6-2021

Analysis of Demand under Time and Quantity Restriction Frames

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ANALYSIS OF DEMAND UNDER TIME AND QUANTITY RESTRICTION FRAMES

by

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A dissertation submitted to the Graduate College
in partial fulfillment of the requirements
for the degree of Doctor of Philosophy
Psychology
Western Michigan University
June 2021

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For decades, behavioral economists and behavior analysts have borrowed techniques from one another to investigate human decision making. While there has been little overlap in their work, the union of the two may help to answer important questions about behavior. An emerging behavioral economic topic of interest in the behavior analytic literature is the analysis of how framing affects demand. The purpose of the present studies is to investigate some conditions under which demand is affected by framing and provide a behavior analytic interpretation of those effects. To assess the effects of framing, demand for marketplace items was assessed under time and quantity restrictions. This work consisted of four studies. The first study was an Item Purchase Assessment which was conducted to identify several commonly purchased items. The six items participants indicated they had purchased most and were most likely to purchase in the future were selected for use in subsequent experiments. The second two studies were Restriction Assessments. In these experiments, participants completed hypothetical purchase tasks under three quantity restrictions and three time restrictions. The first Restriction Assessment included quantity restrictions of 1, 10, or 50 items available for purchase, and 1 hour, 1 day, or 1 week available to purchase items. The second Restriction Assessment included restricting items to 100, 10,000, or 100,000 available, and 1 month, 6 months, or 1 year available

to purchase items. The results of these experiments were analyzed for differences in demand curve fit parameters (demand intensity and rate of change in elasticity), essential value, and P_{max}. From these assessments, three time and three quantity restrictions were selected for the final study.The final study was the Analysis of Demand Under Restriction. In this study, participants completed hypothetical purchase tasks for the six selected items. Quantities of items were restricted to 1, 100, or 100,000. Times to purchase items were restricted to 1 hour, 1 month, or 1 year. Data were analyzed for differences in demand curve parameters, rate of change in elasticity and demand intensity, as well as essential value and P_{max}. No significant differences were detected between demand curve parameters. Descriptive statistical analyses revealed that essential value and P_{max} increased as restriction increased, suggesting that the value of items increases as they are restricted. These studies represent a successful integration of traditional behavioral economics and behavior analysis. These data provide preliminary evidence to support the conclusion that product scarcity can lead to increased valuation. However, there is still much to be discovered about the conditions under which decision frames affect behavior and the underlying behavioral processes that are involved. The latter will likely requirean analysis of verbal behavior in economic contexts.

ACKNOWLEDGMENTS

My time at WMU has been defined by many happy accidents, from accidentally ending up at my "safety school" for undergrad where I first learned about behavior analysis, to applying to grad school the same year my advisor accepted a faculty position, to getting to pursue my dream career, to meeting the love of my life. It's always a great day to be a Bronco!

My first and greatest thanks go to my doctoral advisor, Dr. Anthony DeFulio. Anthony, I have grown more personally, academically, and professionally under your mentorship than I ever could have imagined a few years ago as a cashier at a hardware store who wanted to become a behavior analyst. Thanks for teaching me how to be persistent in working toward my goals, resilient in the face of challenges, and confident in my own abilities. You have been a great role model. I truly cannot thank you enough for your mentorship.

My next thanks go to my dissertation committee: Drs. Lisa Baker, Doug Johnson, and Steve Hursh. Thank you all for lending your guidance and expertise to me. I also want to thank Dr. Lindsay Schwartz, who feels like a bonus committee member and enthusiastically jumped in to help me with my demand analyses. I feel privileged to have worked with all of you.

I have been incredibly fortunate to have worked with so many amazing faculty throughout my time at WMU. I have learned so much from each and every person I have been mentored by. I want to thank Dr. Lisa Baker again, for introducing me to behavioral pharmacology, giving me my first tastes of research, and putting me in touch with Anthony. Lisa, you have had such a pivotal role in my journey and I am forever grateful.

Acknowledgements – Continued

I also owe special thanks to Dr. Stephanie Peterson. Stephanie, you have felt like a second mentor to me throughout grad school. You are the epitome of a female role model: smart, driven, and professional. I have learned so much from you over the years. Thank you.

Thank you to my lab mate, best friend, and fiancé, Sean Regnier. I did not expect to find the love of my life in grad school, let alone in my lab. This was perhaps the happiest accident of all. Sean, thank you for supporting me through all the ups and downs, even as you pursued a Ph.D., yourself. You have made me better in so many ways. I love you.

To my other lab mates, Mark Rzeszutek, Amanda Devoto, David Cosottile, Hayley Brown, and Cristal Cardoso Sao Mateus Churchill, thank you! I am so lucky to have had you as lab mates and as lifelong friends. Special thanks to Mark for helping me out on this project. Thanks for going the extra mile to help me with the stats for my project.

To all my friends in the program: thank you for your support. Grad school is such a strange time. I'm happy to have had friends to commiserate, celebrate, and spend all those late nights with (whether on campus, at Fourth Coast, or at Harvey's).

Finally, thank you to my mom, my dad, and my sister. Thank you for believing in me, for giving me a safe place to land, a shoulder to cry on, a voice of reason, comic relief, and endless support. I could not have gotten through this without you. I love you.

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Introduction

For decades, behavioral economists and behavior analysts have been borrowing techniques from one another to investigate how humans make decisions. Behavioral economists often seek to predict irrational decision making by looking at economics through a psychological lens. Among the phenomena behavioral economists are interested in is how framing affects decision making. Behavior analysts often use microeconomic techniques, such as demand analyses, to quantify changes in preferences under a variety of parameters. While there has been little overlap in traditional behavioral economics and behavior analytic approaches to microeconomics, the union of the two may help to answer important questions about decision making. An emerging behavioral economic topic of interest in behavior analytic literature is the analysis of how framing affects demand. The purpose of this experiment is to investigate some conditions under which demand is affected by framing and provide a behavior analytic interpretation of those effects. Thus, a brief review of decision framing is appropriate.

Decision Framing

Economic models have traditionally incorporated the assumptions that all human decision making is optimal, rational (preferences are transitive and complete; unchanging), and neatly aligned with self-interest (Tversky & Kahneman, 1981). However, predictions resulting from many economic models do not account for the full range of human decision making. Indeed, there are many conditions under which actual human behavior departs from traditional economic predictions. The principle goal of behavioral economics is to identify these conditions and develop models that more accurately characterize human behavior in economic contexts.

Behavioral economics differs from traditional economics in many important ways. For example, traditional economic theory relies on the expected utility model. This model is based on the principal assumption that humans behave rationally. That is, choices are consistent and coherent (Tversky & Kahneman, 1981). Under the expected utility model, it is assumed that preferences remain constant under a variety of conditions. However, in 1981, Tversky and Kahneman described the phenomenon of "decision framing" which challenged the traditional economic notion of consistent preferences. Decision framing is defined as "the decision-maker's conception of the acts, outcomes, and contingencies associated with a particular choice" (pp. 453). This conceptualization of decision making emphasizes the role of norms, habits, and personal characteristics as important determinants of human behavior. While traditional economists would argue that preferences remain constant regardless of context, Tversky and Kahneman posited that the presence of a frame can shift preference (Tversky & Kahneman, 1981).

To explain how humans deviate from the expected utility model of preferences and decision making, Tversky and Kahneman described the decision making process in two parts (Tversky & Kahneman, 1981). Part one involves assessing the situation by which it is framed. Part two involves evaluating the potential choices. Tversky and Kahneman identified three components of frames that can be varied to shift and reverse preferences. These variations include framing of acts, contingencies, and outcomes (Tversky & Kahneman, 1981). Scenarios frames in terms of acts are those in which the choices available to participants are differentially framed to shift preference. Framing of contingencies refers to contingent decision making, in which options offered in one component of a problem depend on previous outcomes. Framing of coutcomes occurs when available choices vary in meaningful ways in relation to a reference point (Tversky & Kahneman, 1981).

In addition to the three types of frames outlined by Tversky and Kahneman, Levin and colleagues identified three more types of decision frames, including risky choice frames, goal frames, and attribute frames. Of particular interest in the current study are attribute frames. Attribute framing involves manipulating a characteristic of an object or event within a context. Rather than evaluating risks or outcomes, individuals evaluate selections in reference to a particular attribute. Attribute frames make it possible to assess how descriptions of characteristics affect decision making. Attribute frames are often used to assess consumer decision making. Rather than relying on how manipulations to risk reverse preferences, different qualities of available options are modified (Levin et al., 1998). One way that attribute frames are manipulated is by advertising a deal in terms of scarcity of a product. Framing deals in terms of scarcity often leads to increases in demand (Shi et al., 2020; Inman et al., 1997).

Scarcity Framing

Two common types of scarcity decision frames are limited time and limited quantity frames. Limiting the time and quantity available for purchasing items is a common tactic employed by retailers and human service providers. In a study conducted by Aggarwal and colleagues (2013), time and quantity frames were examined for their relative effectiveness in driving up consumer demand. Consumer demand was measured in terms of intention to purchase items. Intention to purchase was measured through a 7-item Likert scale. Participants were asked to rate their intention of purchasing a wristwatch (Study 1) and laptop (Study 2) under time restricted, quantity restricted, or unrestricted scenarios. The authors hypothesized that limited quantity scenarios would result in higher demand because there is an implication of competition between other shoppers when quantities are limited. The results of these studies revealed that quantity restrictions were more effective than time restrictions at driving up consumer demand.

Consumer demand was higher under the quantity and time restrictions than the unrestricted condition. Consumer competition also mediated the relationship between scarcity and intention to purchase (Aggarwal et al., 2013).

Outcome measures in framing experiments are largely measured indirectly. This limits the explanatory power of the theories due to reliance on hypothetical constructs such as “intention”. Directly measuring behavior may help to fully account for preference shifts and reversals. The theories and cognitive accounts currently accepted by behavioral economists may serve well as a basis for forming hypotheses, rather than as well-developed accounts of preferences shifts and reversals.

In summary, researchers have outlined several subtypes of decision frames. Of particular interest are scarcity frames, under which demand for items is driven up when availability is limited. Current understanding of the mechanisms underlying framing effects is limited by cognitive interpretations which rely on using hypothetical constructs to measure inner states. Thus, a new approach to studying decision frames is needed. A behavior analytic account of decision frames may help to close the gaps in what is understood about framing effects.

A Behavior Analytic Account of Framing

Behavior analysts are uniquely equipped with tools for investigating causal relationships between antecedents and consequences. The primary unit of behavior analysis is behavior, rather than hypothetical constructs that are not directly observable. This allows behavior analysts to discover mechanisms of behavior change by analyzing objective and measurable phenomena in the environment. Behavior analysts analyze phenomena in terms of the antecedents, behaviors, and consequences involved in events, rather than hypothetical constructs and other indirect causes. By keeping analyses external, a behavior analytic account of framing can provide objective information about the relationship between preference shifts and framing. More integration of behavior analytic research into traditional behavioral economics has benefits for both approaches.

To study framing effects is to study how differences in the presentation of verbal statements influence behavior. Without understanding how phrasing can modify the function of verbal statements, interpreting *why* these phrasing changes lead to different behavioral outcomes is puzzling. However, by adopting a behavior analytic approach to understanding decision framing, researchers may be able to develop more precise accounts for the shifts in preference. In behavior analysis, a unique philosophical approach is taken in the analysis verbal behavior (see Skinner, 1957). This involves assessing the function of verbal stimuli. A functional approach to analyzing the verbal behavior involved in decision framing may further enhance interpretations of the framing effect.

Traditional behavioral economists tend to focus on hypothetical constructs and indirect observations of behavior to understand human decision making problems, while behavior analysts look to the environment for causal explanations. Behavior analysts have already begun adopting microeconomic techniques but have seldom directly studied more traditional behavioral economic concepts like decision framing. A behavior analytic account of traditional behavioral economic concepts could result in a more precise and quantifiable science of behavioral economics. Additionally, behavior analysts may help to broaden the reach of behavioral economics since behavior analysis falls within the broader field of psychology. While traditional behavioral economists often focus on consumer behavior (e.g., Fama, 1998; Schulze et al., 2003), behavior analysts have adopted microeconomic techniques to address issues such as addictive behaviors (e.g., Reed et al., 2016), substance use (e.g., Bruner & Johnson, 2014) medical decision making (e.g., Bruce et al., 2018) and preferences in applied behavior analytic interventions (e.g., Frank-Crawford et al., 2018).

Traditional Behavioral Economics in Behavior Analysis

Some behavior analysts have integrated behavior analysis and traditional behavioral economics (TBE). For example, in 1998, Fantino provided an account of what behavior analysis can add to TBE. Fantino described the concepts of base-rate neglect, the conjunction fallacy, and probability matching. These concepts have not been well understood by traditional economists due to reliance on hypothetical constucts. However, a behavioral analysis of stimulus control, conditioned reinforcement, and behavioral history can account for the underlying processes behind these concepts (Fantino, 1998).

There are three major interests shared across TBE and microeconomic analyses of behavior (MAB). These include interest in understanding human decision making, learning more about the proximity in time and space of behavior related to environmental events, and learning about why organisms behave against self-interest (Furreboe & Sandaker, 2017). There are at least three ways that MAB is distinct from TBE, which include that MAB involves the principle of reinforcement, single-subject design, and a selectionist perspective (Furreboe & Sandaker, 2017). The distinguishing features of MAB from TBE partially represent how MAB can be used to improve TBE analyses.

