Consumer Search and the Choice Overload Hypothesis

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Abstract

We use an experimental approach to study the relationship between consumer's preference for variety and subsequent search and purchase behavior. By imposing a search cost, and a preference for variety, we induce search behavior that leads the participants to make both single, and multiple-purchase decisions. This paper shows that the ability to shop more efficiently allows consumers to focus on finding products that meet their exact specifications in differentiated product categories. With uncertainty over product attributes, no single choice stands out as a clear favorite *a priori*, so utility rises in the number of choices that are available, but at a decreasing rate. Our results suggest that retailers can broaden their assortments to persuade consumers to patronize their store, but not without bound. Because search is costly consumers will eventually become overwhelmed by the number of products offered and search a competing store as well, or possibly instead. The degree to which consumers are overburdened by the variety offered exhibits significant heterogeneity among consumers.

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1 Introduction

Consumers differ in the number of differentiated products they would like to have available, or their preference for variety. If firm managers understand that consumers demand variety, we would expect to see a proliferation of choices. Indeed, this was the case from 1992 to 2007 when food and beverage manufacturers introduced hundreds of new products each year. However, the number decreased by 5% in 2008 and another 16% in 2009 (USDA-ERS 2013). If consumers prefer more options to fewer, how can this be? Surely, the recession is responsible for some of the decline, but it appears to have accelerated a trend that was already well underway. Have consumers reached their limit in their demand for variety? Kuksov and Villas-Boas (2010) argue that consumers have a search cost that leads to a finite optimal number of alternatives being desired. Still others argue that less variety is preferred and only a small number of alternatives is ideal (Iyengar and Lepper 2000; Chernev 2003; and Iyengar, Huberman, and Jiang 2004). The objective of this research is to test the three competing ideas that (1) more variety is preferred to less, (2) there is an optimal level of variety demanded dependent on the cost of search, or (3) less variety is preferred to more.

Experiments that consider the validity of the "choice overload hypothesis," or the notion that too many options cause consumer dissatisfaction, have had mixed results.[1] Through a number of experiments, Iyengar and Lepper (2000) found that more consumers preferred smaller choice sets compared to larger ones. Using unfamiliar products, for example exotic jams, Iyengar and Lepper (2000) gave participants the option of choosing a product from either 6 or 24 choices and found that consumers chose more often from the smaller of the two. In another experiment, Iyengar and Lepper (2000) gave participants the option to choose from the larger or smaller assortment or the option to forego making a selection at all and receive $1. They found that participants who were presented with more options were more

[1] There is no specific consensus on the term used to describe the phenomenon. We follow Iyengar and Lepper (2000) (among others Diehl and Poynor 2007; Mogilner, Rudnick, and Iyengar 2008; and Scheibehenne, Greifender, and Todd 2010). It has also been referred to as the "overchoice effect", "paradox of choice", "the tyranny of choice", or the "excessive-choice effect" (Schwartz 2000; Schwartz 2004; Gourville and Soman 2005; and Norwood 2006).

likely to choose the monetary compensation rather than make a selection. Support for the choice overload hypothesis also lies in less exotic products such as pens, gift boxes, and coffee (Chernev 2003; Shah and Wolford 2007; and Mogilner, Rudnick, and Iyengar 2008).

Others find support for the more traditional notion that a consumer's overall satisfaction increases with variety. For example, Berger, Draganska, and Simonson (2007) use a number of experiments to show that manufacturers introducing new products, even with only minor characteristic differences, are able to increase consumers' perception of quality. Similarly, a number of field studies have shown that the probability of choosing a particular retailer to patronize increases with the depth of assortment. That is, a larger variety offered by a retailer provides a competitive advantage (Koelemeijer and Oppewal 1999; Boatwright and Nunes 2001; Borle, Boatwright, Nunes, and Shmueli 2005; Oppewal and Koelemeijer 2005; Richards and Hamilton 2006; Briesch, Chintagunta, and Fox 2009). One of the reasons why this question has not been resolved is that there is no precise definition for what constitutes a "large choice set" because the mechanism driving preference for variety is unclear.

Differences among purchase situations may dictate why the choice overload hypothesis is prevalent in some situations, and not others. Through a meta-analytic review Scheibehenne, Greifeneder, and Todd (2010, pg. 421) conclude that "...more choice is better with regard to consumption quantity and if decision makers had well-defined preferences prior to choice..." They also suggest that the choice overload hypothesis is likely to be more prevalent in situations where an individual is unfamiliar with the choices, and has little or no preference for the specific choices at hand. The choice overload hypothesis is more likely to apply when the consumer does not have a clear favorite among the choices, or if there are many options in which no subset of them is clearly dominant.

Differences among choice-specific situations may also be due to heterogenous search costs. When search costs are high, as would be the case when an individual is unfamiliar with a product category, the cost of searching a large number of options may deter choice. On the other hand, if someone is familiar with the products, then

search costs are likely perceived to be lower so a larger variety of differentiated goods may be preferable. Search costs, therefore, provide a more precise explanation as to why the choice overload hypothesis is prevalent in certain cases and not others.

Search costs may explain why there is a finite optimal number of products desired. Norwood (2006) develops an analytical model that explains the choice overload hypothesis as due to heterogenous consumer search costs. He shows that it is possible for markets to provide too many options, but argues that the lower revenue from losing customers due to too much variety will push variety back down to an optimal level. Similarly, Cachon, Terwiesch, and Xu (2008) find that as search costs decrease and search intensity increases, the assortment of goods offered by firms will increase, leading to higher equilibrium prices. Firms are able to raise prices because the probability that their products are searched, and purchased, increases. Recognizing the possibility that the number of products offered by the firm also affects consumers' propensity to search, Kuksov and Villas-Boas (2010) find that consumers have an optimal preference for variety based on their search costs.

These analytical models explain why researchers find support for the choice overload hypothesis in experiments where the number of choices is exogenously chosen by the experimenter, but field studies find that retailers gain a competitive advantage by offering larger varieties. Namely, in experimental studies the number of options is fixed throughout the entire experiment and does not change in response to participant's choices. In contrast, retailers adjust the number of products offered over time based on consumers' reactions and decrease the variety offered if sales fall. Witness the 2007 - 2009 experience of food and beverage manufacturers. That said, there is no empirical evidence to support these analytical models.

This paper contributes to the literature by testing the ability of consumer search to explain the choice overload hypothesis. While numerous studies have tested the choice overload hypothesis in different contexts, and for different product categories, none have explicitly tested the ability of search costs to explain the phenomenon (Norwood 2006; and Kuksov and Villas-Boas 2010). The results provide strong support for consumer search costs to explain the choice overload hypothesis. In particular, when search costs are low consumers want a wider range of products to

choose from which is consistent with the findings of Scheibehenne, Greifeneder, and Todd (2010) who find that more products are preferred when preferences are well defined. In addition, this paper contributes to the choice overload literature by conducting a non-hypothetical two sided experiment that allows for retailer responses to consumers prior purchase decisions. There are no experimental tests of the choice overload hypothesis, that we are aware of, that allow for retailers' dynamic reactions to consumers in adjusting the number of products they offer.

2 Market Experiment

2.1 Overview

In order to test the relationship between the degree to which variety is preferred and whether or not the cost of search plays a role, we develop a non-hypothetical experiment that aims to simulate a manager's assortment and pricing decision as well as a consumer's subsequent search and purchase decision. Prior experimental studies of consumer search are often built around a sequential search framework with a single choice offered and the option to stop searching and select that choice, or search another candidate for a cost. While a sequential search framework may be applicable to situations in which consumers are viewing apartments (Zwick, Rapoport, Lo, and Muthukrishnan 2003) they are less representative of a typical retail shopping experience in which a large number of SKUs are all presented on a retailer's shelf.

