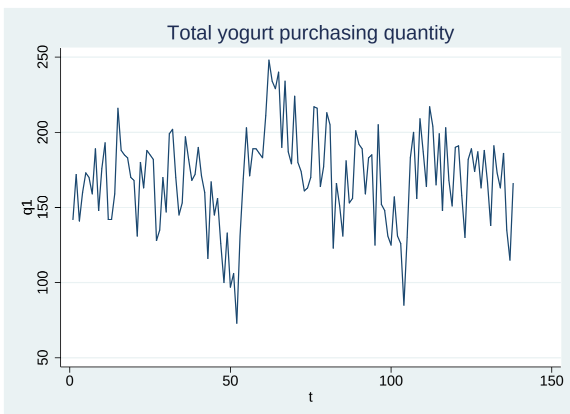


Figure A.2: Total Yogurt Purchasing

A.2 Brand Price Issue of IRI Yogurt data sets

In the IRI data sets, we have a larger sub-brand category for each brand and a better definition of the sub-brand. IRI data sets uses a 5-level[1] measure to categorize each product. Our choice model is built on level 4 which is the "vendor" level. Table A.4 shows the relationship between "vendor" and "brand". In our paper, we group similar brands under the same vendor and we refer each specific brand as a sub-brand to that vendor. Comparing with ERIM data sets (in which, we used a similar but a heuristic way to distinguish among sub-brands.), we can see that the sub-brand categories have expanded significantly.

Table A.4: Information of Brand Sub-categories: IRI Data Sets

Brand	Subbrand	Share	Brand	Subbrand	Share
1. COLOMBO			5. OLD HOME		
	COLOMBO	2.830		OLD HOME	30.190
	COLOMBO CLASSIC	49.740		OLD HOME 100 CALORIE	31.550
	COLOMBO LIGHT	47.430		OLD HOME FOR KIDS	8.910
2. BREYERS				OLD HOME GAYMONT	24.290
	BREYERS	54.720		OLD HOME SHAKERS	0.700
	BREYERS CRME SAVERS	25.810		OLD HOME SMOOTHIE	0.610
	BREYERS FRUIT PARFAIT	0.780		OLD HOME VELVET DELIGHT	3.740
	BREYERS LIGHT	11.240	6. STONYFIELD FARM		
	BREYERS LIGHT N LIVELY	2.240		STONYFIELD FARM	78.940
	BREYERS SMOOTH AND CREAMY	5.210		STONYFIELD FARM KIDS	2.330
3. DANNON				STONYFIELD FARM ORGANIC	4.260
	DANNON	19.070		STONYFIELD FARM OSOY	1.650
	DANNON CREAMY FRUIT BLENDS	4.710		STONYFIELD FARM PLANET PROTEC	2.240
	DANNON DANIMALS	3.820		STONYFIELD FARM SQUEEZERS	3.710
	DANNON DANIMALS DRINKABLE	5.150		STONYFIELD FARM YOBABY	5.400
	DANNON DOUBLE DELIGHTS	0.370		STONYFIELD FARM YOSELF	1.480
	DANNON FAT FREE	1.780	7. WELLS BLUE BNNY		
	DANNON FRUIT ON THE BOTTOM	6.470		WELLS BLUE BNNY DISNY SWRLN M	0.720
	DANNON FRUSION	0.880		WELLS BLUE BNNY DISNY YO-PA	0.320
	DANNON LA CRME	5.560		WELLS BLUE BNNY LITE 85	98.950
	DANNON LA CRME MOUSSE	0.550	9. YOPLAIT		
	DANNON LIGHT N FIT	40.410		YOPLAIT EXPRESSE	1.190
	DANNON LIGHT N FIT CREAMY	5.480		YOPLAIT GO GURT	6.220
	DANNON LIGHT N FIT SMOOTHIE	0.450		YOPLAIT GRANDE	0.070
	DANNON NATURAL	0.300		YOPLAIT KIDS	0.710
	DANNON NATURAL FLAVORS	1.290		YOPLAIT LIGHT	20.530
	DANNON PREMIUM	0.220		YOPLAIT NOURICHE	1.330
	DANNON SPRINKLINS	1.190		YOPLAIT ORIGINAL	37.710
	DANNON WHIPPED	2.320		YOPLAIT THICK AND CREAMY	14.570
4. KEMPS				YOPLAIT TRIX	6.150
	KEMPS CLASSIC	17.880		YOPLAIT WHIPS	11.070
	KEMPS FREE	29.840		YOPLAIT YUMSTERS	0.460
	KEMPS NONFAT 100 CALORIES	29.990			
	KEMPS SPOONZ N YOGURT	0.510			
	KEMPS YO J	8.740			
	KEMPS YO STIX	4.180			
	KEMPS YOGURT JRS	8.860			

[1] Large category(Yogurt), small category (Yogurt/ Yogurt drinks), parent company, vendor, brand

A.3 Brand Experience

Most of the consumers are experienced with multiple brands. In figure A.3 and A.4, we show the histogram of consumers' experience within yogurt market. The horizontal axis represents the number of brands that consumers have attempted (at least twice) during the 3 years. More than 50% of the consumers involve purchasing 3 or 4 brands. The high level of brand experience combined with the unexplained switches in the market may suggest that, instead of learning effects, diversity seeking behavior also exists in the market.