The use of single subject research can aid in the precision of behavioral economic investigations (Furreboe & Sandaker, 2017). Through conducting aggregate analyses of behavior, meaningful individual differences are lost. The goal of behavior analytic research is to investigate *why* behavior occurs. Through an operant analysis applied to single subject research, behavior analysts can study how environmental events and behavioral history influence responding. Behavior analysts are able to exert control over variables that could lead to differential outcomes. Using group analyses, the amount of experimental control possible is limited compared to single subject research (Furreboe & Sandaker, 2017).

In addition to single subject research, behavioral principles such as the principle of reinforcement provide better explanations for the occurrence of behavior than terms adopted by traditional behavioral economists (Furreboe & Sandaker, 2017). The principle of reinforcement is analogous to the concept of “utility” in TBE. What behavior analysts describe as reinforcement, economists refer to as the value of goods (Hursh & Roma, 2013). It is important to distinguish utility from reinforcement. A reinforcer is a stimulus that increases the future probability of a response it follows (Skinner, 1969, pp. 7). Utility is a measure of how an outcome is valued (Furreboe & Sandaker, 2017). While the concept of utility quantitatively accounts for value, it is not analyzed in terms of operant selection. This leaves room for subjectivity in analyses of utility. Value is measurement more precisely through an operant selection account. MOs and their place in the three-term contingency, for example, add a level of precision to understanding reinforcer strength that is not present in the concept of utility. Thus, the behavior analytic contributions of the principle of reinforcement and the three term contingency provide a better account for decision making.

By approaching decision making problems from a selectionist perspective, behavior analysts keep all causal agents in the environment. Through operant selection, or ontogenic selection, behaviors are selected over the course of an organism’s lifetime. A selectionist perspective can aid in interpretations of framing effects. The framing effect occurs when preferences change based on the way that a scenario is presented (Tversky & Kahneman, 1981). Each subtype of framing adds complexity to understanding framing as a whole. Many attempts have been made to try and understand the phenomena underlying preference reversals in each of these scenarios. Many of these interpretations have involved speculation about inner events, often conceptualized in terms of hypothetical constructs, as causes for shifts in preference. The selectionist perspective aids in interpreting framing because it keeps causes environmental.

Often in TBE, causes of behavior are explained in terms of the person's intent. Rather than speculating at "intention" as a cause of shifts in preference, behavior analysts analyze decisions in terms of the environmental contingencies that influence choice. Decisions are also analyzed in terms of the contingencies that have been reinforced in the past, both phylogenically and ontogenically. Environmental events and behavioral history may lead to variability both across participants and when compared with what economic theory predicts.

Understanding the three term contingency is essential to understanding operant selection. The three term contingency describes the relationship between antecedent events, behaviors, and the consequences that follow (Skinner, 1969, pp. 7). By using the three term contingency, functional relationships between behavior and its consequences can be identified. It can be used to examine when behavior will occur and whether it will be maintained based on setting events and the consequences of engaging in a behavior within a particular context. The three term contingency can be used to analyze framing effects. Behavior analysts can analyze the discriminative stimuli, motivating operations, and consequences that influence preference under presented framing conditions. Of particular interest are the motivating operations that influence responding.

Previous research has outlined several ways in which behavior analysts can contribute to a more precise science of behavioral economics. Among these include that behavior analysts primarily use single subject designs over group designs. Behavior analysts also contribute by using behavioral principles like reinforcement and stimulus control to define and understand behavior. Finally, behavior analysts use an operant selectionist perspective to understand how behavioral history and contingencies of reinforcement predict future behavior. In addition to these contributions, behavior analysts add a unique analysis of verbal behavior which may be especially important for understanding framing effects.

Frames as Verbal Behavior

Frames may best be conceptualized as a form of verbal behavior. Frames are antecedent events and bear many similarities to motivating operations. Motivating operations (MOs) are antecedent events that alter the reinforcing effectiveness of other events and the frequency of occurrence of behavior relative to those events as consequences (Michael, 1993). Through analyzing MOs, differences in reinforcer valuation can be assessed. This may be important when examining preference reversals due to framing effects.

Operant behavior is either contingency-shaped or rule-governed. Contingency-shaped behavior is behavior that is learned through direct experience. Rule-governed behavior is behavior under the control of a contingency-specifying stimulus, or rule (Skinner, 1969, pp. 160-162). Rules can serve as MOs by specifying the conditions under which behaviors will lead to reinforcing or punishing outcomes. One type of rule that serves as a verbal MO is the augmental rule. There are two types of augmental rules, which are formative and motivative augmental rules (Leigland, 2005).

Formative augmental rules are rules that establish a stimulus as a reinforcer or punisher. Motivative augmental rules are a type of rule that temporarily changes the effectiveness of the consequence (Plumb et al., 2009). Frames may best be described as augmental rules. For example, a goal frame, such as "getting the COVID-19 vaccine will help prevent the spread of

COVID-19" could be conceptualized as a formative augmental rule that establishes the vaccine as a reinforcer. Scarcity frames may serve as motivative augmental rules that increase the reinforcing effectiveness of established reinforcers.

Formative and motivative augmental rules are a critical component of relational frame theory (RFT; Plumb et al., 2009). Augmental rules are important because they establish the value of a stimulus (Leigland, 2005). Augmental rules derive their function through involvement in relational networks. Their function is derived through a history of multiple exemplar training and socially mediated consequences. Because rules can serve as MOs and many, if not all decision frames are rules, then decision frames may have a place in RFT.

First, it is important to establish the distinction between relational frames and decision frames. RFT involves the analysis of contextual factors that lead to derived relations. Derived relations occur due to associations between stimuli, responses, and consequences in a variety of contexts. Context determines which behaviors will be evoked. Relational framing occurs when an arbitrarily applicable response is evoked within a context where it has historically been reinforced (Hayes, 1991). It is responding that is contextually controlled (Hayes, 1991). To analyze decision frames through RFT, it is appropriate to view decision frames as the contextual cues. Decision frames are verbal statements that have been associated with a variety of other stimuli throughout an individual's lifetime. The decision frames included in a decision making problem can evoke different behaviors depending on behavioral history.

Stimuli and responses that are related through contextual and functional properties are said to participate in the same "frame of coordination" (Barnes-Holmes & Barnes-Holmes, 2000). Therefore certain words or phrases will likely evoke specific types of derived responses due to their membership in a particular frame of coordination. Derived responses may be evoked due to an individual's history of responding to other words and events associated with those words and phrases. They also may be evoked due to a history of responding to those words and phrases in a variety of contexts. For example, if a decision frame refers to the limited availability of a commodity, it is likely that the behavior that will be evoked, such as increased responding to obtain the commodity, is behavior that has been reinforced in other comparable situations. "Limited availability" may participate in the same frame of coordination as stimuli like "high demand" and/or "lack of access". Purchasing increased amounts of a commodity or purchasing items at higher prices could be evoked due to a history of reinforcement for behaving similarly under other conditions within the same frame of coordination.

In summary, decision frames serve as augmental rules that help to establish the context for relational framing behaviors. Behavior analysts can add to interpretations of the framing effect through conceptualizing frames as verbal behavior, and especially through analyzing stimulus equivalence and stimulus relations. Behavior analysts can also predict what behavior will be evoked and when through a careful analysis of operant conditioning and behavioral history. Behavior analysts are experienced in investigating how stimuli acquire reinforcing and punishing properties. Conceptualizing frames as augmental rules helps to account for the processes involved in the framing effect. Frames as augmental rules establish the value of stimuli. The next step in this analysis is to quantify the value of stimuli affected by decision frames. To quantify the value of stimuli, behavior analysts can borrow techniques from TBE.

Microeconomic Analyses of Behavior

Behavior analysts contribute abundantly to TBE through concepts like reinforcement, the use of single subject design, the selectionist perspective, and RFT. Significant contributions to behavior analysis have also been made by TBE. Behavior analysis has been greatly enhanced by the adoption of TBE concepts like the matching law, which predicts that the rate of responding allocated to each option out of an array will match the rate of reinforcement available on each option (Herrnstein, 1961). The matching law is useful for predicting patterns of responding in choice tasks. Two value assessments that have greatly enhanced behavior analysis and analyses of choice include delay discounting and demand analyses.

Through the use of the demand analysis, response strength and reinforcer value can be precisely measured across a range of conditions (e.g., price increases). Demand analyses are a technique adopted by behavior analysts which is used to investigate how consumption changes as a function of price increases (Hursh, 1984). Price can be increased either through schedules of reinforcement (typically fixed ratio schedules) or through increasing monetary price to obtain a reward. Demand analyses provide information about value and response strength. The two variables of interest in a demand analysis are demand intensity and demand elasticity. Demand intensity is most analogous to value, as it is a measure of the amount of behavior that will be maintained and the amount of reinforcement earned. Demand elasticity is analogous to response strength as it is a measure of rate of change in responding across price increases. However, response strength sometimes differs from elasticity, as response strength can be a measure of other disrupters as well (Hursh, 1984). Demand curves are generated to show rate of change in consumption across a range of prices. Demand analyses can be used to analyze single commodities or to compare consumption of concurrently available commodities (Hursh, 1980).

The addition of these value assessments to behavior analysis has helped behavior analysts to better understand the conditions under which subjects value certain commodities over others, and how preference shifts as a function of price, delay, magnitude of reinforcement, or probability. Using the demand analysis to interpret framing effects can provide information about the range of conditions under which decision frames affect the value of commodities.

The Demand Analysis

The demand analysis is a microeconomic technique used to assess the value of commodities. In the late 1970s, the demand analysis became an emerging topic of interest by behavior analysts (e.g., Lea & Roper, 1977; Hursh, 1978; Lea, 1978; Hursh, 1980) and its clinical utility continues to grow (Barnes et al., 2019; Dolan et al., 2020; Strickland et al., 2020). The demand analysis is used to determine how consumption changes as a function of price (Hursh, 1980). Price is typically manipulated by changing the fixed ratio (FR) schedule required to obtain reinforcement across sessions (Hursh & Silberberg, 2008). Demand curves are produced by plotting consumption as a function of price (Hursh & Silberberg, 2008).

Demand analyses have been conducted in laboratory and clinical settings (e.g., Tan & Hackenberg, 2015; Frank-Crawford et al., 2018) and through hypothetical purchase tasks (HPTs) (e.g., Roma et al., 2019; Wilson et al, 2016). While price manipulations in physical demand analyses involve increasing response requirements on an FR schedule, price manipulations in hypothetical demand analyses occur through survey format. The use of hypothetical demand analyses has greatly expanded the applications of demand analyses. Recent applications have included analyzing fuel consumption (Reed et al., 2014), skin cancer risk (Kaplan et al., 2014), pornography purchases (Mulhauser et al., 2018), tanning (Reed et al., 2016), excessive eating (Epstein et al., 2018), and demand for marketplace items (Roma et al., 2019).

Prior to 2008, demand was analyzed using a linear model, called the linear-elasticity function. The linear elasticity function,

$$\ln Q = \ln L + b \ln P - \alpha P$$

shows consumption as a function of price wherein Q is the quantity consumed, P is the price set by the FR schedule, L is the level of consumption as P approaches 0, b is the slope of the demand curve after an infinitesimally small increase from zero or level price, and a is a coefficient (Hursh & Silberberg, 2008).

In 2008, the demand analysis was improved when the exponential model of consumption was adopted,

$$\log Q = \log Q_0 + k(e^{-\alpha \mathrm{P}} - 1)$$

where Q is demand, Q_0 is the quantity consumed when price is 0, P is price which is determined by the FR schedule, k is a constant for specifying range of data, and α indicates changes in elasticity (sensitivity to price) (Hursh & Silberberg, 2008). Commodities that are more inelastic relative to others are considered more valuable, as demand decreases at a slower rate (Hursh & Silberberg, 2008).

While demand curves are helpful for assessing the relationship between price and consumption, they are limited in that they do not provide information about the "true value" of a commodity relative to others. Therefore, the concept of essential value (EV) was created to improve upon the information that the exponential model of demand can provide (Hursh & Silberberg, 2008). EV is used a measure of demand. EV allows for comparisons in demand across commodities. It is a single number used to represent elasticity of demand (Hursh & Silberberg, 2008). EV is a measure of reinforcing efficacy that is theoretically constant and independent of unit size (Hursh & Roma, 2016). EV is inversely related to elasticity. The following equation has been used to calculate EV:

$$EV = \frac{1}{100 * \alpha * k^{1.5}}$$

Given that inelastic commodities are viewed as more valuable, and elasticity is inversely related to EV, a higher EV indicates higher reinforcing efficacy of a commodity.

In addition to EV, other values of interest in demand analyses are P_{max} and O_{max}. P_{max} is the point at which a commodity changes from inelastic to elastic. That is, the point at which an x% increase in price results in a greater than x% decrease in consumption (Roma et al., 2019). O_{max} is the maximum output at P_{max} (Roma et al., 2019). Greater values of P_{max} and O_{max} can be used as additional indices of value.