Our non-hypothetical experimental design builds on that of Yuan and Han (2011) in which 'sellers' simulate a category manager role by selecting the number of products to offer and the prices. Once all sellers have made their decision, 'buyers' are shown the assortment and pricing decision of one of the sellers at no cost. Buyers then decide to purchase from the 'no cost' seller, or pay a fee and purchase from an additional seller as well as the 'no cost' seller. Buyers in the experiment represent a simplified version of a typical consumer who is deciding whether or not to purchase all their groceries from a single retailer, or incur the cost of travel and visit another grocery store as well. SymphonyIRI's MarketPulse survey (2012), for example, found that fully 40% of consumers shop at multiple stores to obtain the lowest price possible. The experimental design is, therefore, more aligned with the

fixed-sample size search process and allows for a more direct test of how the number of products offered effects consumers' decision to search.

We use a non-hypothetical experiment design in which the participants are rewarded based on their performance within the experiment. Hypothetical experiments are often used to investigate consumer search behavior, but participants in stated choice exercises have no real incentive to reveal their true demand, nor to put cognitive effort into the decision making process. Non-hypothetical experiments, on the other hand, provide the participants with real economic incentives to make decisions that provide the most benefit at the lowest cost. For example, List and Gallet (2001) find that participants overstate their willingness to pay by 2-20% in hypothetical experiments compared to non-hypothetical experiments. Consequently, we conduct a non-hypothetical experiment in which real economic incentives are used to motivate participants to make realistic purchase decisions.

2.2 Method

Seventy six subjects from the general public, and forty eight undergraduate students were recruited to participate in the experiment. A detailed description of the recruitment method, and experiment process can be found in appendix A. Participants were randomly assigned to either a seller or buyer role at the ratio of 2 sellers for every 4 or 5 buyers. Buyers and sellers were then randomly matched together at the beginning of the experiment but maintained a consistent matching throughout (i.e. the same buyer always had the same 'no cost' seller). Buyers and sellers made a number of transactions with each other over the course of the experiment and at the end, the sellers with the highest profit, and the buyers with the highest welfare were rewarded with an additional cash prize.

The experiment used a completely fictitious product referred to as a 'widget' to avoid biases that might confound participant's decisions. Participants were introduced to widgets through verbal explanation and by participating in a number of practice transactions between buyers and sellers. Before beginning the actual experiment participants were able to publicly ask questions, and then privately in-

dicated whether or not they fully understood how the experiment worked, and what a widget was.

To keep the experiment tractable, widgets were differentiated along a single dimension based on their value to buyers. Consistent with the brand loyalty measurement of Raju, Srinivasan, and Lal (1990) and Agrawal (1996) buyers had a well defined brand loyalty measures for each unique widget. The brand loyalty for each widget was consistent across all buyers throughout the entire experiment, and known to sellers. Buyers, therefore, had a stronger incentive to purchase widgets they were more loyal to, but could be persuaded to purchase a less desirable widget if a deep enough price discount was offered by the seller (Narasimhan, 1998). Sellers had the option to offer any, or all, of the 5 unique widgets for sale each period and determined the prices of each. However, for each unique widget offered an 'inventory cost' was incurred to avoid sellers offering the widest assortment possible at each period. The inventory cost in the experiment is analogous to retailers' fixed shelf space providing a trade-off between offering more variety, but having to stock shelves more frequently resulting in more cost, for example (van Ryzin Mahanajan 1999). The inventory cost sellers incur makes the additional cost of offering a wider assortment of widgets more salient.

Consumer demand for variety is well documented and shown to be a key driver of store choice (Kahn 1995; Hoch, Bardlow, and Wansink 1999; Borle, Boatwright, Nunes, and Shmueli 2005; and Briesch, Chintagunta, and Fox 2009). To replicate this phenomena within the experiment buyers are rewarded for each unique widget purchased. The value each unique widget contributes to the buyer's welfare is the same across widgets, but differs across buyers and periods. By allowing buyers' preference for variety to vary we are able to indirectly observe the cognitive effort spent considering and selecting the optimal combination of widgets to purchase. In particular, buyers are aware they will have a positive preference for variety when deciding whether or not to search the additional seller, but do not know the exact value in the current period. The buyer's decision to search the additional seller is directly driven by the search cost, and indirectly driven by the knowledge that the

buyer will have a preference for variety. Among both samples there is a total of $N = 1045$ search/purchase observations among buyers.

In summary, sellers have an incentive to offer sufficient variety and/or low enough prices to persuade prospective buyers not to search the other seller's widget offerings. Buyers, on the other hand, determine whether or not to search the additional seller based on their cost of search and what the initial seller offered. A buyer's decision to search, therefore, is a signal to the seller that the expected benefit from searching the additional seller's product and price offerings outweighed the cost of search. Sellers did not know how many buyers purchased from them, nor who decided to search, and adjusted their product and price decisions based on the units sold and profit made in the previous period. The data collected from the buyers provides information on their search decision, as determined by their cost of search, the initial seller's product and price decision, and their expectation about the other seller's offerings. Observing the buyers' decision to search an additional seller, their search cost, and the number of products offered provides the information needed test whether there is an optimal number of options since the cost of search should largely drive the decision to search.

3 Empirical Model of Search Decision

We test the effect a retailer's variety decision has on a consumer's propensity to search, while controlling for the search cost. Specifically, we test the implication of Kuksov and Villas-Boas (2010 pg. 517) that consumers have a finite, optimal number of products they will search against the alternatives that more (less) variety is preferred independent of search costs. Support for this hypothesis implies a non-linear relationship between the propensity to search and the number of products offered. Kuksov and Villas-Boas' (2010) hypothesis is similar to the argument made for the choice overload effect. Namely, if search costs are indeed the moderating factor leading consumers to prefer fewer items when products are unfamiliar and search costs are high, then we expect the same non-linear relationship. On the other hand, if there is a strictly positive linear relationship between search and

variety, then we would reject the choice overload hypothesis in favor of the more usual notion that consumers always prefer more variety to less.

We model the probability a consumer searches by extending the logistic regression model proposed by Yuan and Han (2011). Specifically, our model allows for consumer heterogeneity and controls for the endogeneity in price and the number of products (Widgets) offered by sellers. The indirect utility consumer i obtains from searching at time t is the sum of a deterministic and stochastic part and is written as:

$$U_{it} = \boldsymbol{\beta}_z^{\intercal}\mathbf{z}_i + \boldsymbol{\beta}_x^{\intercal}\mathbf{x}_{it} + \varepsilon_{it} \tag{1}$$

where $\boldsymbol{\beta}_z^{\intercal}\mathbf{z}_i + \boldsymbol{\beta}_x^{\intercal}\mathbf{x}_{it}$ is the deterministic component of utility, and ε_{it} is an independent and identical extreme value distributed error term. The deterministic utility function is made up of a vector of consumer specific attributes ($\mathbf{z}_i$) and a vector of search specific attributes ($\mathbf{x}_{it}$). Consumer-specific attributes are demographic characteristics such as income and the number of individuals in the household, as well as intrinsic preferences such as the desire to shop around, as opposed to quickly purchasing needed items. Consumer-specific attributes also include a binary indicator variable that is equal to one if the participant was in the public sample, and 0 if in the student sample. Including this binary variable permits a test of whether there is a fundamental difference between the public sample's desire to search compared to the student sample. Search specific attributes, $\mathbf{x}_{it}$, include the price of the Widgets at the time the search decision is made, the cost of search, and the number of Widgets offered by the initial seller. The number of Widgets squared is also included in the search specific attributes to test for a non-linear relationship between search and the assortment size offered.

All estimated parameters are allowed to vary randomly over subjects, reflecting heterogenous preferences otherwise ignored by a fixed parameter model (Berry, Levinsohn, and Pakes 1995; Nevo 2001). We assume the parameters are normally distributed to allow for each effect to be either positive or negative. For example, we expect that as prices charged by the initial seller increase, buyers would be more likely to search and view the prices charged by the other seller because the gains

from search would intuitively increase. However, we do not want to impose this assumption *a priori* in order to test the specific relationship between search and prices. Formally, we assume the parameters are normally distributed such that:

$$\begin{pmatrix} \boldsymbol{\beta}_z \\ \boldsymbol{\beta}_x \end{pmatrix} = N\left[\begin{pmatrix} \bar{\boldsymbol{\beta}}_z \\ \bar{\boldsymbol{\beta}}_x \end{pmatrix}, \begin{pmatrix} \boldsymbol{\sigma}_z & \mathbf{0} \\ \mathbf{0} & \boldsymbol{\sigma}_z \end{pmatrix}\right] \tag{2}$$

where $\bar{\boldsymbol{\beta}}_z$, and $\bar{\boldsymbol{\beta}}_x$ represent the mean of the parameters and $\boldsymbol{\sigma}_z$, and $\boldsymbol{\sigma}_x$ capture consumer specific variations across parameters, or the standard deviation of the normally distributed parameter. Allowing the parameters to vary randomly not only accounts for consumer heterogeneity, but also defines the utility from search as being correlated according to the attributes of the decision at hand.