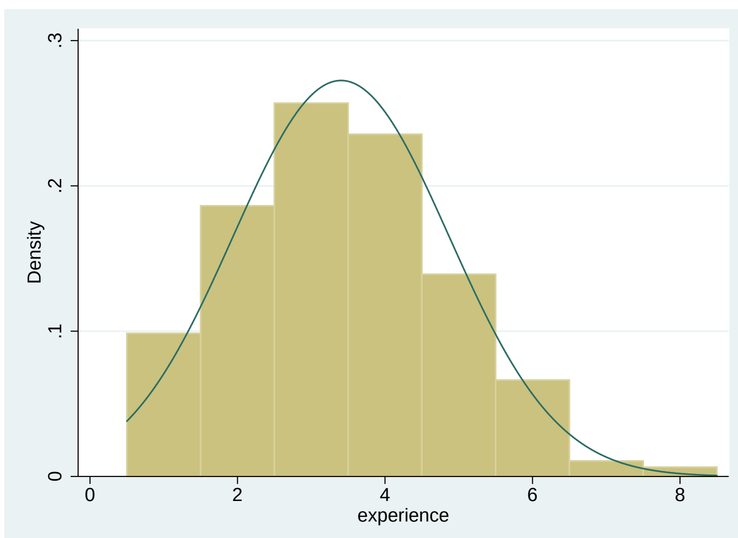


Figure A.3: Consumers' Experience: Sioux Falls

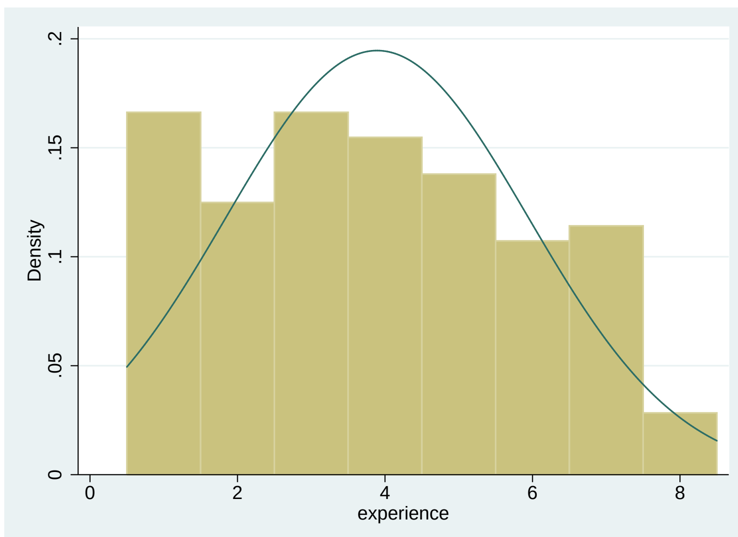


Figure A.4: Consumers' Experience: Eau Claire & Pittsfield

APPENDIX B

SOCIAL PREFERENCE AND BUYERS’ RESPONSE

B.1 Instructions Used in the Experiment

We provide here the instructions used in the 2 treatments, a treatment with computer buyers and a treatment with human buyers. The instructions were both read aloud and seen from the screen. After the instructions, participants were required to answer some questions to ensure that they understood how to play the game.

B.1.1 Sessions with Computer Buyers

Instructions

Today, you will be participating in an economics experiment. The experiment tests how people make decisions involving money. The decisions you make in this experiment will determine your earnings, which will be converted to cash and paid at the end of this session. You will make all of these decisions on the computer in front of you. Please pay attention to these instructions so you will understand how to make money.

If you have any questions, please raise your hand, and the experimenter will quietly answer your question. Please do not talk to any other person during this experiment.

Each of you will be randomly assigned into a group of two participants in each period. You will be a ”seller” in a market of 2 ”sellers”. There are 24 **”computer buyers”** in the market and they will visit the sellers in the market sequentially. (A **computer buyer** is a piece of computer code which tries to maximize its expected payoff from purchasing items from the sellers). As a seller, you are endowed with supply of items and will choose a price and an offer type (will explain later) for all ”computer buyers”. Each seller has enough items to sell to every buyer and the **production cost** is 0. ”Computer buyers” will randomly encounter a seller's item and choose to buy that item or search to examine the other seller's item. They have **zero search cost**. Depending on the terms of the first seller's offer, examining the second seller's item may cause the first seller's offer to be no longer available.

The stage of a game

You are a seller in a market of 2 sellers and 24 ”computer buyers”. Each of the computer buyers can purchase at most 1 unit in each period.

You and the other seller will choose to set a price which can be 25, 30 or 35. Along with setting the price, you can also choose one of two offer types. A price and an offer type will be the same for all buyers in the market. These offer types will be explained on the next page.

Each seller will earn points equal to the price multiplied by the number of items the buyers buy from you.

Each of the buyers has specific, randomly determined, point values for each seller's item. This value is randomly determined from a distribution that will be explained in more detail later.

If a buyer buys an item, she will earn points equal to her point value for that item minus the item's price.

Each computer buyer will immediately learn the prices and the offer types of both sellers. However, it will initially only learn a point value of the item from the first seller. For each buyer, a computer program will decide whether to buy from the initial seller or to search the market to discover its value for the other seller's item. At this point, the buyer will have the option to buy from the second seller and **may** have the option to buy from the first seller.

Two types of offers

You can make two types of offers:

Offer A: if a buyer passes on the offer, the offer will be no longer available for her (but still available for others). In other words, Offer A is only accessible at the initial visit for each buyer.