While the exponential model greatly improved analyses of demand, its major drawback is lies in the fact that it is a logarithmic function and therefore has asymptotes at zero (Koffarnus et al., 2015). Thus, it is not possible to calculate zero levels of consumption using the exponential model of demand. To avoid issues caused by including zeros in the data, researchers in the past have either omitted zeros from their analyses; replaced zero consumption with small, nonzero values such as 0.1 or 0.01; or restricted analyses to only group models that average consumption, therefore reducing the number of zeros included in the data (Koffarnus et al., 2015). However, all of these approaches are limited. By omitting zeros from analyses, researchers lose legitimate data. In addition, this can inflate the data because only nonzero values are included when averaging group data. By transforming all zero values to non-zeros, curve fits can be affected. On a logarithmic scale, the difference between 0.01 and 0.1 is the same as the difference between 10 and 100. Koffarnus and colleagues produced demand curves using the exponential equation with zero included, zero removed, and with values of 0.001, 0.01, and 0.1 in place of zero. Each of these manipulations produced meaningfully different curves (see Figure 1). Finally, using only group models of consumption is limited because individual differences in consumption are lost (Koffarnus et al, 2015).

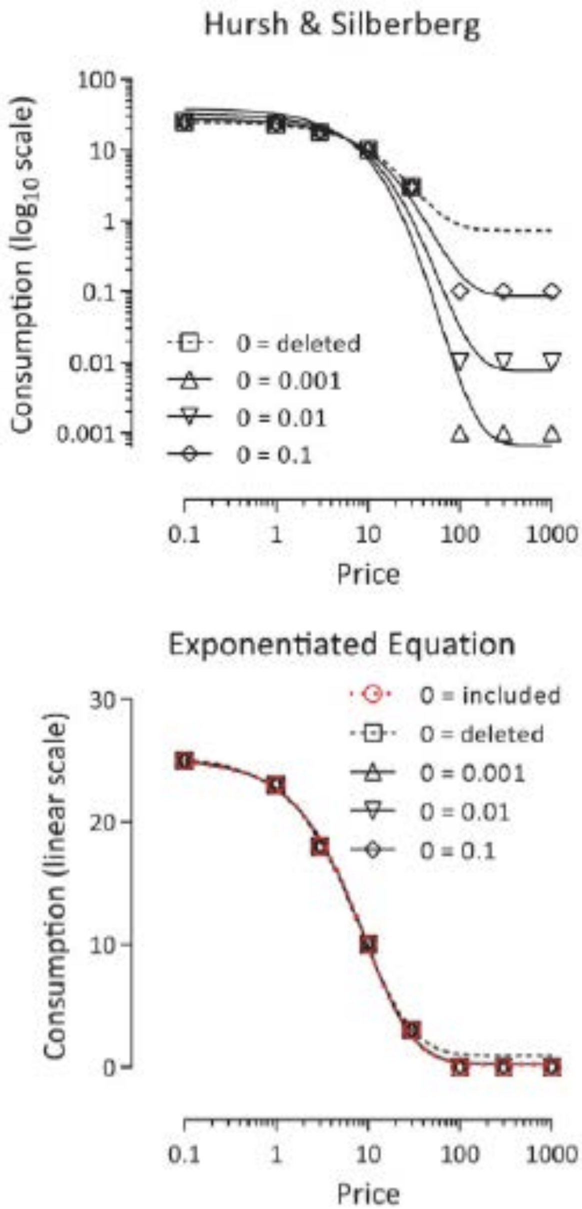


Figure 1. Exponential vs. exponentiated nonzero curve fits (Koffarnus et al., 2015).

To address these limitations, Koffarnus and colleagues generated a modified version of the exponential model, which is the exponentiated model of demand:

$$Q = Q_0 * 10^{(k(e^{-\alpha Q_0 C - 1}))}$$

The exponentiated model of demand is a version of the exponential model wherein both the left and right side of the equation have been raised to the power of 10. By exponentiating this equation, zeros can be included in analyses (Koffarnus et al., 2015). Consumption is fitted on a linear scale while the regression remains logarithmic (Gilroy et al., 2020). While this equation addresses the drawbacks of the exponential equation, it also is limited in several ways.

Despite that the exponentiated equation supports the inclusion of zeros, it is important to note that consumption using the exponential and exponentiated equations should be interpreted differently (Gilroy et al., 2020). Because the exponentiated model is linear, differences in consumption are measured as *absolute* change while differences in consumption in the exponential model are *relative.* This could lead to different estimates because the difference in the error terms may result in varied levels of uncertainty. Error variance has been found to be skewed on the linear scale and may present more normally distributed than on the log scale.

Although the exponentiated model accommodates zeros during fitting, it retains the log scale functional form of the exponential model when curves are fit. The rate of change (α) is bound to the scaling constant, *k*, in both models. Because it retains the log scale bounded by the *k* parameter, demand curves generated with the exponentiated model remain undefined at zero. To address the drawbacks of both the exponential and exponentiated models, Gilroy and colleagues proposed an inverse hyperbolic sine transformation called the Zero-Bounded Model of Operant Demand, or ZBE:

$$IHS(Q) = IHS(Q_0) * (e^{-\frac{\alpha}{IHS(Q_0)} Q_0 x})$$

$$\text{where } IHS(Q_0) = \log_{10}(0.5\, Q_0 + \sqrt{0.25\, Q_0{}^2 + 1}\,)$$

This model advances on the exponential and exponentiated models because it is $\log_{10}$-*like.* Because it is not a log scale, it is advantageous because it accommodates the inclusion of zero in the regression. The span of the demand curve in IHS units is between a minimum of zero and a maximum of IHS(Q_0). Therefore, this model is also advantageous because it is not bounded to k. Because fits are not bounded to the parameter, k, the issue of not being able to compare demand curves that span different k parameters is avoided. Because α is no longer bounded to k, the equation for essential value also changes (Gilroy et al., 2020):

$$EV = \frac{1}{100 * \alpha}$$

An EV equation unbounded by the parameters of the model fit will help make comparisons between commodities possible. Analyses of the ZBE and the normalized ZBE (ZBEn) models demonstrated that models perform well across hypothetical and physical demand tasks (Gilroy et al., 2020). The ZBEn model corresponded well with the exponentiated model of demand, which suggests that this model may be suitable for addressing the limitations of the exponentiated model. However, Gilroy and colleagues still recommending the exponential and exponentiated models when those models better answer the proposed research question.

Framing and Demand

Introducing frames into decision making scenarios can result in preference shifts and reversals (Tversky & Kahneman, 1981). The demand analysis is a value assessment that may have utility in quantifying differences in reinforcer strength and value across different framing conditions. Currently, little research has been conducted directly examining the effects of framing on demand. Research on framing typically involves the use of hypothetical demand analyses, where demand is assessed in survey format and participants are required to indicate the amount of a commodity they would purchase across various monetary prices. Recent research that has been conducted on framing effects often involves the use of the Alcohol Purchase Task (APT), which is a type of HPT specifically tailored to alcohol consumption. Manipulating frames in APTs has been used to examine the effects of time constraints on alcohol purchases (Kaplan et al., 2017), the effect of 'happy hour drink specials' on consumption (Kaplan & Reed, 2018), the effect of next-day exam times on alcohol purchases during the night before (Gentile et al., 2012), the effect of left-digit price manipulations on alcohol purchases (Salzar et al., 2019), and combinations of price and time manipulations on alcohol purchases (Skidmore & Murphy, 2011). Currently, little research on framing effects has been conducted outside of APTs. However, APTs have illustrated that the use of an HPT lends itself well to analyzing framing effects.

Recent research on HPTs has provided framework for conducting hypothetical demand analyses. In a study conducted by Roma and colleagues in 2019, an HPT was implemented to analyze purchases of various arbitrary items. Six items were selected, including three small-ticket items (hamburger/sandwich, roll of toilet paper, and pay-per-view movie) and three big-ticket items (meal at a fine-dining restaurant, refrigerator, and vacation package). Consumption was assessed across three sets of price densities. Researchers assessed quantity of purchases and probability of purchase at each price point. Price densities were analyzed to determine an adequate number of prices to include in a demand analysis. Researchers assessed demand across three levels of price density (i.e., low = 5 prices, medium = 9 prices, high = 17 prices). Based on their results, Roma and colleagues suggested that a minimum of 9 and maximum of 17 or more price points is appropriate. Higher price densities led to higher elasticity but were more resistant to distortion in the demand curve. Low price densities led to inflated demand compared to high price densities, making comparisons across price density conditions difficult (Roma et al., 2019).

Roma et al. also examined quantity and probability of purchases at each price point. They found that value was higher in probability tasks than quantity. However, quantity and probability

HPTs produced consistent results for the rank order of demand of all commodities. Prior to this study, probability had never been used to estimate demand. While quantity and probability were equally effective for examining demand, quantity analyses provided more information about values such as O_{max}, which were impossible to calculate using probability as a measure. Additionally, comparisons of quantity and probability demand curves were not possible, since a 1 point increase in probability of consumption is not equal to a 1 unit increase in quantity consumed (Roma et al., 2019). Despite differences in interpretation, probability and quantity HPTs provide useful information about changes in consumption relative to price.

In summary, previous research on framing and APTs supports the use of framing techniques in demand analyses. A study by Roma et al. (2019) provides important framework for structuring HPTs. The purpose of the current study is to evaluate the conditions under which framing effects change demand for marketplace commodities in an HPT. Attribute frames will be used to examine how changes in characteristics of stimuli influence consumption. Attribute frames will include manipulating the amount of time allowed to make purchases and limiting the quantity of each commodity that is available. Based on prior research that suggests that attribute frames can lead to changes in consumption, it is hypothesized that manipulating quantity and time to purchase each commodity will lead to changes in demand (Levin et al., 1998). Further, it is hypothesized that limiting quantity and time will lead to increased consumption, consistent with research on product scarcity (e.g., Shi et al., 2020; Inman et al., 1997). A secondary purpose of the current study is to conceptualize framing in a behavior analytic context.

To evaluate some conditions under which framing effects change demand for marketplace commodities, demand for several items was assessed under various time and quantity restriction conditions. The first step in this analysis was to identify items to use in the demand analyses. The first study was the Item Purchasing Assessment which was used to evaluate participants' experience with various items and their purchasing patterns of each item. Six items were selected from this analysis for use in the subsequent studies. Following the Item Purchase Assessment, two Restriction Assessments were conducted to evaluate several time and quantity restrictions. HPTs were implemented to assess demand under various levels of restriction. Demand model fits were assessed and the best fit model was selected during the first Restriction Assessment. A demand model was selected for use throughout the study. Demand curve parameters including rate of change in elasticity and demand intensity were analyzed for significant differences across all conditions. EV and P_{max} were also calculated to assess the direction of changes in responding relative to restriction level.

From the Restriction Assessments, three time and three quantity restrictions were selected for use in the final study, the Analysis of Demand Under Restriction. The final study involved implementing an HPT with a sample size powered to detect an effect. Differences in demand curve paramaters, rate of change in elasticity and demand intensity, were assessed. EV and P_{max} were analyzed for the direction of change in responding in relation to restriction. A general discussion follows all studies to further analyze decision framing using a behavior analytic approach.

Item Purchasing Assessment Methods

Participants

Fifty-one participants were included in the Item Purchasing Assessment (IPA). Participants were Workers on the online crowd-sourcing platform, Amazon Mechanical Turk (MTurk; https://www.mturk.com). Participants were included if they were located in the United States, had a Human Intelligence Task (HIT) approval rate of at least 95% and at least 100 approved HITS (see Kaplan et al., 2017; Kaplan & Reed, 2018; Salzar et al., 2019). These values were selected to increase the probability of obtaining non-random data at a rapid rate. Approval rates are the proportion of HITs completed by the Worker approved by Requesters (Amazon Mechanical Turk, 2017). Using 95% as the approval rate ensures the quality of the answers provided (Robinson et al., 2019). The number of approved HITs refers to the number of HITs successfully completed by Workers (Amazon Mechanical Turk, 2017). A study conducted by Robinson and colleagues (2019) suggested that participants who have successfully completed at least 100 HITs are likely to complete future HITs at a faster rate than naïve Workers. Workers with 100 approved HITs are also likely to provide data at least as valid as more experienced Workers (Robinson et al., 2019).

Setting and Materials

The IPA survey was generated using Qualtrics Software (Qualtrics, Provo, UT, USA) and distributed through MTurk. Participants were asked to indicate their hypothetical purchasing patterns for various items. Participants were asked about 75 items, 25 of which were categorized as grocery, 25 were retail (non-grocery/non-luxury), and 25 were luxury items. Data were exported and sorted using Microsoft © Excel. Data were graphed and analyzed using GraphPad Prism version 9.0 (GraphPad Software, Inc., La Jolla, CA, USA).

Procedure

Participants completed a 540 item survey through Qualtrics on MTurk to determine which items would be assessed in the subsequent studies. Participants were asked to provide information about their purchasing patterns for 75 items classified as either grocery, retail, or luxury (see Appendix A). Participants were asked to provide information about their history of purchasing each item, including the most recent purchases of each item, frequency of purchasing, and probability of purchasing each item in the future (see Appendix B for list of questions). Participants were compensated with $8.00 for completing the IPA.