Given the indirect utility definition in equation (1) above, let $\mathbf{u}_{it1} = \boldsymbol{\beta}_z^{\intercal}\mathbf{z}_{i1} + \boldsymbol{\beta}_x^{\intercal}\mathbf{x}_{it1}$ represent the deterministic utility the consumer obtains from searching, and $\mathbf{u}_{it0} = \boldsymbol{\beta}_z^{\intercal}\mathbf{z}_{i0} + \boldsymbol{\beta}_x^{\intercal}\mathbf{x}_{it0}$ be the utility from not searching. The probability that a consumer decides to search is then given by:

$$\begin{aligned} \underset{it}{\Pr} &= \Pr\left[\mathbf{u}_{it1} + \varepsilon_{it1} > \mathbf{u}_{it0} + \varepsilon_{it0}\right] \\ &= \Pr\left[\varepsilon_{it0} - \varepsilon_{it1} < \mathbf{u}_{it1} - \mathbf{u}_{it0}\right] \end{aligned} \tag{3}$$

which is the cumulative distribution expression for $\varepsilon_{it0} - \varepsilon_{it1}$ evaluated at $\mathbf{u}_{it1} - \mathbf{u}_{it0}$. In order to consistently estimate equation (3), we address the apparent endogeneity between the price and number of product variables in $\mathbf{u}_{it}$.

The number of Widgets offered and the prices chosen in period t are likely to be endogenous because the experiment is two-sided. Namely, the prices and assortment offered (or sellers' decisions) are based on the quantities sold in the previous period which are determined by, among other factors, the search decision. So, the total quantity sold depends on the error the buyers collectively make in determining whether or not to search. As a result, the prices in the current period may be correlated with the error in determining whether or not to search. We assume that the error an individual buyer makes is independent over time. Therefore, we use an instrumental variable approach to control for endogeneity in modelling the probability of search.

We use the control method approach (Petrin and Train 2010; Park and Gupta 2009), which is based on the sample-selection models of Heckman (1978) and Hausman (1978). Using simulation, Andrews and Ebbes (2013) show that when instrumental variables are available, the control function approach performs better than competing methods of addressing endogeneity (Berry, Levinsohn, and Pakes 1995; Park and Gupta 2009; Villas-Boas and Winer 1999) in estimating price elasticities. Intuitively, the control function approach derives a proxy variable that conditions on the endogenous part of the price and assortment variables, thus making the remaining variation independent of the error term. Then, the standard simulated maximum likelihood approach will be consistent.

The utility that a consumer obtains from searching is a function of both exogenous and endogenous variables. We partition the set of variables $\mathbf{x}_{it}$ into a vector of exogenous variables, $\dot{\mathbf{x}}_{it}$, and endogenous variables, $\{N_{it}, (N_{it})^2, \bar{p}_{it}\}^\top$, where N_{it} is the number of products available to buyer i at time t, and $\bar{p}_{it}$ is the average price of the N_{it} Widgets. The decision to search is made based on the prices of the available products, the search cost, and other exogenous factors. So, the utility of searching is given by:

$$U_{it} = \boldsymbol{\beta}_z^\intercal \mathbf{z}_i + \boldsymbol{\beta}_{\dot{x}}^\intercal \dot{\mathbf{x}}_{it} + \beta_N N_{it} + \beta_{N^2} (N_{it})^2 + \beta_{\bar{p}} \bar{p}_{it} + \varepsilon_{it}. \tag{4}$$

Let η_{it}, and ϱ_{it} represent the errors associated with N_{it}, and $\bar{p}_{it}$, respectively, that is not independent of ε_{it}. The average price of the offered products, $\bar{p}_{it}$, is used instead of each actual price because not all products are offered each period. As a result, price information for each individual product is not available every period. Using the average price of all the offered products at time t is similar to assuming the response to price is the same for all the products (i.e. $\beta(p_{it1} + \cdots + p_{itN})$). While the amount paid by the experimenter is different for different products, it remains constant throughout the experiment and is well known by both buyers and sellers at the start of the experiment. So, while the buyers may not be as sensitive to a price change for a product that they are paid more for, sellers know this information as well, and would be expected to capitalize on it by setting slightly higher prices for higher valued goods. The variation between product prices is likely to lead to very

similar, if not the same, price response for each product. Using the average price as a proxy for the effect prices have on the consumer's decision to search helps avoid the lack of price information for products that are not offered in a particular period by normalizing the sum of prices by the number of products that were offered. Using the average price also helps alleviate the endogeneity associated with each offered product by normalizing it by the total number of products available in that period.

Following Petrin and Train (2010), we assume that observed and unobserved covariates N_{it}, $(N_{it})^2$, and $\bar{p}_{it}$ are additive, or $\tilde{\eta}_{it} + \eta_{it}$ and $\tilde{\varrho}_{it} + \varrho_{it}$ respectively. Let η_{it} and ϱ_{it} represent the parts of $N_{it} + (N_{it})^2$ and $\bar{p}_{it}$, respectively, that is correlated with the error term and $\tilde{\eta}_{it}$ and $\tilde{\varrho}_{it}$ are not. We then decompose the error term associated with the decision to search, ε_{it}, into a general function of the observed and unobserved covariates of the endogenous variables leading to:

$$\varepsilon_{it} = CF\left[\eta_{it}, \varrho_{it} | \boldsymbol{\lambda}\right] + \tilde{\eta}_{it} + \tilde{\varrho}_{it} \tag{5}$$

where $CF\left[\eta_{it}, \varrho_{it} | \boldsymbol{\lambda}\right]$ is the control function with parameter vector $\boldsymbol{\lambda}$, and $\tilde{\eta}_{it}$, and $\tilde{\varrho}_{it}$ are the error components that are independent of ε_{it}. We approximate the control function as linear in $\tilde{\eta}_{it}$, and $\tilde{\varrho}_{it}$, or $CF\left[\eta_{it}, \varrho_{it} | \boldsymbol{\lambda}\right] = \lambda_1 \eta_{it} + \lambda_2 \varrho_{it}$.[2] The error terms η_{it}, and ϱ_{it} are recovered by, separately, regressing N_{it}, and $\bar{p}_{it}$ onto a set of instrumental variables.

The instrumental variables are the costs of each of the 5 available products as well as the seller margins (Berto Villas-Boas 2007; Draganska and Klapper 2007). The instrumental variables determine selling prices, and number of products chosen by the seller, but exogenous to an individual buyer's search decision.[3] We assume that the control function is normally distributed and that $\tilde{\eta}_{it}$, and $\tilde{\varrho}_{it}$ are defined such that $\tilde{\eta}_{it} + \tilde{\varrho}_{it}$ is type 1 extreme value (see Bertin and Clusel (2006) for the distributional properties of $\tilde{\eta}_{it}$, and $\tilde{\varrho}_{it}$ that lead to $\tilde{\eta}_{it} + \tilde{\varrho}_{it}$ being type 1 extreme value distributed).

[2] An interaction term was included, but provided little to no explanatory power, and had almost no effect on the parameter estimates of other variables so was excluded from the final analysis.

[3] The quantities sold in the prior period are also likely candidates for instrumental variables, but may not be exogenous, and so were not used.