Offer B: if a buyer passes the offer, she can come back later to purchase. In other words, Offer B is always available to buyers.

Value of each item

Each buyer's value of each item is independently and randomly drawn from a deck of 8 cards with values of 10, 25, 40, 55, 65, 65, 70, 70.

In other words, each buyer's value will have a probability of 1/8 to be 10, 25, 40, 55 for each of these values and 2/8 to be 65, 70. Each time when a buyer (computer buyer) makes a draw, she makes a draw from a **new** deck of 8 cards. (independently and randomly drawn)

Your payment

You will get paid for only one period. After 20 periods of the game, you will need to draw a number to determine the period. You will get paid based on the profit you have made in that period. Since you do not know which period the payment will be based on, you should do your best for every period. The conversion rate for the game is one point = 4 cents. In other words, if you earn x points, you will get 4*x cents + $5 for a show-up payment.

Summary

You are a seller in a market of 2 sellers and 24 computer buyers. In each period, you need to choose a price and an offer type for your items. The price and the offer type will be the same for all buyers in the market. Remember that, an offer of type A will not be available to any buyers who examine your item first and choose to examine the item of the other seller. An offer of type B will always be available.

After you have made a decision, 24 computer buyers will visit the market and make purchase attempts:

1. All buyers will immediately learn the prices and offer types of both sellers.

2. Half of the buyers (12 buyers) will visit you first and immediately learn the value of your item. These values are determined at random from 8 cards of 10, 25, 40, 55, 65, 65, 70, 70.

3. The above buyers will make decisions whether to buy your item or examine the item of the other seller. You will earn points equal to the price you charge for every item you sell.

4. The other 12 buyers will visit and learn the value of the other seller's item first. They may choose to buy that item immediately or alternatively to examine the value of your item. You will earn points equal to the price you charge for every item you sell.

5. If you use an offer B, buyers who examine your item first (in step 3), and choose to examine the item of the other seller, will still have an opportunity to buy your item. On the other hand, if you use an offer A, those buyers will not have the opportunity to buy your item. That is Offer A only allows initial purchase, not a later recall.

This process will be repeated for twenty periods. You will be randomly matched with **different** sellers in each period.

The payment will be randomly paid from one period and the conversion rate is one point = 4 cents.

2. Sessions with Human Buyers

In this treatment, each participant was assigned a role as either a seller or a buyer. All participants were given the same instructions until the summary page (the last page of the instructions) that they were told their roles in the experiment.

Instructions

Today, you will be participating in an economics experiment. The experiment tests how people make decisions involving money. The decisions you make in this experiment will determine your earnings, which will be converted to cash and paid at the end of this session. You will make all of these decisions on the computer in front of you. Please pay attention to these instructions so you will understand how to make money.

If you have any questions, please raise your hand, and the experimenter will quietly answer your question. Please do not talk to any other person during this experiment.

There are 24 participants in the session today. 16 participants will be assigned as buyers and 8 participants will be assigned as sellers. You will know your assigned role when we get into a summary page. Your role will be fixed for the entire 20 periods. In each period, there are 4 markets and each market consists of 2 sellers and 4 buyers. You will be randomly selected into one of the 4 markets.

There are 2 sellers and 4 buyers in each market. Each buyer will make 6 purchase attempts, so in total there are 24 purchase attempts. For each attempt, each buyer will visit the sellers in the market sequentially. Sellers are endowed with supply of items and will choose a price and an offer type (will explain later) for all buyers. Each seller has enough items to sell to every buyer and the **production cost** is 0. Buyers will randomly encounter a seller's item and choose to buy that item or search to examine the other seller's item for 6 attempts. 2 buyers will visit one firm first and the other 2 buyers will visit the other firm first. In other words, 12 purchase attempts will visit one seller first and the other 12 purchase attempts will visit the other seller first. Each buyer has **no cost** to search. Depending on the terms of the first seller's offer, examining the second seller's item may cause the first seller's offer to be no longer available.

Decisions

There are 2 sellers and 4 buyers in each market. Each buyer will make 6 purchase attempts, so in total there are 24 purchase attempts.

The 2 sellers will choose to set a price which can be 25, 30 or 35. Along with setting the price, the sellers can also choose one of two offer types. A price and an offer type will be the same for all buyers in the market. These offer types will be explained on the next page.

In each attempt, each buyer has a specific, randomly determined, point value for each seller's item. This value is randomly determined from a distribution that will be explained in more detail later.

Each buyer will immediately learn the prices and the offer types of both sellers. However, for each attempt she will initially only learn a point value for the item of one seller. A buyer must decide whether to buy from the initial seller or search the market to discover a point value for the item of the other seller. At this point, a buyer will have the option to buy from the second seller and may have the option to buy from the first seller.

Each seller will earn points equal to her price multiplied by the quantity sold.

Each buyer will earn points equal to her point value for that item minus the item's price. For example, if a buyer buys an item worth x points, at a price of y, she will earn x-y points. A buyer will earn 0 points if she does not buy an item.

Two types of offers

Sellers can make two types of offers:

Offer A: if a buyer passes on the offer, the offer will be no longer available for her (but still available for others). In other words, Offer A is only accessible at the initial visit for each buyer.

Offer B: if a buyer passes the offer, she can come back later to purchase. In other words, Offer B is always available to buyers.