Data Analysis

Bar graphs were generated displaying whether participants had ever purchased each of the items, how frequently participants purchased each item, and their future probability of purchasing each item. Data were first analyzed by identifying the participants' most purchased items. Once several items from each category were identified, the top five from each category were ranked by probability of future purchase. The top two items from each category were selected for the subsequent studies.

Item Purchase Assessment Results

Figures 2, 3, and 4 display participants' reported history of purchasing each of the items, sorted by category. Based on these data, nine items from the grocery category were identified as items that 100% of participants had purchased (i.e., toilet paper, bread, cheese, shampoo, chocolate chip cookies, potato chips, cereal, toothbrush, and toothpaste). In the retail category, at least 94% of participants had reported purchasing underwear, socks, blue jeans, sneakers, cotton t-shirts, and lightbulbs. From the luxury category, participants' most purchased items included dining furniture, original wall art, 500 thread count cotton sheets, a luggage set, and designer brand perfume/cologne.

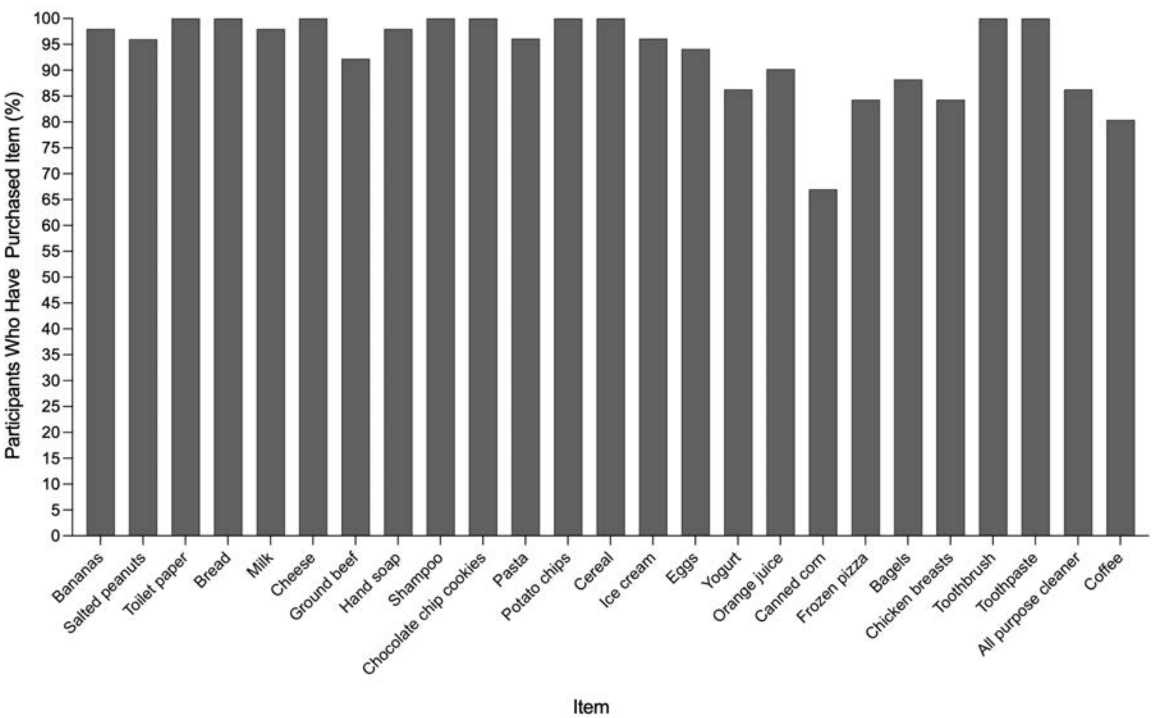


Figure 2. Grocery: Participants' history of purchasing.

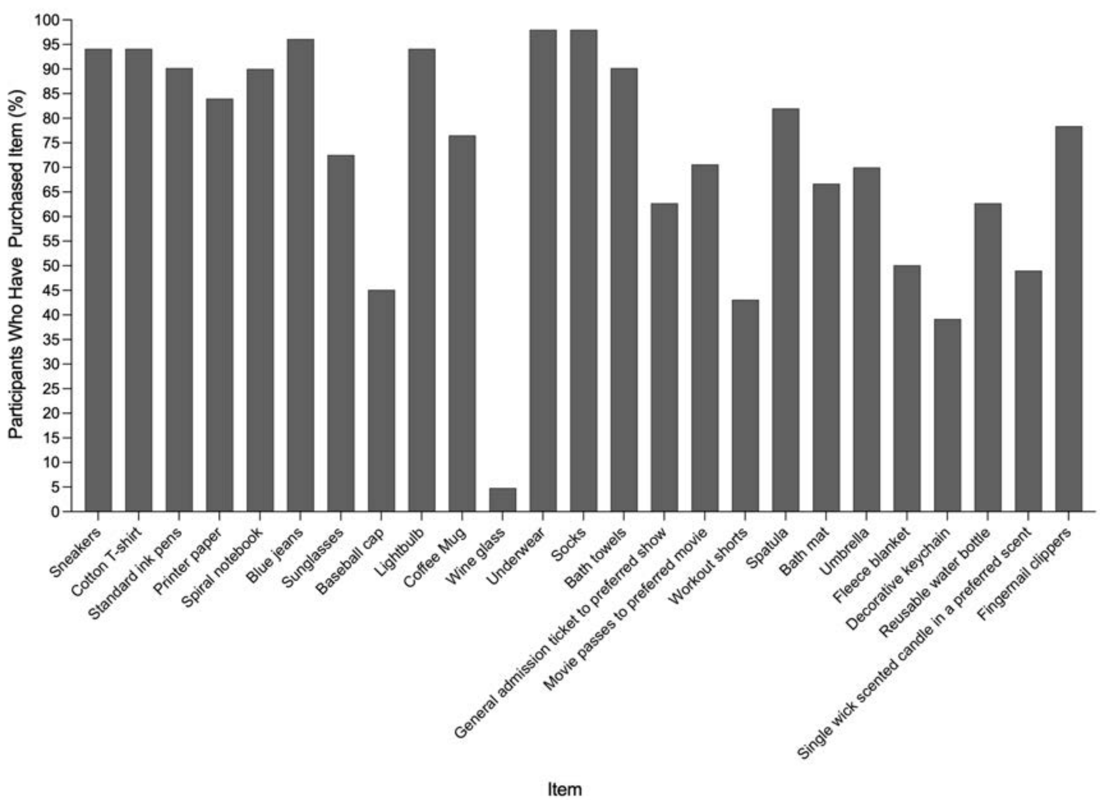


Figure 3. Retail: Participants' history of purchasing.

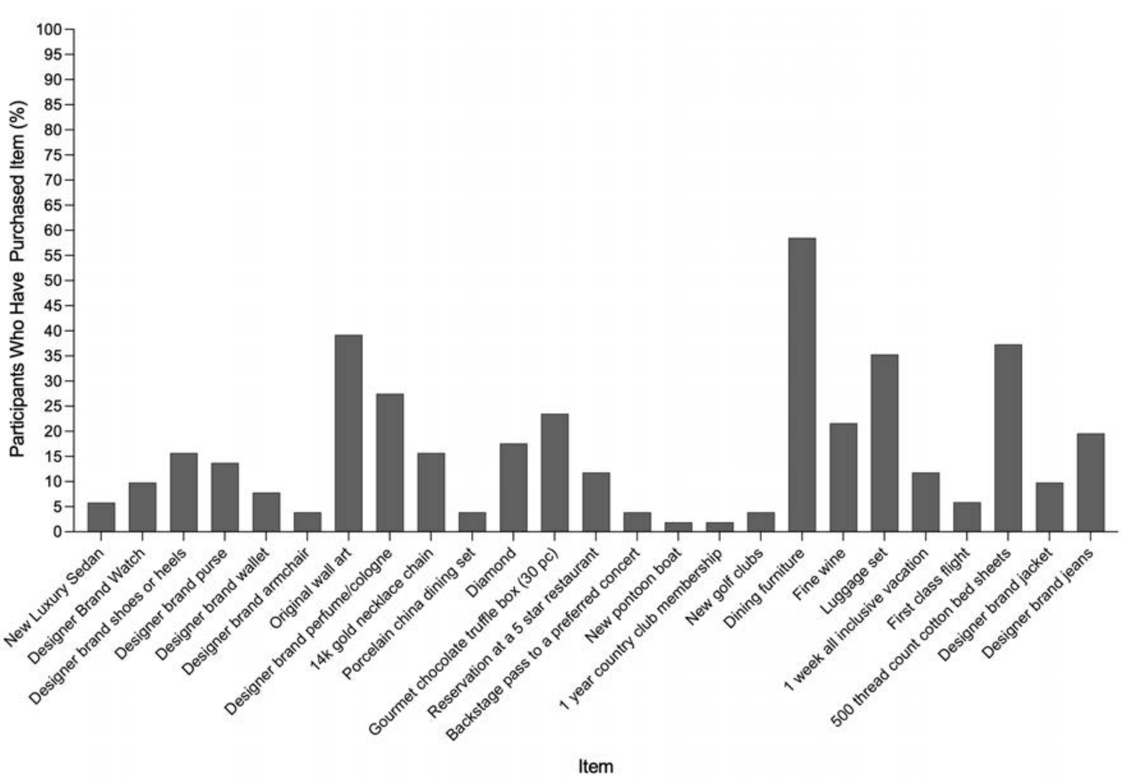


Figure 4. Luxury: Participants' history of purchasing.

Overall participants had the most experience purchasing grocery items, followed by retail, and then luxury. Figures 5, 6, and 7 display participants' reported frequency of purchasing each of the 75 items, sorted by category. Figures 8, 9, and 10 shows participants' probability of purchasing each of the items in the future. The five grocery items participants reported highest probability of future purchase for included 1) toilet paper, 2) bread, 3) toothpaste, 4) a toothbrush, and 5) shampoo. The top five retail items participants reported that they would purchase in the future were 1) underwear, 2) socks, 3) a lightbulb, 4) sneakers, and 5) blue jeans. The top five luxury items that participants reported a probably of future purchasing included 1) dining furniture, 2) 500 thread count cotton sheets, 3) original wall art, 4) a luggage set, and 5) chocolate truffles.

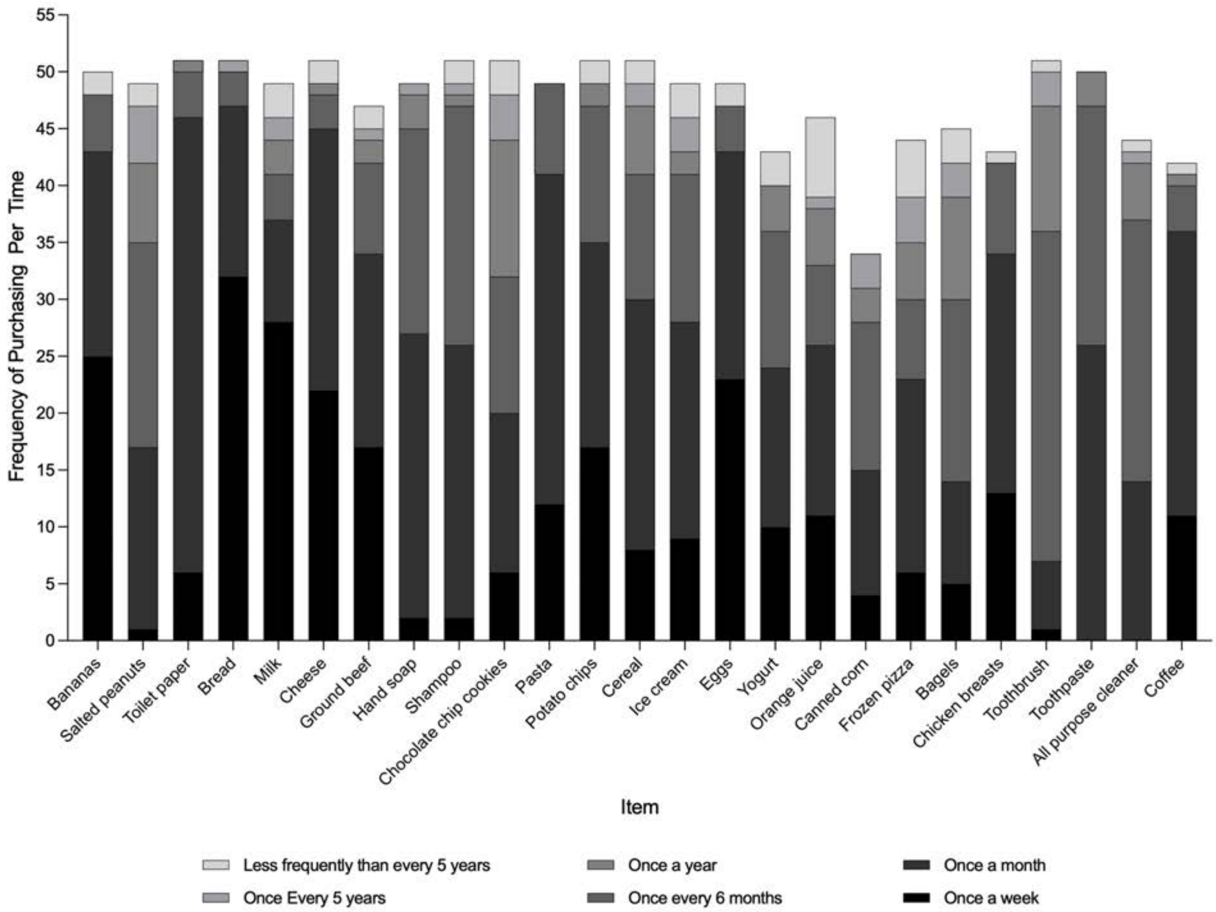


Figure 5. Grocery: Participants' frequency of purchasing.