Combining the utility function given in equation (1) with the error term in equation (5), indirect utility is written as:

$$U_{it} = \boldsymbol{\beta}_z^{\intercal}\mathbf{z}_i + \boldsymbol{\beta}_x^{\intercal}\mathbf{x}_{it} + \lambda_1\eta_{it} + \lambda_2\varrho_{it} + \tilde{\epsilon}_{it}, \tag{6}$$

where $\tilde{\epsilon}_{it} = \tilde{\eta}_{it} + \tilde{\varrho}_{it}$, and $\lambda_k \sim N(\lambda_k, \sigma_{\lambda_k})$ for $k = 1, 2$ similar to the parametric definitions given in equation (2) above. Estimating the models sequentially in this way can cause a compounding error problem (Cameron and Trivedi 2005; and Petrin and Train 2010). However, this is unlikely as the estimated parameters are very similar to those found without the control function. Therefore, we conclude that the compounding error problem is, at most, negligible.

Empirical consumer search studies commonly assume that ε_{it} is type 1 extreme value distributed and, combined with the random parameter assumption, yields the familiar mixed logit model. However, the type 1 extreme value distribution requires all ε_{it} be independent across all choice situations. Therefore, we estimate the model twice. One estimation assumes that ε_{it} is type 1 extreme value distributed and another assumes ε_{it} is jointly normally distributed across all choice situations. The joint normal distribution does not require an independence assumption, and generates a mixed Probit model. The mixed Probit model can accommodate random taste variation, flexible substitution patterns, and is applicable to panel data with temporally correlated errors ε_{it} (Train 2009). In general, the type 1 extreme value distribution is nearly identical to the normal distribution except that is has a slightly fatter tail which allows for more aberrant behavior. Since there is no closed form for either the mixed logit, or the mixed probit model, we use simulated maximum likelihood to estimate the probability of search. Simulated maximum likelihood provides consistent parameter estimates under general error assumptions and is readily able to accommodate complex structures regarding consumer heterogeneity. To aid in the speed and efficiency of estimation, we use a Halton draw sequence. Bhat (2003) provides experimental evidence that suggests a Halton sequence can reduce the number of draws required to produce estimates at a given accuracy by a factor of 10. We found that $R = 500$ draws were more than sufficient to produce stable estimates.

4 Results and Discussion

In this section, we report the results obtained from tests of the main hypotheses of the paper, specifically how variety is related to the costs of search. Prior to investigating the parameter estimates from the formal econometric search model, we first present some summary statistics on the experimental search data. Table 1 presents summary statistics for the participants in both the student sample, and general-population sample that were selected to be "buyers" in the experiment. The samples appear to be similar, although, not surprisingly, the average age of the student sample is 22.5 years old, whereas that in the public sample is 35 years old. Moreover, the age range is much wider in the public sample compared to the student sample. The only other notable difference across the samples is the frequency with which they made a purchase online, or had something delivered to them that was purchased online. In this regard, students are more frequent online purchasers than the general public.

[Insert Table 1]

We find that seller profit and the number of products offered are negatively correlated and statistically significant at the 1% level ($N = 475$). This relationship holds even when considering sellers' gross profit before inventory costs are subtracted, although it is no longer significant. Therefore, even though consumers' had an incentive to purchase a wider range of products, even from different sellers, sellers did not see this preference for variety reflected in their profit. Consistent with Yuan and Han (2011), there is a slightly positive correlation between price dispersion and search intensity (0.06) but this is not statistically different from 0. So, our results do not appear to support Varian (1980) in that the more consumers search, prices are less competitive and more variable. In contrast to Yuan and Han (2011), we find no correlation between buyer search intensity and seller profit.

Finally, we find a negative correlation between search intensity and the buyer's search cost (-0.225) as well as the number of products offered (-0.243), both of which are significant at the 1% level. These negative correlations imply that buyers searched less when the cost of search is high, as expected. It also suggests that as

sellers increased the number of unique Widgets offered, buyers were more likely to spend their entire budget on that seller and not view the products offered by the other seller. This is consistent with prior research that suggests a wider assortment of products offered provides retailers with a competitive advantage (Koelemeijer and Oppewal 1999; Boatwright and Nunes 2001; Borle, Boatwright, Nunes, and Shmueli 2005; Oppewal and Koelemeijer 2005; Richards and Hamilton 2006; Briesch, Chintagunta, and Fox 2009). We test these relationships more formally next.

The negative correlation between search intensity and the number of products offered does not take into account the degree to which prices may be driving the consumer's decision to search. If the buyer's search cost is reasonably high, but the prices offered by the seller are even higher, then the correlation between searching and the cost of searching may be understated. In other words, prices may be masking what is actually a stronger negative relationship between the buyer's cost of search and the decision to do so. Modeling the probability of search, as discussed above, accounts for these inter-correlations between the variables driving the consumer's search decision.

We test whether unobserved heterogeneity is indeed important using the likelihood ratio (LR) test. A LR test compares a model that assumes heterogeneity is not present to the model that incorporates random parameters described in equation (2). The LR test statistic is 127.30 for the mixed logit model, and 77.87 for the mixed probit model, both of which are Chi-square distributed and significant at the 5% level. For either model, therefore, the random parameter specification is preferred.[4]

The search model is estimated both as a mixed logit and a mixed probit. The results of both are presented in table 2. From a qualitative perspective, the assumption that the error terms are normally distributed versus extreme value distributed does not appear to make a substantive difference to the conclusions of our hypothesis tests. Since the majority of empirical consumer search studies use an extreme value distribution, we interpret the mixed logit results in order to maintain comparability (Mehta, Rajiv, and Srinivasan 2003; Wildenbeest 2011; and Yuan and Han 2011).

[4] The results of the fixed parameter alternative are available from the authors upon request.

The results presented in table 2 summarize the relationship between the probability of searching, and the factors affecting that decision. Consistent with the current search literature, we find that the probability a consumer searches decreases with the cost of search (Mehta, Rajiv, and Srinivasan 2003). Consistent with the experimental results of Yuan and Han (2011), we find that subjects are more likely to search when observed prices increase.[5] In addition, we find that excluding the number of products offered biases the coefficient on price towards zero. Without considering the number of products offered, the results of the mixed logit model (left columns of table 2) suggest that prices have less bearing on the consumer's decision to search relative to when variety is included.

[Insert Table 2]

The bias induced by excluding the retailer's variety decision is not surprising given the importance of variety to the subject's propensity to search. Based on the magnitude of the parameter estimates reported in table 2, the number of products offered by the retailer plays a more important role in guiding the consumer's search decision compared to both the average price, or the search cost (Kadiyali, Vilcassim, Chintagunta 1999; Briesch, Chintagunta, and Fox 2009). As variety increases, the probability the consumer decides to search decreases – precisely as the seller intends. Since the initial seller offers a larger variety to persuade the buyer not to search the other seller, a negative coefficient is expected. Consistent with Briesch, Chintagunta, and Fox (2009), our results suggest that retailers can use variety as a competitive tool to keep consumers from shopping at other retailers. Moreover, our results provide evidence that this relationship is non-linear, or there is an optimal number of products a retailer should offer, consistent with Kuksov and Villas-Boas (2010).

The choice overload hypothesis states that too many options overwhelm consumers and can lead to him avoiding making a purchase at all. Kuksov and Villas-Boas (2010) formalize the concept underlying the choice overload hypothesis by explaining it in terms of consumer search costs. When the cost of search is small, consumers prefer a wider choice set, and as the cost of search increases, the demand for variety falls because searching a large number of options is too costly. We test

[5] Positive parameter estimates are also found if each price is allowed its own parameter.

this effect directly as it relates to the consumer's propensity to search. The positive parameter estimate on $(N_{1t})^2$ is statistically different from 0 at the 5% level for both the mixed logit and probit results, which provides support for search costs explaining the choice overload hypothesis. More variety causes consumers to search more, thereby reducing the probability of actually making a choice. Consistent with Scheibehenne, Greifeneder, and Todd (2010) the variance of the parameter estimate is statistically different from 0. This implies that there is considerable heterogeneity among consumers regarding the precise point at which the overload-effect begins. Therefore, the results of the mixed logit and probit models suggest that the choice overload hypothesis may have been accurate for some, but not all, experiment participants. Perhaps more important, however, is the comparison between the linear and non-linear parts of the search function. Some argue that retailers use larger product assortments to attract consumers to the store (Koelemeijer and Oppewal 1999; Boatwright and Nunes 2001; Borle, Boatwright, Nunes, and Shmueli 2005; Oppewal and Koelemeijer 2005; Richards and Hamilton 2006; and Briesch, Chintagunta, and Fox 2009), while others find that consumers are put off by too much variety (Iyengar and Lepper 2000; Chernev 2003; and Iyengar, Huberman, and Jiang 2004). We find that search is a non-linear function of the number of products offered. In addition, the number of products offered has a larger impact on the propensity of an individual to search than either the search cost, or the prices. In other words, because search is directly related to which store a participant chooses to patronize, and precedes purchase and consumption, the non-linear relationship found here suggests there is an optimal number of products that could be offered to get the consumer to avoid searching the other store. Because we use an experimental setting that offers participants, at most, 10 choices we do not compute the precise number of products a consumer would want and leave that for future field studies.