Value of each item

Each buyer's value of each item is independently and randomly drawn from a deck of 8 cards with values of 10, 25, 40, 55, 65, 65, 70, 70.

In other words, each buyer's value will have a probability of 1/8 to be 10, 25, 40, 55 for each of these values and 2/8 to be 65, 70. Each time when a buyer (computer buyer) makes a draw, she makes a draw from a **new** deck of 8 cards. (independently and randomly drawn)

Your payment

Each seller will get paid for only one period. After 20 periods of the game, each seller will need to draw a number (from 1 to 20) to determine a period. She will get paid based on the profit she has made in that period.

Each buyer will get paid for only one attempt in one period. Similar to sellers, each buyer needs to draw 2 numbers at the end to determine a period (from 1 to 20) and an attempt (from 1 to 6). She will get paid based on the profit she has made with that attempt in that period.

Since you do not know which period and attempt (for buyers) the payment will be based on, you should do your best for every period and every attempt. The conversion rates are one point = 4 cents for sellers and one point = 50 cents for buyers. In other words, if you earn x points, you will earn 4*x cents + $5 for a show-up payment if you are a seller and 50*x cents + $5 for a show-up payment if you are a buyer.

Sellers' summary

Summary (You are a Seller)

As a seller you will choose a price and an offer type for your items. The price and the offer type will be the same for all buyers in the market. An offer of type A will not be available to any buyers who examine your item first and choose to examine the item of the other seller. An offer of type B will always be available for buyers.

After you have made your pricing decisions, 24 purchase attempts from 4 participants will visit the market and make purchase attempts:

1. All buyers will immediately learn the prices and the offer types of both sellers.

2. Half of the buyers (12 attempts from 2 participants) will visit you first and immediately learn the value of your item. These values are determined at random from 8 cards of 10, 25, 40, 55, 65, 65, 70, 70.

3. The above buyers will make decisions whether to buy your item or examine the item of the other seller. You will earn points equal to the price you charge for every item you sell.

4. The other 12 purchase attempts (from the other 2 participants) will visit and learn the value of the other seller's item first. They may choose to buy that item immediately or alternatively to examine the value of your item. You will earn points equal to the price you charge for every item you sell.

5. If you use an offer B, buyers who examine your item first (in step 3), and choose to examine the item of the other seller, will still have an opportunity to buy your item. On the other hand, if you use an offer A, those buyers will not have the opportunity to buy your item. That is Offer A only allows initial purchase, not a later recall.

This process will be repeated for twenty periods. You will be randomly matched with **different** seller and buyers each period.

The payment will be randomly paid from one period and the conversion rate is one point = 4 cents.

The payment for buyers will be randomly paid from one item in one period and the conversion rate is one point = 50 cents.

Buyers' summary

Summary (You are a Buyer)

As a buyer you will make 6 purchase attempts in each period. You will immediately learn priced and offer types of both sellers. However, you will only learn the point value of the item from the first seller. You can choose to buy an item or to examine the point value of the item from the other seller.

That is, for each of the 6 purchase attempts:

1. You choose whether to buy an item from seller 1 or examine the item from seller 2. Depending on the type of offer, examining the item from seller 2 may remove the opportunity for that specific attempt to purchase from seller 1.

2. After examining the item from seller 2 and learning the point value for the item, you will have an opportunity to buy from seller 2.

3. If seller 1 makes an ”Offer B”, you will have an opportunity to return to seller 1 and buy the item. However, if seller 1 makes an ”Offer A”, you will not have that opportunity.

4. Your earning is equal to your point value for the item minus the price. If you do not buy any items, your earning will be zero for that item.

This process will be repeated for twenty periods. Your group will be randomly matched each period.

The payment will be randomly paid from one item in one period and the conversion rate is one point = 50 cents.

The payment for sellers will be randomly paid from one period and the conversion rate is one point = 4 cents.

B.1.2 Sessions with Human Buyers

In this treatment, each participant was assigned a role as either a seller or a buyer. All participants were given the same instructions until the summary page (the last page of the instructions) that they were told their roles in the experiment.

Instructions

Today, you will be participating in an economics experiment. The experiment tests how people make decisions involving money. The decisions you make in this experiment will determine your earnings, which will be converted to cash and paid at the end of this session. You will make all of these decisions on the computer in front of you. Please pay attention to these instructions so you will understand how to make money.

If you have any questions, please raise your hand, and the experimenter will quietly answer your question. Please do not talk to any other person during this experiment.

There are 24 participants in the session today. 16 participants will be assigned as buyers and 8 participants will be assigned as sellers. You will know your assigned role when we get into a summary page. Your role will be fixed for the entire 20 periods. In each period, there are 4 markets and each market consists of 2 sellers and 4 buyers. You will be randomly selected into one of the 4 markets.

There are 2 sellers and 4 buyers in each market. Each buyer will make 6 purchase attempts, so in total there are 24 purchase attempts. For each attempt, each buyer will visit the sellers in the market sequentially. Sellers are endowed with supply of items and will choose a price and an offer type (will explain later) for all buyers. Each seller has enough items to sell to every buyer and the **production cost** is 0. Buyers will randomly encounter a seller's item and choose to buy that item or search to examine the other seller's item for 6 attempts. 2 buyers will visit one firm first and the other 2 buyers will visit the other firm first. In other words, 12 purchase attempts will visit one seller first and the other 12 purchase attempts will visit the other seller first. Each buyer has **no cost** to search. Depending on the terms of the first seller's offer, examining the second seller's item may cause the first seller's offer to be no longer available.