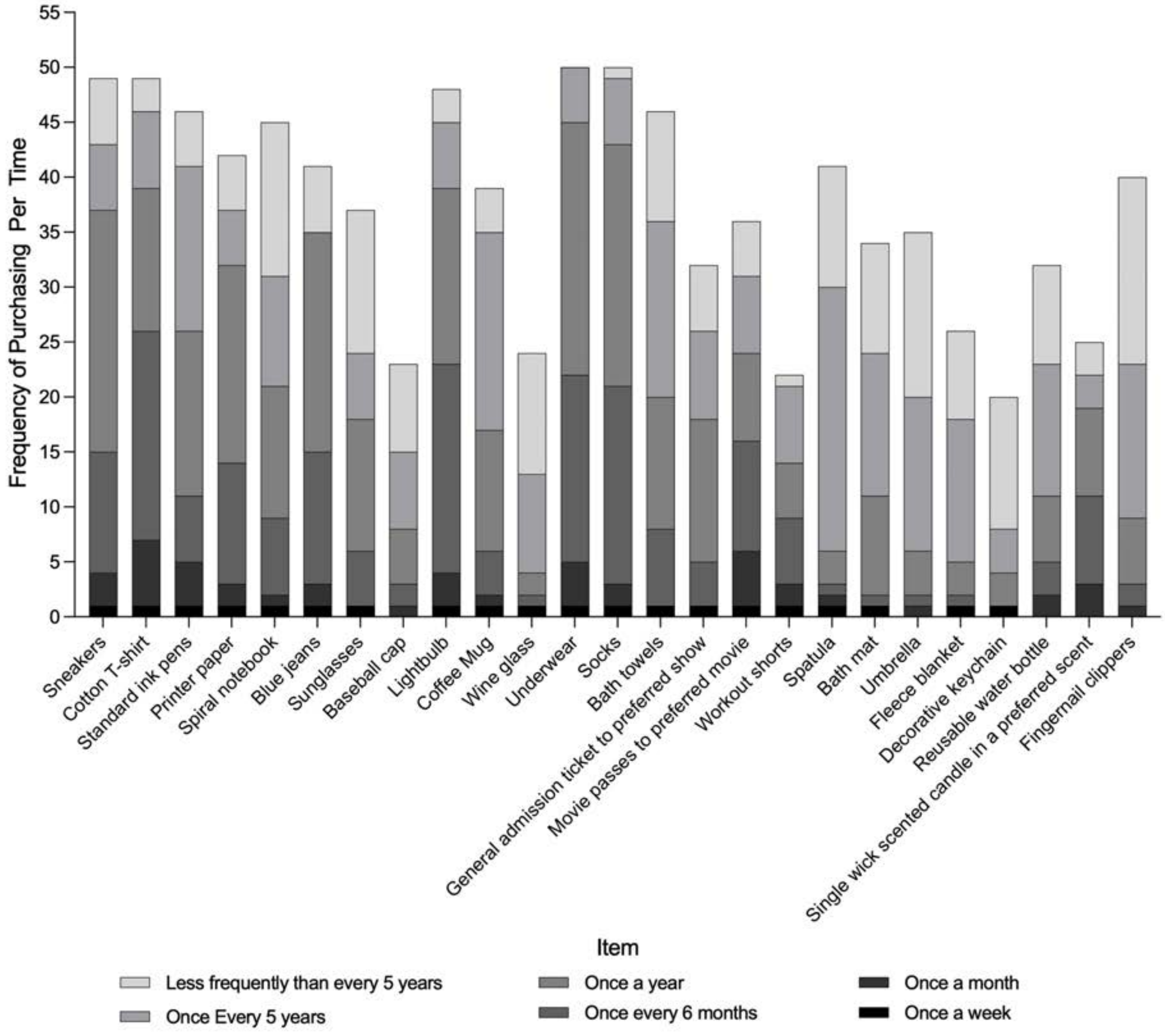


Figure 6. Retail: Participants' history of purchasing.

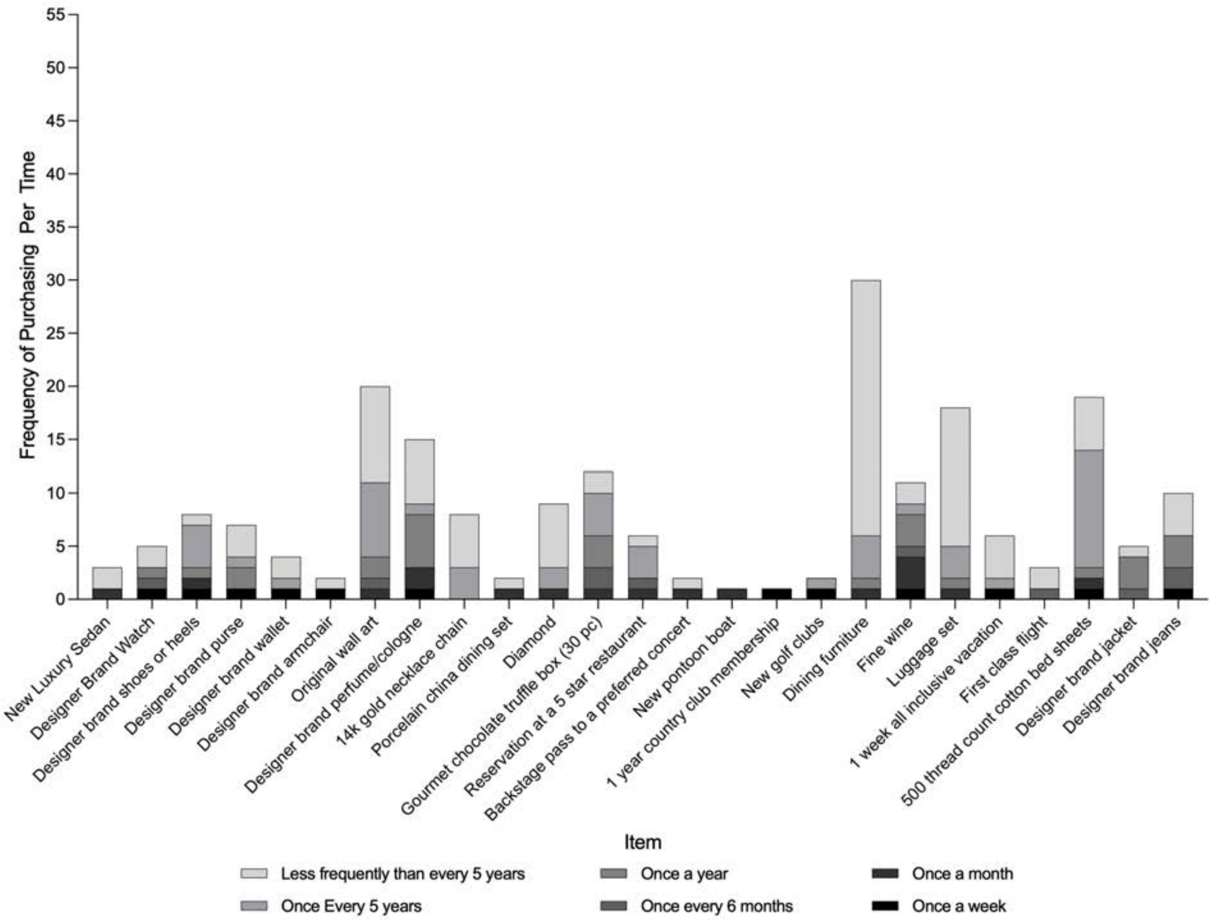


Figure 7. Luxury: Participants' history of purchasing.

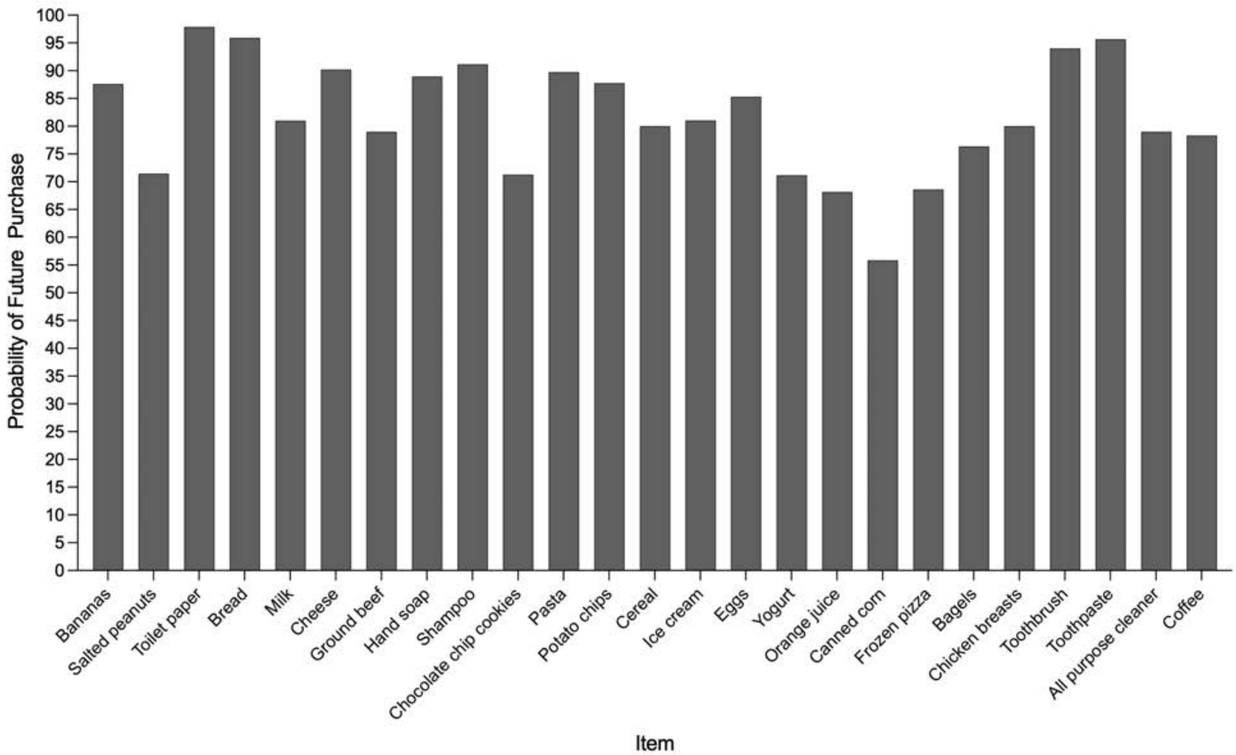


Figure 8. Grocery: Participants' probability of future purchase.

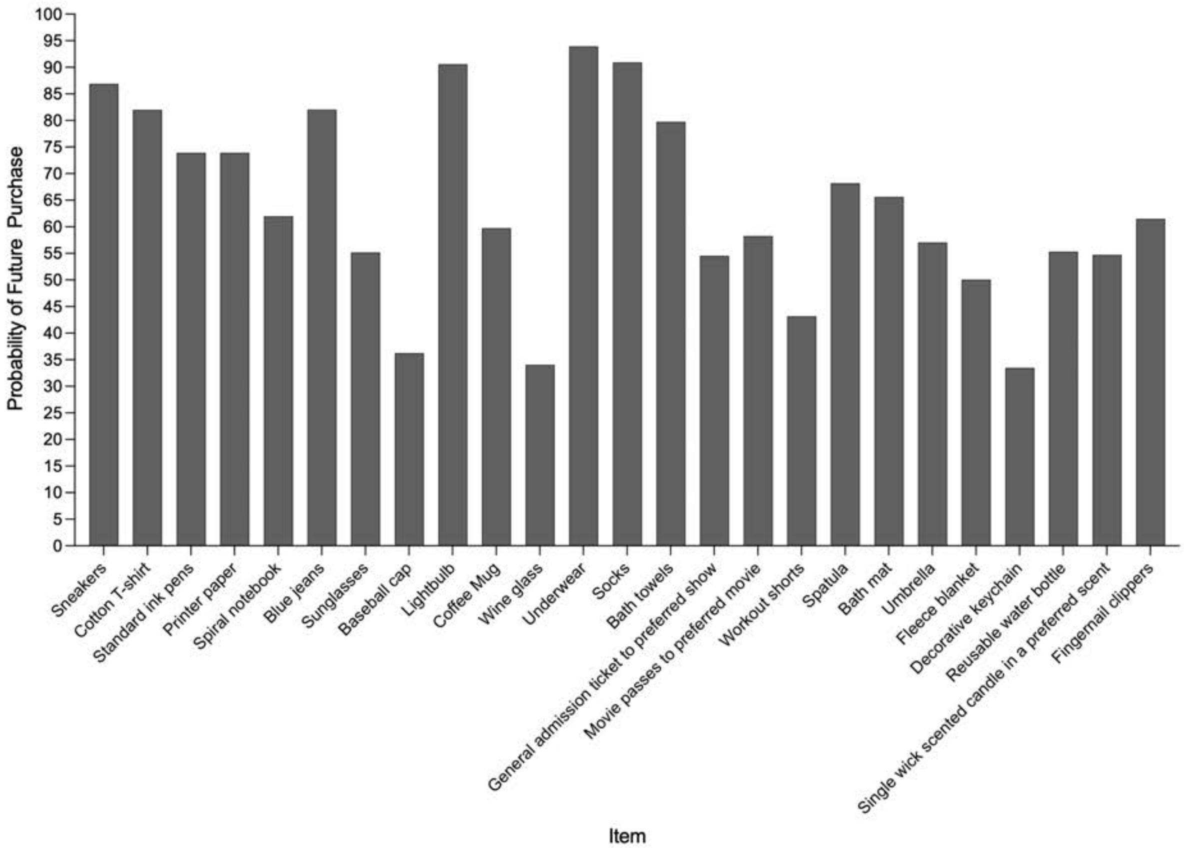


Figure 9. Retail: Participants' probability of future purchase.