Our results also highlight the importance of considering the number of products sold by a retailer in field experiments. Prices, the cost of searching, and variety can all be used as competitive tools by a retailer to persuade a consumer to shop only with them, but variety appears to be the most important.

In addition to the cost of search and prices, we find that there are a number of consumer specific demographic attributes that play an important role in the consumer's propensity to search. First, the results in table 2 show that the public sample is considerably less likely to search compared to the student sample. This is consistent with the probability of search reported in table 1. This finding suggests that a student sample may not be representative of the actual search behavior of the general public, because students are more likely to undertake search. Second, the consumer's revealed preference for variety in the previous period has no bearing on their decision to search in the current period. This result is expected and shows that the participants understood that their preference for variety was independent across periods. The current period's preference for variety was also found to not have any bearing on the consumer's propensity to undertake search in that period. Since the preference for variety was revealed to them after they made the search decision, this result is expected. Third, male participants were much more likely to undertake search compared to female participants. Fourth, in contrast to Bucklin (1969) there is some evidence that as the participant's income increases they are less likely to undertake search. This is an interesting result because the consumer's own income has no bearing on their profit in the experiment. However, it is consistent with the notion that the most important component of search costs is the opportunity cost of time. Fifth, the results suggest that consumer who spend more on groceries are more likely to search across different retailers. Participants' monthly grocery bill should have no effect on their decision to search within the experiment's framework, yet we find evidence that consumers who have a higher monthly grocery bill are more likely to search the additional seller's product assortment. This is perhaps because participants who spend a lot on groceries each month inherently perceive the expected benefit from search to be greater. Sixth, participants were asked whether they had a bachelors or advanced degree in business, or an analytical field

of study.[6] The results suggest that more technically-educated participants were less likely to undertake search.

Taken together, the results begin to answer the question of whether too much variety is indeed a bad thing. We find that the assortment offered by a retailer is a critical component of the consumer's decision to search, even more than the prices charged. Variety not only has a larger impact on the consumer's decision to search compared to prices and the cost of search, its exclusion from the analysis actually biases the results of those parameters. Therefore, it is critically important to take variety into consideration when studying consumer search. Additionally, our results confirm the main hypothesis of Cachon, Terwiesch, and Xu (2008) which states that a larger assortment can support higher prices and deter a consumer from searching a competing retailer. Consumer search studies often test the relationship between search and search costs using a single purchase assumption (Kogut 1990; Sonnemans 1998; and Yuan and Han 2011). However, as our results show, the conclusions of these studies may not be applicable to situations in which a consumer can observe multiple products at the same time. Finally, the results show that consumers have differing intrinsic propensities to search that are not entirely due to observed heterogeneity, or differences in demographic background.

5 Conclusion and Future Research

In this paper we examine the relationship between consumer search and preference for variety when consumers purchase multiple products in continuous quantities. We examine firms' incentives to offer a wider variety of products, and consider how the cost of search affects the "choice overload hypothesis," or whether too much variety deters consumers from making a purchase.

How consumers respond to the assortment offered by a firm remains a debate. While many studies find that variety is valued by consumers, and can be used to attract them, others find that too many options leads to consumer dissatisfaction

[6] In the student sample, freshman and sophomores were instructed to answer no to this question unless they had already taken all their math requirements and had at least 2 business classes. Juniors and Seniors will have fulfilled these requirements based on the school's curriculum and were instructed to answer yes to the question.

and the avoidance of a purchase (choice overload hypothesis). This study bridges these competing schools of thought using experimental methods.

We use a two-sided experiment in which participants use the number of products, prices, and search costs to determine whether or not to search, while knowing that they will have some positive preference for variety that will motivate them to purchase multiple fictitious products. The experiment is conducted on both undergraduate college students and the general public.

My results support the theoretical model of Kuksov and Villas-Boas (2010) who suggest that consumer search explains the choice overload hypothesis and there is an optimal variety that consumers want. We find that the factors affecting the propensity to search can explain both the notion that more variety is better, but too much variety can be a bad thing from a retailer's perspective. In particular, a larger assortment offered by a retailer can be more persuasive than the prices charged when maintaining a competitive advantage. However, variety can not increase without bound as too much assortment makes it difficult for an individual consumer to find the specific product they want due to the cost of search. This study also illustrates the importance of taking variety into account in future consumer search studies as excluding variety results in serious estimation bias.

The results have a number of managerial implications for retailers. In particular, retailers can increase the assortment available to persuade a consumer to patronize their store and avoid searching another store. However, this effect does not occur without bound. My results show that, eventually, a consumer will be overwhelmed by the number of products offered and search the other store as well, or possibly, instead. The degree to which consumers are overburdened by the variety offered differs significantly across consumers and may not be as prevalent in some as in others. This finding lends further evidence as to why the choice overload hypothesis has had mixed support.

Future work may benefit from also taking into consideration consumer's price expectations in the presence of a preference for variety. Yan and Han (2011) show how consumer price expectations can also affect the decision to search. However, they assume that consumers do not have a preference for variety and only a single

purchase is made. Price expectations in the presence of a heterogenous preference for variety may cause consumers to be more, or less, sensitive to the number of products offered. Future work may also benefit by considering collusion among retailers when selecting the prices and number of products available. My results show that variety is more important than prices when deciding whether or not to search. Retailers may, therefore, be able to capitalize on this information by setting higher prices and offering a wider assortment. If retailers know that other retailers are also offering a large variety, but not too much, then equilibrium prices may rise since consumers are less likely to search.

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Table 1: Experiment Summary Statistics.

Variable	Student Population		Public Population	
	Mean	Std. Dev.	Mean	Std. Dev.
Search Decision	0.594	0.310	0.544	0.369
Preference for Variety	1.525	0.208	1.455	0.251
Search Cost	1.911	0.279	1.954	0.359
Budget Not Spent	4.548	3.848	8.269	10.212
Number of Products Purchased	1.995	0.754	2.075	0.773
Number of Products offered - Seller 1	2.698	0.759	3.527	1.223
Number of Products offered - Seller 2[1]	1.612	1.018	1.764	1.499
Total Products Observed	4.310	1.288	5.292	1.868
Age	22.562	3.600	35.114	16.795
% of Female	0.468	-	0.400	-
# in the Household	2.156	1.547	2.542	1.596
Income	8.093	5.909	7.714	5.344
Education	3.125	0.941	3.457	1.291
Analytical Bach. Degree	0.750	-	0.057	-
% with Job in AR/AP	0.312	-	0.400	-
$ spent on Groceries	4.031	2.162	4.000	2.029
% that favors Prod. offered[2]	0.562	-	0.285	-
% that like shopping around[3]	0.406	-	0.657	-
Frequency of online purchases[4]	3.125	1.263	2.485	1.245
Frequency of delivered items[4]	3.062	1.162	2.314	0.993
	Min.	Max	Min.	Max
Search Decision	0.000	1.000	0.000	1.000
Preference for Variety	1.169	2.061	0.742	2.014
Search Cost	1.371	2.651	0.960	2.534
Budget Not Spent	0.272	15.404	0.373	38.625
Number of Products Purchased	1.000	4.786	1.000	4.047
Number of Products offered - Seller 1	1.556	4.462	1.227	5.000
Number of Products offered - Seller 2[1]	0.000	3.583	0.000	5.000
Total Products Observed	1.900	6.538	1.909	9.454
Age	18.000	32.000	19.000	71.000
# in the Household	1.000	6.000	1.000	6.000
Income	1.000	19.000	1.000	16.000
Education	1.000	5.000	1.000	6.000
$ spent on Groceries	2.000	9.000	1.000	9.000
Frequency of online purchases[4]	1.000	6.000	1.000	6.000
Frequency of delivered items[4]	1.000	6.000	1.000	4.000
	$H = 32$		$H = 35$	

The household statistics reported here are only for those participants who were selected to be 'buyers' in the experiment. Additionally, the average experiment variables are calculated as the average per buyer, then average over the sample. So, the averages reported here are not weighted by the number of periods each individual got through.