Decisions

There are 2 sellers and 4 buyers in each market. Each buyer will make 6 purchase attempts, so in total there are 24 purchase attempts.

The 2 sellers will choose to set a price which can be 25, 30 or 35. Along with setting the price, the sellers can also choose one of two offer types. A price and an offer type will be the same for all buyers in the market. These offer types will be explained on the next page.

In each attempt, each buyer has a specific, randomly determined, point value for each seller's item. This value is randomly determined from a distribution that will be explained in more detail later.

Each buyer will immediately learn the prices and the offer types of both sellers. However, for each attempt she will initially only learn a point value for the item of one seller. A buyer must decide whether to buy from the initial seller or search the market to discover a point value for the item of the other seller. At this point, a buyer will have the option to buy from the second seller and may have the option to buy from the first seller.

Each seller will earn points equal to her price multiplied by the quantity sold.

Each buyer will earn points equal to her point value for that item minus the item's price. For example, if a buyer buys an item worth x points, at a price of y, she will earn x-y points. A buyer will earn 0 points if she does not buy an item.

Two types of offers

Sellers can make two types of offers:

Offer A: if a buyer passes on the offer, the offer will be no longer available for her (but still available for others). In other words, Offer A is only accessible at the initial visit for each buyer.

Offer B: if a buyer passes the offer, she can come back later to purchase. In other words, Offer B is always available to buyers.

Value of each item

Each buyer's value of each item is independently and randomly drawn from a deck of 8 cards with values of 10, 25, 40, 55, 65, 65, 70, 70.

In other words, each buyer's value will have a probability of 1/8 to be 10, 25, 40, 55 for each of these values and 2/8 to be 65, 70. Each time when a buyer (computer buyer) makes a draw, she makes a draw from a **new** deck of 8 cards. (independently and randomly drawn)

Your payment

Each seller will get paid for only one period. After 20 periods of the game, each seller will need to draw a number (from 1 to 20) to determine a period. She will get paid based on the profit she has made in that period.

Each buyer will get paid for only one attempt in one period. Similar to sellers, each buyer needs to draw 2 numbers at the end to determine a period (from 1 to 20) and an attempt (from 1 to 6). She will get paid based on the profit she has made with that attempt in that period.

Since you do not know which period and attempt (for buyers) the payment will be based on, you should do your best for every period and every attempt. The conversion rates are one point = 4 cents for sellers and one point = 50 cents for buyers. In other words, if you earn x points, you will earn 4*x cents + $5 for a show-up payment if you are a seller and 50*x cents + $5 for a show-up payment if you are a buyer.

Sellers' summary

Summary (You are a Seller)

As a seller you will choose a price and an offer type for your items. The price and the offer type will be the same for all buyers in the market. An offer of type A will not be available to any buyers who examine your item first and choose to examine the item of the other seller. An offer of type B will always be available for buyers.

After you have made your pricing decisions, 24 purchase attempts from 4 participants will visit the market and make purchase attempts:

1. All buyers will immediately learn the prices and the offer types of both sellers.

2. Half of the buyers (12 attempts from 2 participants) will visit you first and immediately learn the value of your item. These values are determined at random from 8 cards of 10, 25, 40, 55, 65, 65, 70, 70.

3. The above buyers will make decisions whether to buy your item or examine the item of the other seller. You will earn points equal to the price you charge for every item you sell.

4. The other 12 purchase attempts (from the other 2 participants) will visit and learn the value of the other seller's item first. They may choose to buy that item immediately or alternatively to examine the value of your item. You will earn points equal to the price you charge for every item you sell.

5. If you use an offer B, buyers who examine your item first (in step 3), and choose to examine the item of the other seller, will still have an opportunity to buy your item. On the other hand, if you use an offer A, those buyers

will not have the opportunity to buy your item. That is Offer A only allows initial purchase, not a later recall.

This process will be repeated for twenty periods. You will be randomly matched with **different** seller and buyers each period.

The payment will be randomly paid from one period and the conversion rate is one point = 4 cents.

The payment for buyers will be randomly paid from one item in one period and the conversion rate is one point = 50 cents.

Buyers' summary

Summary (You are a Buyer)

As a buyer you will make 6 purchase attempts in each period. You will immediately learn priced and offer types of both sellers. However, you will only learn the point value of the item from the first seller. You can choose to buy an item or to examine the point value of the item from the other seller.

That is, for each of the 6 purchase attempts:

1. You choose whether to buy an item from seller 1 or examine the item from seller 2. Depending on the type of offer, examining the item from seller 2 may remove the opportunity for that specific attempt to purchase from seller 1.

2. After examining the item from seller 2 and learning the point value for the item, you will have an opportunity to buy from seller 2.

3. If seller 1 makes an ″Offer B″, you will have an opportunity to return to seller 1 and buy the item. However, if seller 1 makes an ″Offer A″, you will not have that opportunity.