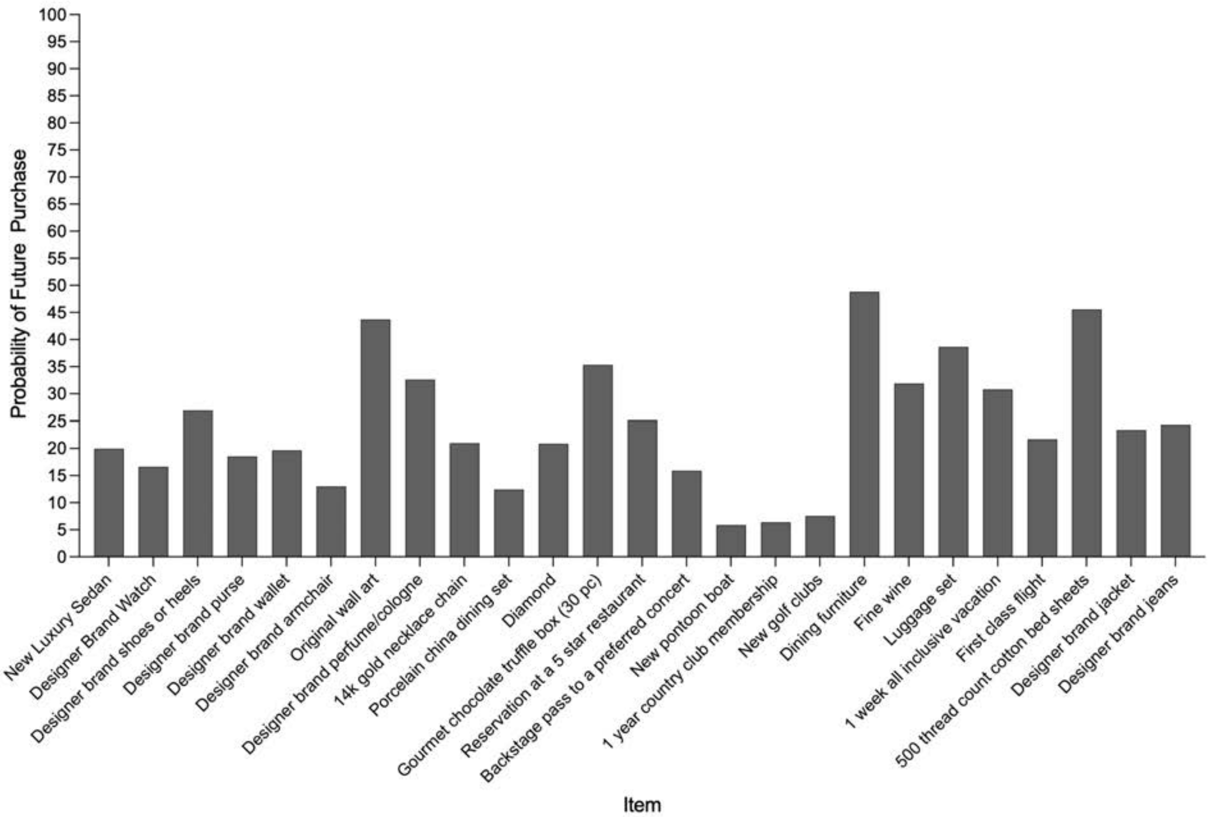


Figure 10. Luxury: Participants' probability of future purchase.

Item Purchase Assessment Discussion

The purpose of the IPA was to identify two items from each category (grocery, retail, and luxury) that would be used in the subsequent studies. The seventy-five items were appraised for participants' history of purchasing, frequency of purchasing, and probability of purchasing in the future. Several items from the grocery, retail, and luxury categories were identified that participants reported a history of purchasing. Of the identified items, participants also tended to report that they would be likely to purchase the items that they had previously purchased again in the future. From these analyses, the two items from the grocery category that were selected for study were toilet paper and bread. The two items from the retail category were underwear and socks, and the two items from the luxury category were dining furniture and 500 thread count cotton sheets. These six items were selected because most participants were familiar with them and had indicated intention to buy them again in the future.

The six identified items were included in the subsequent studies. After identifying the items, RA1 was conducted. The purpose of RA1 was to test three potential time and quantity restrictions for use in the final analysis of demand under restriction.

Restriction Assessment 1 Methods

Participants

Fifty participants completed Restriction Assessment 1 (RA1) on Amazon MTurk. Participants were included if they were located in the United States, had a HIT approval rate of 95%, and at least 100 approved HITS (see Kaplan et al., 2017; Kaplan & Reed, 2018; Salzar et al., 2019). Participants were excluded if their responses indicated non-systematic data. Eleven participants' data were excluded using algorithms for identifying nonsystematic data (Stein et al., 2015). The algorithms identified data that violated criteria for trend, bounce, and reversals from zero (Stein et al., 2015). The law of demand states that consumption should decrease as price increases (Stigler, 1954). Therefore, data violated the trend criterion if they increased, rather than decreased, as price increased. Because consumption should be expected to decrease with price increases, data were excluded on the bounce criterion if a subsequently higher price resulted in a consumption increase by greater than 25% from the previously presented price. Finally, data were excluded if a reversal from zero occurred. That is, consumption increased from a previous point in which consumption was indicated as zero. These data were excluded, as the zero should serve as a "breakpoint" in operant demand which is the lowest price at which consumption is zero (Stein et al., 2015). After exclusion criteria were applied, a total of 39 participants were included in RA1.

Setting and Materials

All surveys were administered through Qualtrics on MTurk. Participants were asked to make decisions about their hypothetical purchases of two grocery items (toilet paper, bread), two retail items (underwear, socks), and two luxury items (dining furniture, 500 thread count cotton sheets). All items were assessed within the context of making an online purchase. By controlling the context of purchases, the probability that participants responded to extraneous variables rather than the framed scenario was reduced. Participants were asked to assume that all items would be delivered the next day.

Data were exported, sorted, and screened for exclusion criteria on Microsoft © Excel. Demand curves were graphed on GraphPad Prism version 9.0 (GraphPad Software, Inc., La Jolla, CA, USA). Templates for the Exponential Model of Demand and Zero-Bounded Exponential Model of Demand, and the P_{max} calculator were retrieved from the Institutes for Behavioral Resources, Inc. website (https://ibrinc.org/behavioral-economics-tools/). The template for the Exponentiated Model of Demand for GraphPad Prism 7.0 software was retrieved from the University of Kansas Applied Behavioral Economics Lab website (http://www.behavioraleconlab.com/resources---tools.html).

Procedure

An HPT was implemented to assess demand during RA1. Previous research has shown that HPTs produce data consistent with real purchase tasks (Amlung et al., 2012; Wilson et al., 2016). For example, Amlung and colleagues validated the use of the alcohol purchase task for real and hypothetical alcohol purchases. Wilson and colleagues provided evidence for the use of HPTs to assess real and hypothetical cigarette purchases.

RA1 was conducted to assess several potential framing conditions for possible use in the final study. Three quantity and three time restrictions were evaluated to determine if they differentially affected demand. The three quantity restrictions included 1, 10, and 50 items available for purchase. The time restrictions included 1 hour, 1 day, and 1 week. Items in RA1 included toilet paper and bread from the grocery category, underwear and socks from the retail category, and dining furniture and 500 thread count cotton sheets from the luxury category. Participants were asked to indicate their probability of purchasing one of each of the items under each of the quantity and time restrictions framed in the HPT. To indicate the probability of purchase, participants were asked to use a sliding bar to select an answer between 0 and 100%. A *probability* of purchase HPT was selected over the *quantity* of purchase HPT to account for the different purchasing patterns that would be observed for one-time versus multi-purchase items.

Four batches of the survey were released to randomize the order of the items presented and control for potential sequencing effects. Table 1 shows the order of conditions and items per batch. The order of conditions was either ascending (most to least restrictive) or descending (least to most restrictive). Some participants received time restrictions first while others received quantity restrictions first. Participants were compensated with $9.34 for completing RA1.

Table 1

Order of conditions and items presented during Restriction Assessment 1.

Batch A (*n*=12)	
Condition Sequence	Quantities: 1, 10, 50; Times: 1 hour, 1 day, 1 week
Item Sequence	underwear, dining furniture, bread, toilet paper, socks, sheets
Batch B (*n*=13)	
Condition Sequence	Quantities: 50, 10, 1; Times: 1 week, 1 day, 1 hour
Item Sequence	bread, underwear, toilet paper, socks, dining furniture, sheets
Batch C (*n*=12)	
Condition Sequence	Times: 1 hour, 1 day, 1 week; Quantities: 1, 10, 50
Item Sequence	toilet paper, underwear, sheets, bread, socks, dining furniture
Batch D (*n*=13)	
Condition Sequence	Times: 1 week, 1 day, 1 hour; Quantities: 50, 10, 1
Item Sequence	sheets, bread, socks, toilet paper, dining furniture, underwear

Training, test, and CAPTCHA. At the beginning of the survey, participants were asked to complete a brief training. During the training, participants completed three questions, each of which required them to slide the bar to a specified value. Participants were required to answer the training questions correctly before moving onto the test.

During the test, participants were asked to answer three additional questions where they had to slide the bar to a specified value. If participants did not answer correctly, they were excluded from the study without compensation.

At the end of the survey, participants were asked to complete a CAPTCHA challenge question. For the CAPTCHA, participants were required to click a box that stated, “I am not a robot.” The CAPTCHA, in addition to the training and test, was used to ensure that bots were excluded from the analyses.

Assessment of understanding. Periodically during the HPT, participants were asked to complete an Assessment of Understanding (see Appendix C). These assessments were used to ensure that participants were attending to the scenarios to increase the likelihood of valid data. Assessments of Understanding included the presentation of the HPT scenario without presenting the prices. Each scenario referenced one of the six items and the condition. Once participants read the scenario, they could select the button to move on, which took them to an assessment. The assessment included questions about the scenario and assumptions.

An initial sample of 9 participants was run under Batch A at the start of RA1. During the survey, participants completed 18 attention checks, each 6 questions long. However, participants reported dissatisfaction with the frequency and length of these assessments. Participant feedback was considered and for the remainder of the study, participants completed one assessment at the beginning of baseline which consisted of six questions, and two assessments per item (one assessment during quantity conditions and one assessment during time conditions; condition randomly selected). Assessments consisted of three questions for the remainder of the survey, totaling to thirteen attention checks. Participants were required to answer the questions correctly before moving on to the HPT.

Baseline. During baseline, participants were presented with a scenario for each of the six selected items. Participants were asked to indicate the probability they would purchase each item across a series of 11 price points. Eleven price points were selected as this is above the minimum number of prices suggested by Roma et al. (2019). Eleven price points were selected to ensure sensitivity to price manipulations but reduce fatigue effects that would be seen through offering a greater number of prices. Participants were presented with a scenario indicating the hypothetical context and item they were purchasing. Scenarios were set up using the script below.

Please read and consider the following scenario.

Suppose you are planning to purchase [item] online from an internet retailer. All the items that you purchase will be delivered the next day.

What is the probability you would purchase one [item] if it were being offered at the following prices?

Assumptions:

-All items will be delivered the next day.

-The item is the same brand you are familiar with, and the quality is exactly the same at every price.

-You have the same income and savings as you have today.

-The item is the only one available to you and only for you. It much be purchased for personal use, not to save or sell for profit later.

There are no right or wrong answers. Using the sliding scale below, please answer honestly and to the best of your ability, as if you were actually in this situation.

Prices offered in the HPT were determined by using the average market price of the commodity as an anchor. At no point during RA1 was the average market price revealed to participants. The lowest price offered to the participants was $0 (free). The anchor price of the commodity was the middle price offered in the array of price choices. All other prices were determined by using the anchor as the "absolute 0 point" and using the following equation:

$$P=A(2.5)^U,$$

where P is the new price, A represents the anchor price, and U is the number of units away from A. For example, the price above the anchor was 1 unit away from the anchor. Therefore, $U = 1$ was used to identify the next price above the anchor. The price below the anchor was -1 unit away from the anchor. Therefore, $U = -1$ was used when calculating the next price below the anchor to offer.