[1] This is conditional on the 'buyer' choosing to search.

[2] The participants had to choose whether price, or the products offered was more important when choosing a retailer.

[3] The participants had to choose whether the preferred to obtain the items they came for and leave, or shop around and look at different items offered in a retailer.

[4] 1 - Never; 2 - Less than once a Month; 3 - Once a month; 4 - 2-3 times per month; 5 - Once a week; 6 - 2-3 times a week; 7 - Daily. (No one chose 7).

Table 2: Random Coefficient Model Estimates.

Variable	Mixed Logit		Mixed Logit		Mixed Probit	
	Estimate	t-ratio	Estimate	t-ratio	Estimate	t-ratio
Constant	-0.9071	-0.50	2.9620*	3.82	2.7874*	4.50
Public sample	-1.2686*	-5.11	-2.0919*	-7.11	-1.7088*	-7.35
Pref. for variety$_{t-1}$	0.0266	0.68	0.0518	0.63	0.0342	0.51
Female	-0.6967*	-6.08	-1.1148*	-5.99	-0.7240*	-4.91
# People in HH	-0.2419*	-2.95	-0.4193*	-6.12	-0.3908*	-6.89
Income	-0.0688*	-7.01	-0.0807*	-4.76	-0.0797*	-5.61
Education	0.1955*	6.99	0.1011	1.17	0.0256	0.36
Bachelors	-1.1082	-1.07	-1.4374*	-5.56	-1.4638*	-6.81
Grocery costs	0.3455*	7.53	0.4047*	7.01	0.3609*	7.67
Ave. Price	0.3226*	2.13	0.3766*	7.83	0.2738*	7.65
Search Cost	-0.5377*	-7.31	-0.6576*	-9.00	-0.5375*	-9.16
NPO S_{1t}[†]	-	-	-1.2205*	-3.66	-0.9375*	-3.48
(NPO S_{1t})^2	-	-	0.1205*	2.24	0.0870*	1.99
NPO S_{2t-1}[‡]	-	-	-0.0687	-1.30	-0.0561	-1.38
λ_p	-0.0185	-0.74	-0.0185*	-2.08	-0.0144*	-2.07
λ_N	-	-	-0.1901	-1.22	-0.1624	-1.34
	Std. Dev. Of Random Parameters					
Female	0.0727	0.48	0.0727*	6.36	0.9729*	8.57
# People in HH	0.0665	1.75	0.0665	0.15	0.0418	1.75
Income	0.0201	1.89	0.0201*	6.00	0.0034	0.53
Education	0.3152*	9.09	0.3152*	4.55	0.0540*	2.86
Bachelors	0.2587	1.79	0.2587	0.49	0.0895	1.01
Grocery costs	0.0358	1.58	0.0358	1.47	0.0920*	5.75
Ave. Price	0.2230*	12.47	0.2230*	12.07	0.1589*	12.29
Search Cost	0.2643*	5.66	0.2643*	6.18	0.2368*	7.13
NPO S_{1t}[†]	-	-	0.2785*	7.28	0.0696*	3.58
(NPO S_{1t})^2	-	-	0.0861*	8.39	0.0669*	9.73
NPO S_{2t-1}[‡]	-	-	0.1199*	2.38	0.0310	1.16
σ_{λ_p}	0.0438*	6.87	0.0374*	5.39	0.0167*	4.51
σ_{λ_N}	-	-	0.1063	0.91	0.0320	0.49
Log-Likelihood	-451.61		-432.43		-432.16	
LR	243.81		228.11		232.11	
LRI	0.2126		0.2170		0.2208	

An asterisk indicates significance at a 5.0

[†] NPO S_{1t} - Number of products offered by the seller the consumer sees for free at the time the search decision is made.

[‡] NPO S_{2t-1} - Number of products offered by the searched seller in the previous period, if the participant decided to search in the previous period.

Period

Trial 1 out of 1

Remaining Time: 81

Widget:	Alpha:	Beta:	Delta:	Epsilon:	Gamma:
Buyer Resale Value:	10	12	14	17	20
Unit cost of selling:	3.00	4.00	5.00	8.00	9.00

You have been selected to be a Seller for the entire Game.

Your inventory cost per product offered is 2.00

Please set your per unit price for Widget Alpha	100.00
Please set your per unit price for Widget Beta	100.00
Please set your per unit price for Widget Delta	100.00
Please set your per unit price for Widget Epsilon	100.00
Please set your per unit price for Widget Gamma	100.00

The price set for each widget must be lower than the Buyer's reservation price for that Widget, and greater than your selling cost.

Otherwise the per unit price is set to 100 and that Widget is not selected as one to be sold to the Buyers.

Set Price

Example of Participant Screen Shots

A Online Appendix

A.1 Experiment Recruitment

Participants were recruited from the general public as well as students from business classes at a large south western University. Using both public and student participants allows us to see whether there are differences between a student and public sample, and more generally, whether student choices are representative of those made by subjects drawn from the general public.

Participants answered some basic demographic questions (which can be found in appendix B) and were then randomly assigned to either a buyer or seller role. Participants remained in their respective roles throughout the entire experiment. If a participant was assigned to a buyer role, they chose which product to purchase and the quantity. Participants in a seller role decided which products to offer and the prices to charge. Participants remained in their respective roles throughout the entire experiment. Buyers and sellers were also randomly matched to each other such that individual buyers did not know who they were buying from, and sellers did not know who they were selling to. The aim of the random matching protocol is to minimize or eliminate reputation effects and collusion that could come into play (Yuan and Han 2011; and Amaldoss and Rapoport 2005). However, the initial pairing of buyers to sellers was consistent throughout the whole experiment.

Public participants were recruited by advertising the experiment on Craigslist.org. The ad informed potential participants the dates and times available. Doodle.com was used to allow participants to sign up for individual time slots, and showed participants whether or not a particular time slot was full. The first experiment started at 10:00am while the last session started at 4pm, each lasting approximately 1 hour and 30 minutes which provided 30 minutes to pay the participants and get the experiment reset for the next session. Public participants were paid $35 for coming to the experiment and a possible $10 or $15 bonus depending on how well they did as either a buyer or seller compared to the others in the session. A total of 76 individuals participated in the public experiment, with only one individual dropping out of the experiment half way through. Participants in each session were allowed to go at their own pace. Each session was allowed to complete as many rounds of buying and selling as possible. Once an hour passed, the last period was finished and the experiment stopped.

Students were recruited from business classes ranging from freshman to senior level undergraduate classes. Students volunteered to participate in the experiment. However, they did have the opportunity to earn an additional $10 or $15 depending on how well they did in the experiment. A total of 48 students were recruited. Among both samples there is a total of $N = 1045$ search/purchase observations among buyers.

At the beginning of the experiment, general instructions were given to the participants that described how the experiment would work. This general information was followed by screen shots of each screen buyers and/or sellers would see, along with examples of how the inventory cost and preference for variety bonus subtracted from, or added to, sellers' profits or buyers' welfare. An example screen shot is provided below. Participants then went through a practice round. At the end of the practice round, all participants were asked if they understood how the experiment

worked and their individual role as either a buyer or seller. All questions that arose throughout the instructions, or the practice round, were answered publicly. After all questions were answered and everyone publicly acknowledged that they understood, each participant was again asked privately on their individual computer. Anyone that privately answered "no" to one of these questions was removed from the final analysis. Participants were otherwise asked not to talk to one another nor sit near anyone they knew. The experiment was carried out using the z-Tree software system (Fischbacher, 2007), which is an open-source software tool that allows sellers to set prices, assigns sellers to buyers, and calculate profits.