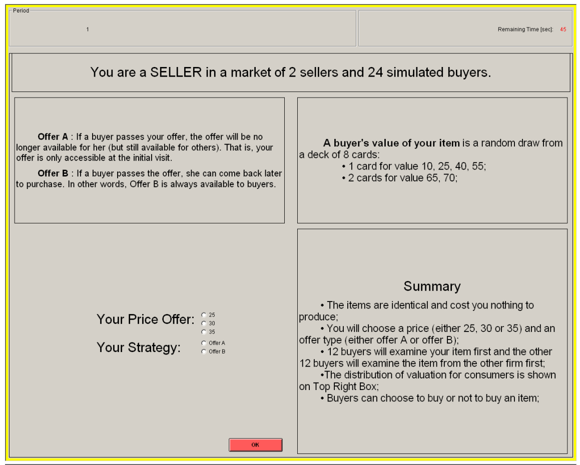
4. Your earning is equal to your point value for the item minus the price. If you do not buy any items, your earning will be zero for that item.

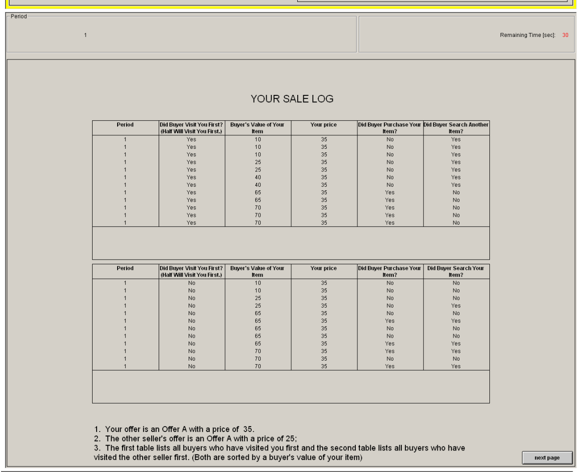
This process will be repeated for twenty periods. Your group will be randomly matched each period.

The payment will be randomly paid from one item in one period and the conversion rate is one point = 50 cents.

The payment for sellers will be randomly paid from one period and the conversion rate is one point = 4 cents.

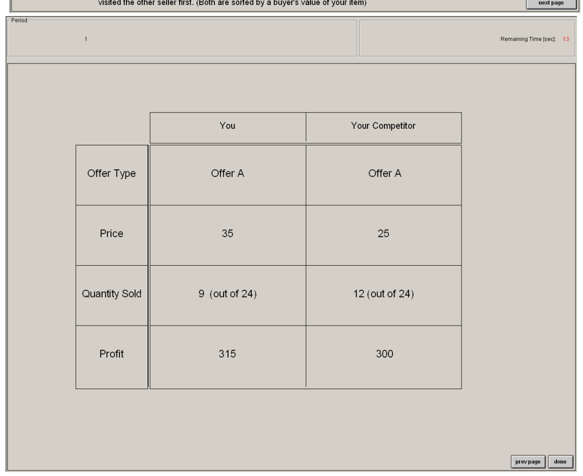
B.2 User Interface


Period
1
Remaining Time [sec]: 45
You are a SELLER in a market of 2 sellers and 24 simulated buyers.
Offer A : If a buyer passes your offer, the offer will be no longer available for her (but still available for others). That is, your offer is only accessible at the initial visit.
Offer B : If a buyer passes the offer, she can come back later to purchase. In other words, Offer B is always available to buyers.
A buyer's value of your item is a random draw from a deck of 8 cards:
• 1 card for value 10, 25, 40, 55;
• 2 cards for value 65, 70;
Your Price Offer:
25
30
35
Your Strategy:
Offer A
Offer B
OK
Summary
• The items are identical and cost you nothing to produce;
• You will choose a price (either 25, 30 or 35) and an offer type (either offer A or offer B);
• 12 buyers will examine your item first and the other 12 buyers will examine the item from the other firm first;
•The distribution of valuation for consumers is shown on Top Right Box;
• Buyers can choose to buy or not to buy an item;

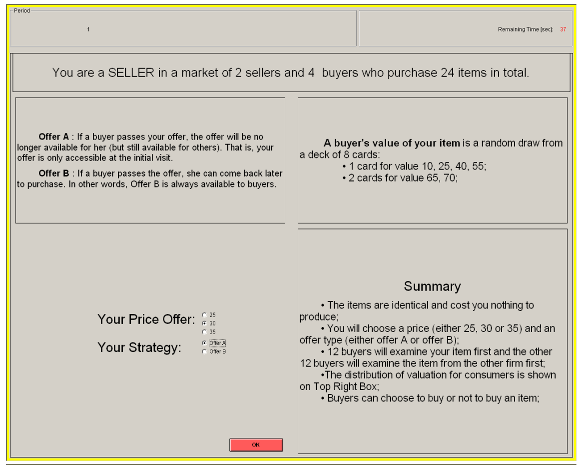
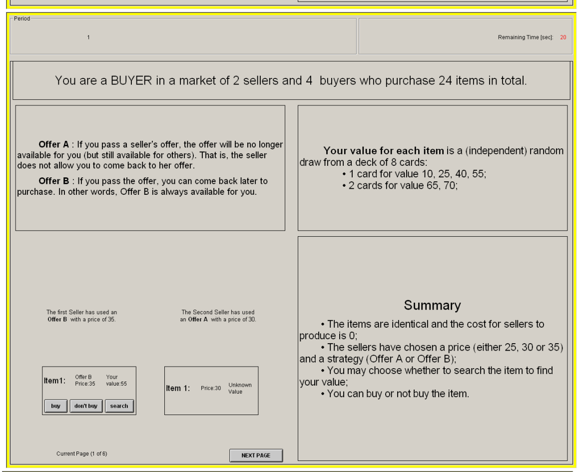
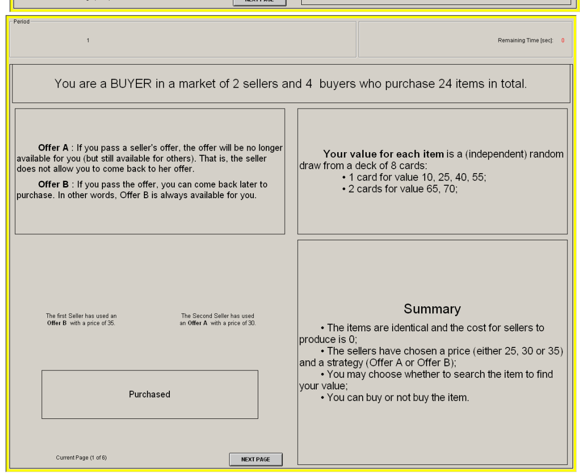