In previous research conducted by Roma and colleagues (2019), the minimum price offered was $0 (free) and the maximum price was 100-times the true price. To best approximate a max value of 100-times the anchor price, 2.5 was used as a constant that would ensure that the max price was nearly 100-times the anchor. It should be noted that this constant works best when 11 price points are offered. If future researchers were to use this equation to determine price points, they would need to change the constant depending on the number of prices offered.

Framing manipulations. Two sets of frames consisting of three conditions each were presented to each participant for each item. One set of frames included manipulating the quantity of items available for purchase. Participants were asked to indicate the probability that they would purchase each item when offered at each of eleven price points. Price points were identical to those in baseline. However, during the framing conditions, participants were given the decision frame indicating that a limited quantity or amount of time for purchasing the commodity was available. In quantity frames, participants were asked to make decisions about purchases when different amounts of each commodity were available. The quantities of each commodity offered included 1, 10, and 50. Participants were given limited quantity scenarios using the following script:

Please read and consider the following scenario.

*Suppose that you are planning to purchase **[item]** from an online retailer. You notice a statement stating that there are only **[quantity]** of **[item]** available for purchase and then **[item]** will be unavailable.*

What is the probability you would purchase one ***[item]*** *if it were being offered at the following prices?*

Assumptions:

- All items will be delivered the next day.

- The item is the same brand you are familiar with, and the quality is exactly the same at every price.

- You have the same income and savings as you have today.

- The item is the only one available to you and only for you. It must be purchased for personal use, not to save or sell for profit later.

There are no right or wrong answers. Using the sliding scale below, please answer honestly and to the best of your ability, as if you were actually in this situation.

The second set of frames included manipulating the time available to purchase each commodity. The limited time scenarios were similar to the limited quantity scenario, except that different timeframes were presented rather than quantities. Participants were asked to indicate the probability they would purchase each of the items at the eleven price points. The time conditions included one hour, one day, and one week. Participants were given limited time scenarios using the following script:

Please read and consider the following scenario, and then answer the questions about the scenario that follow.

Suppose that you plan to purchase ***[item]*** *from an online retailer. You noticed a statement stating that you have* ***[timeframe]*** *to purchase a pair of* ***[item]*** *before* ***[item]*** *will be unavailable.*

*What is the probability you would purchase **one [item]** if it was being offered at the following prices?*

Assumptions:

- All items will be delivered the next day.

- The item is the same brand you are familiar with, and the quality is exactly the same at every price.

- You have the same income and savings as you have today.

- The item is the only one available to you and only for you. It must be purchased for personal use, not to save or sell for profit later.

There are no right or wrong answers. Using the sliding scale below, please answer honestly and to the best of your ability, as if you were actually in this situation.

Debrief survey. Following the last HPT for each item, participants were asked to answer questions about their hypothetical purchases. These questions asked participants to reflect on their purchases and were used to identify extraneous variables that could be built into the scenarios presented in the final study (see Appendix D). In the final debrief corresponding to each item, participants were asked to estimate the true price of the commodity. This question appeared only during the debrief for each item, to reduce the likelihood that the estimate would serve as an anchor value that influenced demand in future HPTs.

Demographics survey. Following the demand analysis, participants were asked to report demographic information. The demographics survey included asking participants to report gender, age, ethnicity, highest education, profession, and income.

Data Analysis

Data were graphed using the exponential, exponentiated, and normalized zero-bounded exponential models of demand. The model that best fit the data was selected and used for subsequent analyses. To assess the fit of demand curves to the data, model fit (R^2) was calculated. Extra-sum-of-squares F tests were run to determine whether there were statistically significant differences between demand curve parameters, rate elasticity (α) and demand intensity (Q_0) were significantly different across conditions. These data were used to identify three additional quantity and three additional time conditions to be assessed in Restriction Assessment 2 (RA2).

Restriction Assessment 1 Results

Demographics data for participants in RA1 are displayed in Table 1. A majority of participants were White males between 25 and 34 years old and had a 4 year college degree.

Table 2

Demographic data for Restriction Assessment 1 participants.

Participant Demographics $N = 39$		
Variable	Category	Percent (%)
Gender	Male	71.80
	Female	28.20
	Other	0
Age	18-24 years	0
	25-34 years	48.72
	35-44 years	35.90
	45-54 years	10.26
	55-64 years	2.50
	65 or older	2.50
Ethnicity	White or Caucasian	76.92
	Black or African American	10.26
	Asian or Pacific Islander	5.13
	Hispanic or Latino	5.13
	Native American or American Indian	2.50
	Other	0
Education	High School or GED	2.50
	Some College	10.26
	2 Year Degree	12.82
	4 Year Degree	53.85
	Master’s Degree	0
	Professional Degree	17.95
	Doctorate	2.50
Occupation	Student	5.13
	Business/Marketing/Accounting	17.95
	Communications/Media	5.13
	Engineering	5.13
	Biology	2.50
	Computer Science/Technology	20.51
	Health Sciences/Medicine/Nursing	7.69
	Education	5.13
	Retail	5.13
	Arts and Entertainment	5.13
	Skilled Trade	0
	Psychology (research)	0
	Food Service	0
	Hospitality/Tourism	0
	Law	0
	Political Science/Government	0

Table 2 - Continued

	English Language and Literature	0
	Other	20.51
Income	<$25,000	17.95
	>$25,000 to <$50,000	25.64
	>$50,000 to <75,000	20.51
	>75,000 to <$100,000	15.38
	>$100,000 to <$125,000	7.69
	>$125,000 to <$150,000	0
	>$150,000	10.26

Model Selection

Data were graphed using each of the three models of demand. Fits of the curves were analyzed against each other. The average R^2 value for curve fit with the exponential model was $R^2 = 0.4195$. The average fit of the exponentiated model was $R^2 = 0.8044$, and the average fit of the ZBEn model was $R^2 = 0.9608$. The ZBEn model produced the best fitting curves but is also advantageous against the exponential and exponentiated models in this experiment because it allows for the inclusion of zeros. Individual data in this experiment included a substantial number of zeros. The ZBEn model also produces essential values that are not bound to the *k* value. This allows for easier comparisons of demand curves. Therefore, the ZBEn model was selected for the duration of the study.

Demand

Individual data were pooled to generate demand curves. Demand curves were generated using the Zero-Bounded Exponential Normalized (ZBEn) model of exponential demand developed by Gilroy et al. (2020). The ZBEn model fit the data well. The median R^2 value was $R^2 = 0.9608$ [range 0.940-0.972]. Extra Sum-of-Squares F-tests with alpha set to .05 were run to analyze differences in the demand intensity (Q_0) and rate of change in elasticity (a) between conditions. Figure 11 displays demand curves for grocery items. Extra Sum-of-Squares F Tests detected no significant differences in demand intensity or the elasticity rate parameter (α) between demand curves for the three tested quantity and three tested time restrictions. Table 2 displays the R^2 values, rate of change in elasticity, intensity, P_{max} and EV for each condition for each commodity. The highest EVs were observed for the most restricted conditions (i.e., one; one hour) for toilet paper and bread. The lowest EVs for toilet paper were observed in the least restricted conditions (i.e., fifty; one week). The lowest EVs for bread were observed for the least restricted quantity condition (fifty) and the moderate restricted time condition (one day).

Demand curves for retail items are shown in Figure 12. Extra Sum-of-Squares *F* Tests revealed no significant differences in demand intensity or elasticity between demand curves for the three quantity and three time restriction conditions. EV for underwear was highest when 10 pairs were available and when 1 hour was available for purchase. EV was highest for socks when quantities and times were most restricted. EV for underwear and socks were lowest for the least restricted time and quantity conditions.

Finally, demand curves for luxury items are shown in Figure 13. Extra Sum-of-Squares *F* Tests detected no significant differences between demand intensity and elasticity for time or quantity restricted demand curves. EVs for dining furniture were highest for the most restricted conditions, followed by moderate, and least restrictive conditions, respectively. The highest EVs for 500 thread count cotton sheets were observed under the most restrictive conditions. Lowest EVs were observed when ten sets of sheets were available and when sheets were available for 1 week.

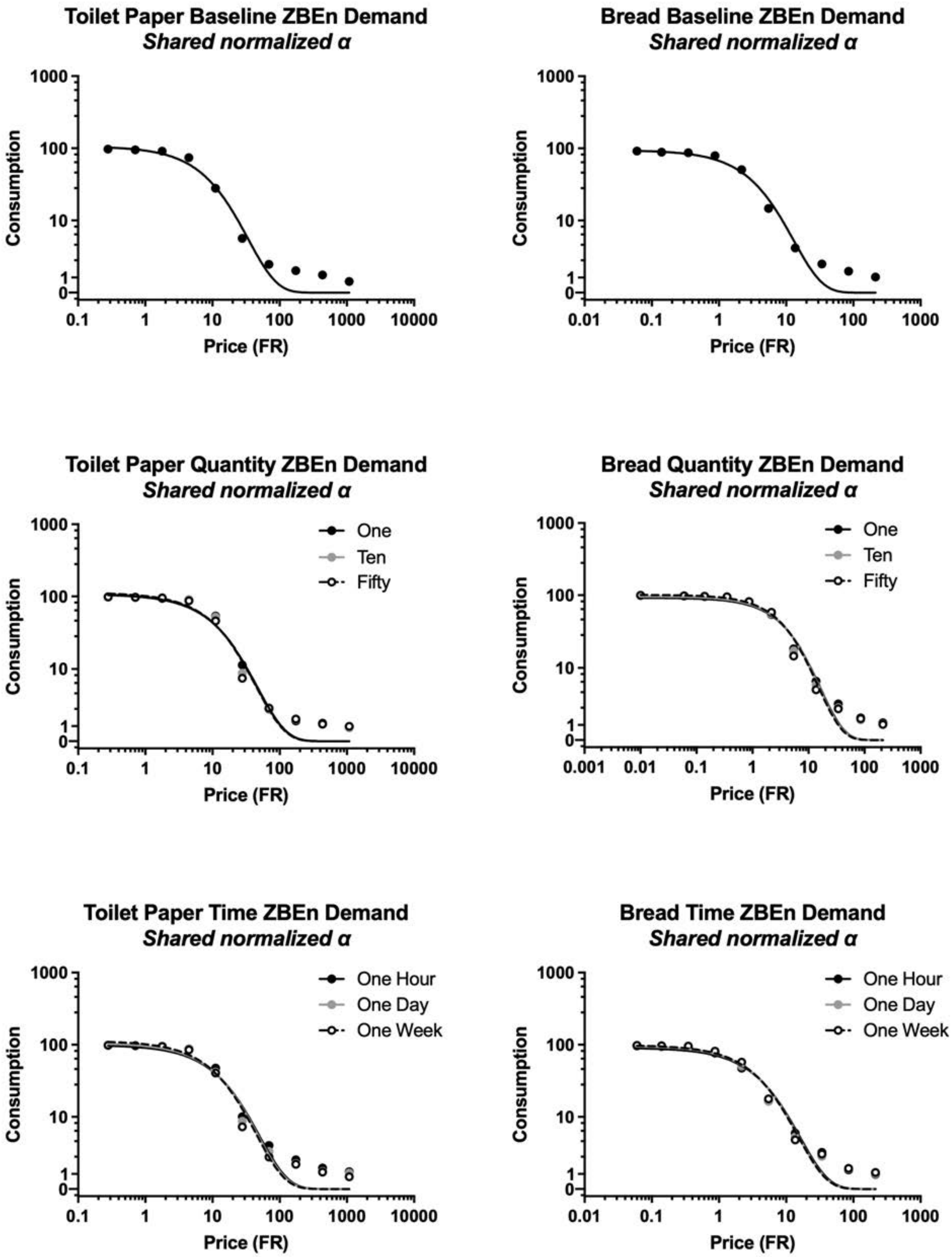


Figure 11. RA1 baseline, restricted quantity, and restricted time demand for grocery items.