A.2 Experiment Process

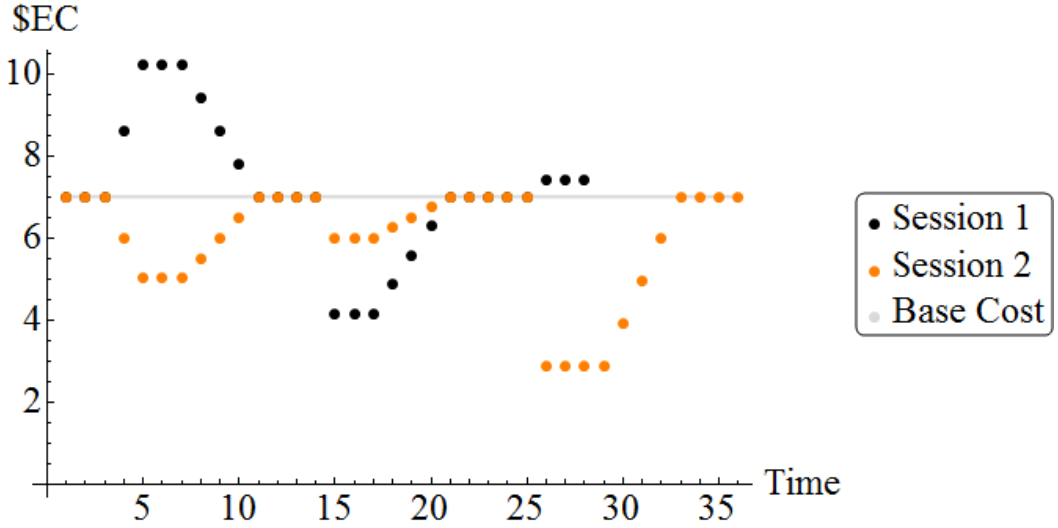
The experiment used a completely ficticous product referred to as a 'widget'. Sellers had the option of offering at least 1 and up to 5 unique widgets to buyers. Widgets were differentiated along a single demension based on their value to buyers. The cost the seller paid for each widget differed in proportion to the value of the widget to the buyer. Namely, the base cost for the cheapest widget was 3EC. The base cost increased for each widget by 1EC such that the base cost to the seller of the highest valued widget was 7EC. All sellers incurred the same cost for each unit of a widget sold, and no cost for unsold widgets.

Sellers paid an 'inventory cost' for each unique widget offered regardless of whether or not they made a sale. The inventory cost was determined randomly following a uniform distribution and differed for each seller and each period. The lowest possible inventory cost per widget offered was 1EC while the max was 6EC. For example, if the seller's inventory cost was 2EC in a particular period, and the seller offered 3 out of 5 possible, the seller paid the experimenter 6EC regardless of the number sold. If the seller did not sell any products in a particular period their total profit decreased by the inventory cost.

To avoid buyers and sellers repeatedly entering the same values for each period, we induced price changes via the seller's widget cost. All participants were informed that there would be price changes periodically throughout the experiment, but did not know when. Buyers did not see the prices sellers paid for the widgets, and were, therefore, not aware which periods had price shocks. After several periods had passed, the sellers' widget cost changed. These price changes were the same for all sellers, and were added to (or subtracted from) the base price. In other words, if the cost of the widgets increased by 1EC it did so for all the sellers. Figure 1 provides an example of the cost sellers paid for the most valuable widget in two different sessions. The magnitude and direction (either positive or negative) of the cost changes were determined randomly following a uniform distribution. The minimum price shock was set to 1EC and the maximum price shock was 3.5EC.[7] Figure 1 illustrates how prices changes lasted for several periods and then moved back to the base cost. The magnitude of the price changes were allowed to differ across widgets, but were all either positive or negative so that all products became cheaper or more expensive. Thereafter, the prices sellers paid the experimenter for the products remained at the base cost for several periods until another series of price shocks began.

[7] In the event that the price shock was lower than -3EC the experimenter sold the cheapest widget for 0.01EC. In other words, the experimenter did not pay the sellers to sell them.

Figure 1: The prices Sellers paid for the most expensive Widgets.



In each period, sellers observed the cost of each widget and their inventory cost on the same screen that they used to determine which products to offer and the prices. For the first 6 periods (including the practice period) a confirmation screen came up that displayed their product and pricing choices and confirmed the seller's selection. If a mistake had been made, they had the opportunity to go back and correct it, or confirm their original decision. The confirmation screen was limited to 6 periods, which we found to be sufficient during pre-testing. Once *all* sellers had made their final assortment and pricing choices, the experiment moved to the buyers.

Buyers selected the number of unique widgets to purchase and their quantity such that a budget of 50EC was not exceeded. Each period a buyer had 50EC to spend and was alerted if it had been exceeded, but the amount spent was not dynamically displayed as they entered values within a single period. The budget constraint was binding, so any remaining budget not spent was lost at the end of the period. Buyers obtained welfare throughout the experiment by buying widgets for less than they valued them. Specifically, buyers had a value of 10EC for the lowest valued widget, 12EC for the second lowest, 14EC, 17EC, and finally 20EC for the highest valued widget. Both buyers and sellers knew the value buyers had for each widget. These values remained constant for all buyers throughout the entire experiment. As with the sellers, the buyers saw a confirmation screen for the first 6 periods that allowed them to go back and re-submit their choices if they realized an error had been made.

We incorporated search into the experiment following Yuan and Han (2011) by allowing buyers to see the assortment and prices offered by one seller for free, and then giving them the option to pay a fee and see another seller's widgets and prices also. If the buyer decided to pay the fee, s/he could then purchase widgets from both sellers. Search costs were determined randomly following a uniform distribution and varied across buyers and periods. The minimum search cost was set to 0 and the maximum search cost was set to 4EC. This search cost was paid out of the buyer's

final welfare (or total EC) at the end of each period, and did not affect the amount the buyer had to spend when purchasing widgets. In other words, if a buyer had a search cost of 3EC and they decided to search, they still had the full 50EC budget to use to purchase widgets from sellers. Once the buyer made their search decision, his or her preference for variety was revealed and purchase decisions made.

Preference for variety was induced by providing additional welfare to the buyers for each unique widget purchased, which contributed to the buyer's total welfare at the end of the period. In this way, we obtained an equilibrium number of products offered. The degree to which a buyer benefitted from a wider product selection depended on the magnitude of his or her preference for variety which was not revealed until after the search decision had been made. Sellers were aware buyers had a preference for variety and would benefit from purchasing a wider assortment of widgets. Widgets of the same type from different sellers were considered unique. Preference for variety varied across buyers and periods and was determined randomly following a uniform distribution. The minimum preference for variety bonus was set to 0.01EC, while the maximum value attained per unique widget purchased was 3EC. At the same time preference for variety was revealed, the buyer made his or her product and quantity selections.

Once all buyers made their final decision, sellers' profits and buyers' welfare was displayed to each participant. Buyers observed the quantities they had selected, their search cost, their welfare in that period, and their total welfare up to that period. Sellers observed the prices they had set, the total quantities sold, their total inventory cost, profit for that period, and their total profit up to that period. After the profit/welfare screen had been displayed the experiment moved on to the next period, or ended if the time was up.

Once all sessions were finished, basic demographic data was collected using Qualtrics.com, and was combined with the experiment data using randomly assigned subject ID numbers. The specific demographic questions can be found in appendix B.