Period
1
Remaining Time [sec]: 30
YOUR SALE LOG
Period	Did Buyer Visit You First? (Half Will Visit You First.)	Buyer's Value of Your Item	Your price	Did Buyer Purchase Your Item?	Did Buyer Search Another Item?
1	Yes	10	35	No	Yes
1	Yes	10	35	No	Yes
1	Yes	10	35	No	Yes
1	Yes	25	35	No	Yes
1	Yes	25	35	No	Yes
1	Yes	40	35	No	Yes
1	Yes	40	35	No	Yes
1	Yes	65	35	Yes	No
1	Yes	65	35	Yes	No
1	Yes	70	35	Yes	No
1	Yes	70	35	Yes	No
1	Yes	70	35	Yes	No

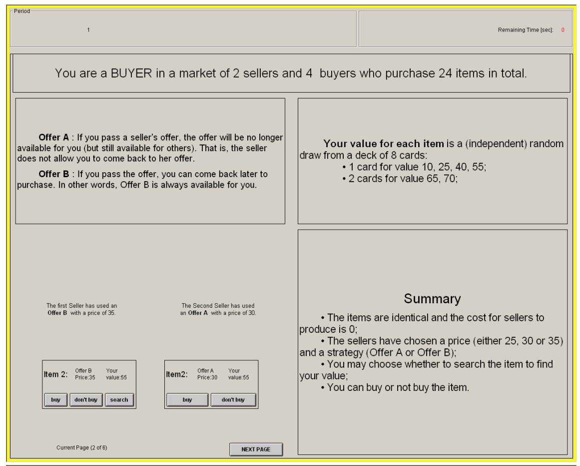
Period	Did Buyer Visit You First? (Half Will Visit You First.)	Buyer's Value of Your Item	Your price	Did Buyer Purchase Your Item?	Did Buyer Search Your Item?
1	No	10	35	No	No
1	No	10	35	No	No
1	No	25	35	No	No
1	No	25	35	No	Yes
1	No	65	35	No	No
1	No	65	35	Yes	Yes
1	No	65	35	No	No
1	No	65	35	No	No
1	No	65	35	Yes	Yes
1	No	70	35	Yes	Yes
1	No	70	35	No	No
1	No	70	35	Yes	Yes

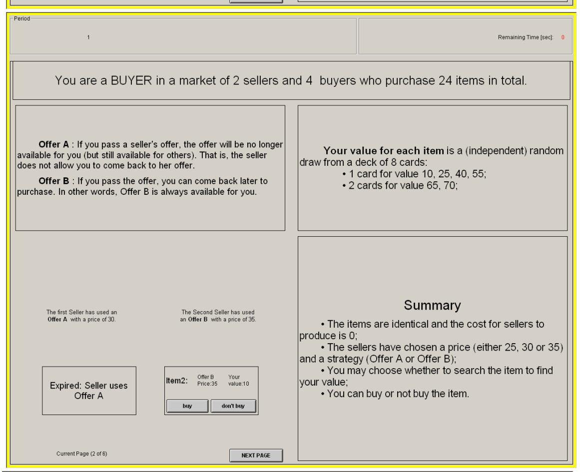
1. Your offer is an Offer A with a price of 35.
2. The other seller's offer is an Offer A with a price of 25;
3. The first table lists all buyers who have visited you first and the second table lists all buyers who have visited the other seller first. (Both are sorted by a buyer's value of your item)
next page

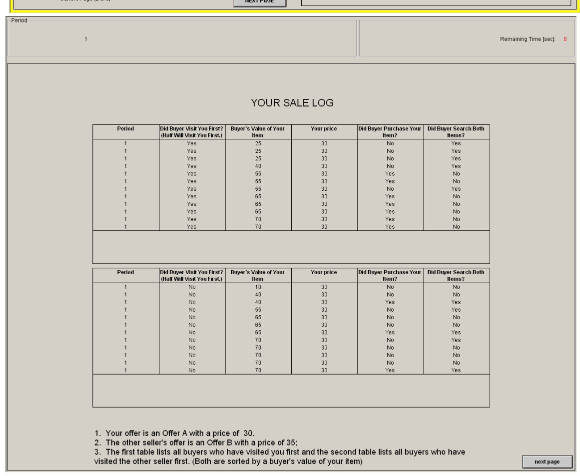

Period
1
Remaining Time [sec]: 13
	You	Your Competitor
Offer Type	Offer A	Offer A
Price	35	25
Quantity Sold	9 (out of 24)	12 (out of 24)
Profit	315	300