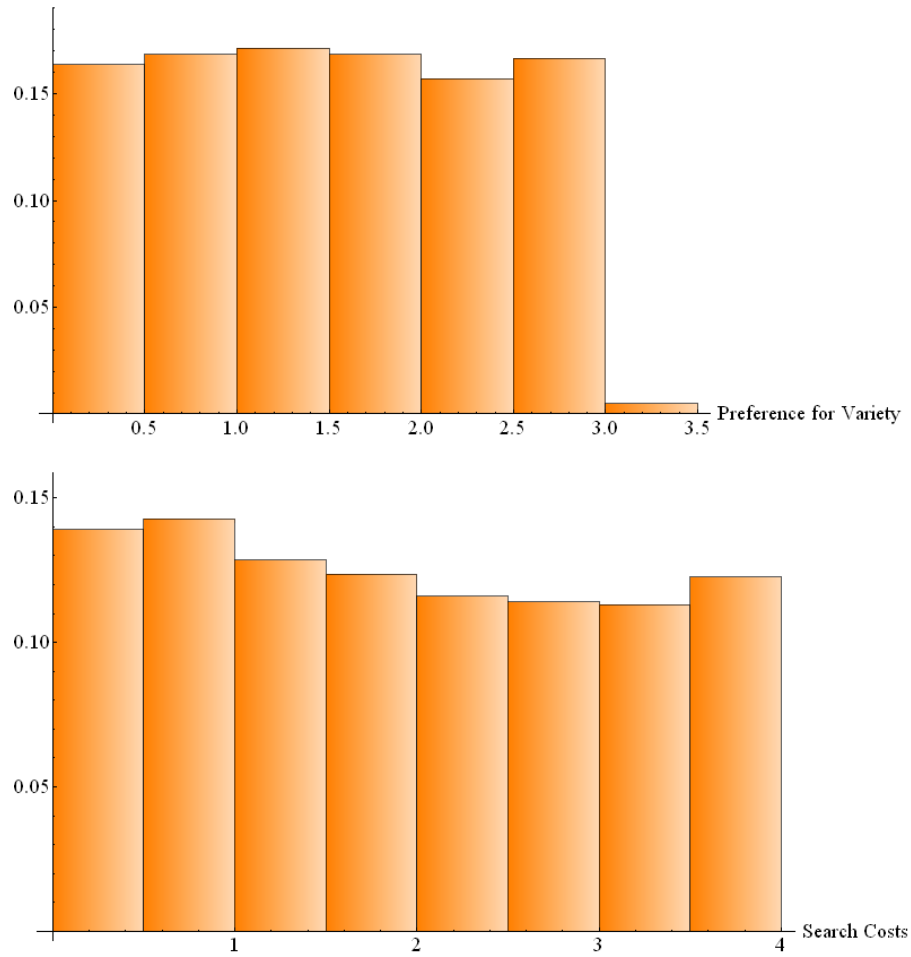
A.3 Ancillary Experiment Results

Within the experiment itself, buyers included in the estimation sample were similar in terms of both the cost of searching and the preference for variety. However, sellers in the student population offered fewer products, on average, compared to the public sample. Namely, students initially had an average of 2.7 products to choose from before searching while sellers in the public sample chose to offer an average of 3.5 products.[8] Despite this, the average number of products purchased by buyers in both samples was very close to two products. So, even though buyers in the public sample saw a higher number of products for free, and had the same preference for variety incentive (not statistically different at the 5% level), the number of products purchased is consistent with the number purchased in the student sample - 2 products. When making purchase decisions, the public sample used their budget less efficiently compared to the students. On average, the public sample had 8.3EC remaining compared to 4.5EC for the student-sample. These differences are statis-

[8] The mean is statistically different at the 1% level.

tically significant at the 6% level of significance.[9] Finally, the difference between the two different sample's search cost and preference for variety are not statistically different. From Figure 2 below, the preference for variety and search costs do represent a uniform distribution reasonably well. The histograms look almost identical if split across the different samples.

Figure 2: Histogram of the Search Cost and Preference for Variety Observed by Buyers



B Demographic Questionnaire

Please take your time and answer all the questions as accurately as possible. If you have any questions, please do not hesitate to ask.

- What is your current age? _____

[9] If the individual purchase observations are used then the difference between the average amount of money that was not used across the two different samples is significant at the 1% level ($N = 1044$).

- Are you male or female?

◊ Male
◊ Female

- How many people live in your household? Include yourself, your spouse and any dependents. Do not include your parents or roommates unless you claim them as dependents.

◊ 1
◊ 2
◊ 3
◊ 4
◊ 5
◊ 6
◊ 7
◊ 8+

- Please indicate the category below that describes the total amount of INCOME earned last year by the people in your household.

◊ Under $5000
◊ $5000-$7999
◊ $8000-$9999
◊ $10,000-$11,999
◊ $12,000-$14,999
◊ $15,000-$19,999
◊ $20,000-$24,999
◊ $25,000-$29,999
◊ $30,000-$34,999
◊ $35,000-$39,999
◊ $40,000-$44,999
◊ $45,000-$49,999
◊ $50,000-$59,999
◊ $60,000-$69,999
◊ $70,000-$99,999
◊ $100,000 - $124,999
◊ $125,000 - $149,999
◊ $150,000 - $199,999
◊ $200,000 +

- What is the highest level of education you attained?

◊ Some High School
◊ High School / GED
◊ Some college
◊ Associates degree
◊ Bachelor's degree
◊ Master's degree
◊ Some Doctorate education
◊ PhD or MD

- Do you have, or will you obtain, a Bachelor's degree, or advanced degree in any of the following areas: - Business Administration (or a major related to business - marketing, accounting, etc.) - Economics - Mathematics - Statistics - Engineering - Physics - Computer Programming?

◊ Yes
◊ No

- Have you ever, or do you currently, work at a job whose duties involves handling the accounts receivable or accounts payable? In other words, have you ever, or do you currently, work at a job in which you handle some or all of the financial aspects of the company?

◊ Yes
◊ No

- Please choose the category below that describes the total amount of money your household spends on groceries in an average month.

◊ $0 - $100
◊ $101 - $200
◊ $201 - $300
◊ $301 - $400
◊ $401 - $500
◊ $501 - $600
◊ $601 - $700
◊ $700 +
◊ I don't know

- When doing day to day grocery shopping, which of the following selections is most likely accurate?

◊ I shop around at multiple stores to obtain the best price on different products.
◊ I check store coupons and advertisements and shop at the grocery store that offers the best deal on the products I plan to purchase.
◊ I check the prices of the products I plan to purchase online and go to the grocery store that makes my total purchase the cheapest.
◊ I shop at the grocery store that is most convenient.

- Which of the following attributes is more important when making a grocery store selection?

◊ Price
◊ Product selection

- Please rate the following categories in terms of how likely you would be to make a purchase on-line, rather than at a local retailer.

	Not Applicable	Unlikely - I almost always purchase this at local retailers - 1	Unlikely 2	...	Likely 6	Very likely - I almost always purchase this online 7
Baby products	◊	◊	◊	...	◊	◊
Beauty and fragrances	◊	◊	◊	...	◊	◊
Books and magazines	◊	◊	◊	...	◊	◊
Clothing, accessories, and shoes	◊	◊	◊	...	◊	◊
Gifts and flowers	◊	◊	◊	...	◊	◊
Health and personal care	◊	◊	◊	...	◊	◊
Computers, accessories, and services	◊	◊	◊	...	◊	◊
Education	◊	◊	◊	...	◊	◊
Electronics and telecom	◊	◊	◊	...	◊	◊
Entertainment and media	◊	◊	◊	...	◊	◊
Food retail and service	◊	◊	◊	...	◊	◊
Sports and outdoors	◊	◊	◊	...	◊	◊
Toys and hobbies	◊	◊	◊	...	◊	◊
Home and garden	◊	◊	◊	...	◊	◊

- In general, when you go shopping, which of the following is more accurate in general, not necessarily for groceries?

◊ I like to get in, obtain what I was looking for, and leave.

◊ I like to shop around a bit and see the different products the retailer carries.

- How often do you make purchases online?

◊ Never
◊ Less than Once a Month
◊ Once a Month
◊ 2-3 Times a Month
◊ Once a Week
◊ 2-3 Times a Week
◊ Daily

- How often do you have something delivered to your home that was purchased online?

◊ Never
◊ Less than Once a Month
◊ Once a Month
◊ 2-3 Times a Month
◊ Once a Week
◊ 2-3 Times a Week
◊ Daily

- If you were thinking about getting into a new hobby and were going to make a purchase, where is the first place you would go for information? For example, if you were going to get into photography, what is the first information source you would use to obtain information on different cameras?

◊ Recommendation of friends
◊ Online retailer's product information
◊ Online manufacturers product information
◊ Local retailer
◊ Other

- What is your Subject ID number? _____

You have completed the demographic portion of the questionnaire. I will begin the actual experiment in a moment. Please wait for further instructions.