prev page
done


You are a SELLER in a market of 2 sellers and 4 buyers who purchase 24 items in total.
Offer A : If a buyer passes your offer, the offer will be no longer available for her (but still available for others). That is, your offer is only accessible at the initial visit.
Offer B : If a buyer passes the offer, she can come back later to purchase. In other words, Offer B is always available to buyers.
A buyer's value of your item is a random draw from a deck of 8 cards:
• 1 card for value 10, 25, 40, 55;
• 2 cards for value 65, 70;
Summary
• The items are identical and cost you nothing to produce;
• You will choose a price (either 25, 30 or 35) and an offer type (either offer A or offer B);
• 12 buyers will examine your item first and the other 12 buyers will examine the item from the other firm first;
•The distribution of valuation for consumers is shown on Top Right Box;
• Buyers can choose to buy or not to buy an item;
Your Price Offer:
Your Strategy:

You are a BUYER in a market of 2 sellers and 4 buyers who purchase 24 items in total.
Offer A : If you pass a seller's offer, the offer will be no longer available for you (but still available for others). That is, the seller does not allow you to come back to her offer.
Offer B : If you pass the offer, you can come back later to purchase. In other words, Offer B is always available for you.
Your value for each item is a (independent) random draw from a deck of 8 cards:
• 1 card for value 10, 25, 40, 55;
• 2 cards for value 65, 70;
Summary
• The items are identical and the cost for sellers to produce is 0;
• The sellers have chosen a price (either 25, 30 or 35) and a strategy (Offer A or Offer B);
• You may choose whether to search the item to find your value;
• You can buy or not buy the item.

You are a BUYER in a market of 2 sellers and 4 buyers who purchase 24 items in total.
Offer A : If you pass a seller's offer, the offer will be no longer available for you (but still available for others). That is, the seller does not allow you to come back to her offer.
Offer B : If you pass the offer, you can come back later to purchase. In other words, Offer B is always available for you.
Your value for each item is a (independent) random draw from a deck of 8 cards:
• 1 card for value 10, 25, 40, 55;
• 2 cards for value 65, 70;
Purchased
Summary
• The items are identical and the cost for sellers to produce is 0;
• The sellers have chosen a price (either 25, 30 or 35) and a strategy (Offer A or Offer B);
• You may choose whether to search the item to find your value;
• You can buy or not buy the item.



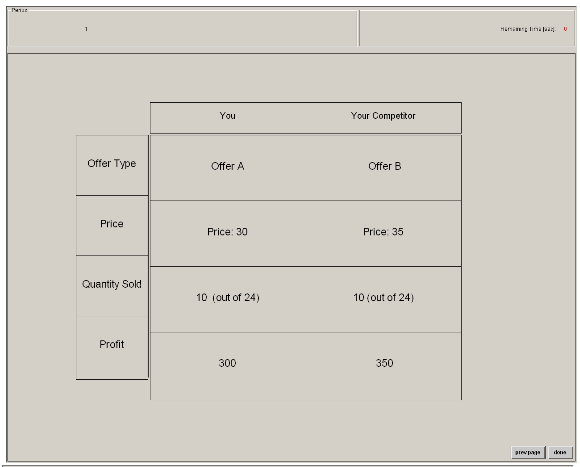




Period	Did Buyer Visit You First? (Half Will Visit You First.)	Buyer's Value of Your Item	Your price	Did Buyer Purchase Your Item?	Did Buyer Search Both Items?
1	Yes	25	30	No	Yes
1	Yes	25	30	No	Yes
1	Yes	25	30	No	Yes
1	Yes	40	30	No	Yes
1	Yes	55	30	Yes	No
1	Yes	55	30	Yes	No
1	Yes	55	30	No	Yes
1	Yes	65	30	Yes	No
1	Yes	65	30	Yes	No
1	Yes	65	30	Yes	No
1	Yes	70	30	Yes	No
1	Yes	70	30	Yes	No

Period	Did Buyer Visit You First? (Half Will Visit You First.)	Buyer's Value of Your Item	Your price	Did Buyer Purchase Your Item?	Did Buyer Search Both Items?
1	No	10	30	No	No
1	No	40	30	No	No
1	No	40	30	Yes	Yes
1	No	55	30	No	Yes
1	No	65	30	No	No
1	No	65	30	No	No
1	No	65	30	Yes	Yes
1	No	70	30	No	Yes
1	No	70	30	No	No
1	No	70	30	No	No
1	No	70	30	No	No
1	No	70	30	Yes	Yes

1. Your offer is an Offer A with a price of 30.
2. The other seller's offer is an Offer B with a price of 35;
3. The first table lists all buyers who have visited you first and the second table lists all buyers who have visited the other seller first. (Both are sorted by a buyer's value of your item)


Period
1
Remaining Time [sec]: 0
You
Your Competitor
Offer Type
Offer A
Offer B
Price
Price: 30
Price: 35
Quantity Sold
10 (out of 24)
10 (out of 24)
Profit
300
350
prev page
done


Period
1
Remaining Time [sec]: 0
You have purchased 2 items from one seller who used an Offer B with a price of 35.
You have purchased 2 items from another seller who used an Offer A with a price of 30.
Each seller's earning is the quantity of items she sold multiplied by the price she set.
Item 1 2 3 4 5 6
Value 55 0 0 70 65 70
Price 35 0 0 35 30 30
NET Value 20 0 0 35 35 40
OK