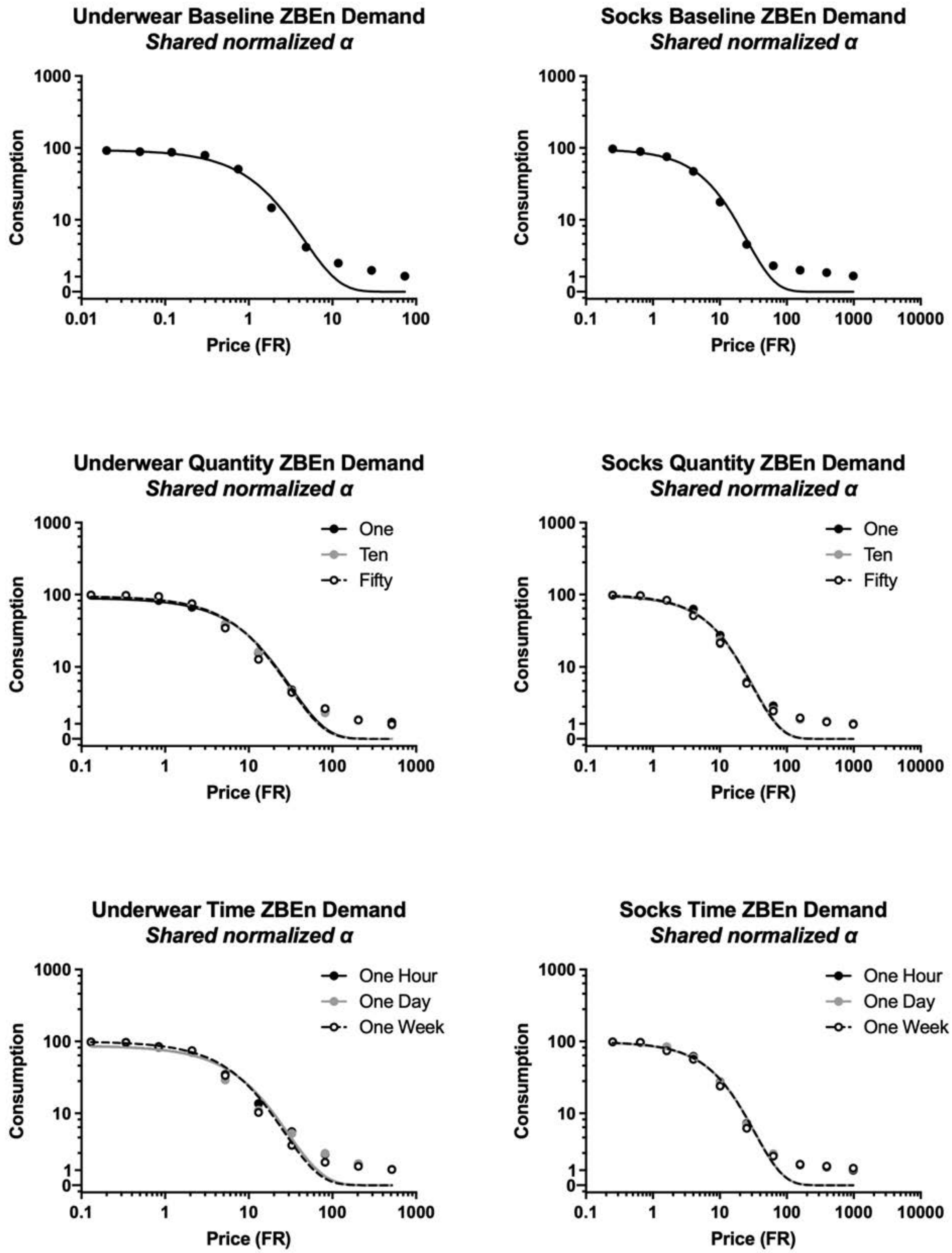


Figure 12. RA1 baseline, restricted quantity, and restricted time demand for retail items.

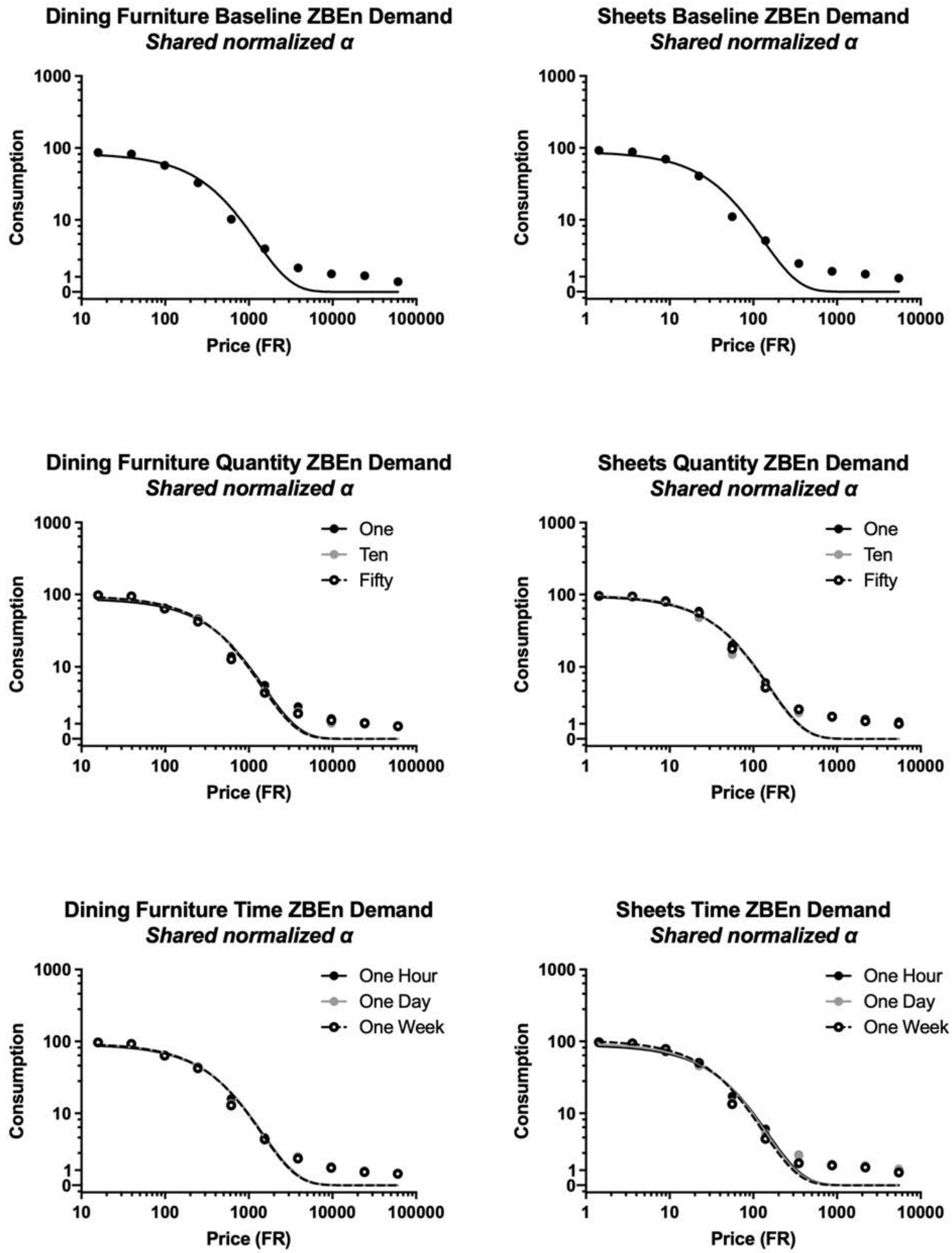


Figure 13. RA1 baseline, restricted quantity, and restricted time demand for luxury items.

Table 3

Restriction Assessment 1 demand parameters.

		Baseline	Quantities			Times		
			One	Ten	Fifty	1 Hr	1 Day	1 Wk
Toilet Paper (G)	Q_0	106	110	111	110	102	105	109
	a	.000562	0.000381	0.000408	0.000436	0.000353	0.000406	0.000454
	EV	17.8	26.2	24.5	22.9	28.4	24.7	22.0
	P_{max}	9.70	13.52	12.64	11.88	16.10	13.46	11.61
	R^2	0.967	0.972	0.969	0.964	0.950	0.961	0.965
Bread (G)	Q_0	94.2	93.6	96.3	99.4	91.1	95.9	98.6
	a	0.00163	0.00120	0.00132	0.00144	0.00131	0.00138	0.00135
	EV	6.15	8.31	7.59	6.93	7.63	7.23	7.39
	P_{max}	3.79	5.18	4.57	4.05	4.89	4.39	4.35
	R^2	0.961	0.956	0.963	0.958	0.959	0.962	0.957
Underwear (R)	Q_0	93.6	89.7	95.8	94.1	88.9	86.7	96.9
	a	0.00463	0.000676	0.000664	0.000724	0.000649	0.000735	0.000866
	EV	2.16	14.8	15.1	13.8	15.4	13.6	11.6
	P_{max}	1.34	9.64	9.13	8.54	10.13	9.20	6.92
	R^2	0.961	0.964	0.970	0.958	0.952	0.940	0.965
Socks (R)	Q_0	96.4	99.4	98.7	98.0	99.2	98.7	96.8
	a	0.000826	0.000606	0.000665	0.000696	0.000582	0.000589	0.000657
	EV	12.1	16.5	15.0	14.4	17.2	17.0	15.2
	P_{max}	7.29	9.62	8.83	8.50	10.03	9.97	9.13
	R^2	0.958	0.964	0.965	0.966	0.968	0.964	0.960
Dining Furniture (L)	Q_0	83.9	89.3	93.6	93.9	92.7	94.0	93.0
	a	.0000188	.0000132	.0000150	.0000156	.0000138	.0000150	.0000154
	EV	533	760	668	642	718	667	650
	P_{max}	372.64	495.89	414.65	397.23	455.35	412.73	406.70
	R^2	0.961	0.956	0.966	0.963	0.966	0.963	0.967
500 Thread Ct Cotton Sheets (L)	Q_0	88.5	98.2	96.7	96.7	91.7	94.6	101
	a	0.000168	0.000123	0.000147	0.000135	0.000132	0.000147	0.000161
	EV	59.6	81.2	68.1	74.2	75.5	68.1	62.0
	P_{max}	39.34	47.99	40.86	44.46	48.20	41.82	35.57
	R^2	0.949	0.957	0.958	0.957	0.959	0.948	0.965

Restriction Assessment 1 Discussion

The purpose of RA1 was to evaluate three potential quantity and three potential time restriction conditions for inclusion in the final study. No significant differences between curve fittings were detected. Despite that curve fits did not significantly differ from each other, there is still evidence to suggest that as restrictions are increased, demand increases. For the three quantity restrictions tested, EVs were highest for the most restricted condition in five out of the six items (i.e., toilet paper, bread, socks, dining furniture, cotton sheets). EVs were lowest for the least restricted quantity condition in five out of six items (i.e., toilet paper, bread, underwear, socks, dining furniture). For the three time restrictions tested, EVs were highest for the most restricted condition in all six items. EVs were lowest in the least restricted condition in five out of six items (i.e., toilet paper, underwear, socks, dining furniture, cotton sheets). These data provide preliminary evidence that when restriction is increased, demand is driven up.

It is possible that significant differences between conditions were not detected because the range of quantities and times were not wide enough to result in differentiated responding. The quantities, 1, 10, and 50, and times, 1 hour, 1 day, and 1 week, may have been too restricted to reflect actual restrictions in a real marketplace. It is possible that participants would respond similarly under all of these conditions and that the difference in restrictions was too small to exert stimulus control over participants' responding. Nevertheless, obtained EVs generally increased as restriction increased. In effort to generate more robust differences in responding under the test conditions, a wider range of test conditions was warranted for RA2.

A number of changes were rolled out during RA1 worth noting. The original script for the HPTs rolled out to the first nine participants included the following assumptions:

- *All items will be delivered the next day.*
- *Your income is identical to your current income.*
- *You have no access to these items outside of the context of purchasing them here.*
- *These items must be purchased for personal use, not to sell for profit later.*

Descriptive self-report data collected on participants' performance revealed that participants felt that this information was too limited to make decisions. As a result, some participants generated their own narratives about the availability of these commodities. Some participants misunderstood that the purchases were taking place in a closed economy. Participants were instructed to respond as though this item was the only one available to them and that the item was not available for use or purchase outside of the purchasing context. However, some participants were not responsive to this caveat.

Some participants generated narratives to explain why items were being offered at lower prices. Some participants were concerned that lower prices meant that the items were lower quality. For example, in response to toilet paper restrictions, one participant wrote, "Do I have Kleenex, baby wipes, bidet, paper towels. What is wrong with the toilet paper at low prices? I'm envisioning wood chips or tree mites." As a result, this participant's demand data showed that demand was highest near the true price of the commodity and lowest at the extreme low and high price points.

These variations in responding suggested that context needed to be further controlled. To address these issues, the assumptions were modified to indicate that the items were not defective at lower prices and to make it clearer that the items were only available in this context. The following assumptions were adopted:

- *All items will be delivered the next day.*
- *The item is the same brand you are familiar with, and the quality is exactly the same at every price.*
- *You have the same income and savings as you have today.*

- *The item is the only one available to you and only for you. It must be purchased for personal use, not to save or sell for profit later.*

In addition to concerns about contextual control, participants reported that the survey was long and that they would like a progress bar to be added to the survey. Therefore, a progress bar was added that allowed participants to see their progression throughout the survey. Additionally, participants were dissatisfied with the number of attention checks throughout the survey, as it originally included 18 checks that were 6 questions in length. Therefore, the number of attention checks was reduced to 13 checks, with the first check consisting of 6 questions and all subsequent checks consisting of 3 questions. All changes made in RA1 were all adopted for RA2 and the final study.

RA2 was run next to further narrow the quantity and time restriction conditions to be used in the final study. All procedures in RA2 were identical to RA1, except that three different quantity and time restrictions will be assessed. The three quantities were 100, 10,000, and 100,000. The three times were 1 month, 6 months, and 1 year.

Restriction Assessment 2 Methods

Participants

Fifty participants were recruited for RA2. Participants were included if they were located in the United States, had a HIT approval rate of at least 95%, and at least 100 approved HITs. Fifteen participants were excluded due to failing attention check criteria. An additional eight participants were excluded due to meeting criteria for nonsystematic data according to algorithms developed by Stein et al. (2015). In total, 26 participants' data were included in the analysis.

Setting and Materials

Participants completed HPTs on Qualtrics through MTurk. Participants were asked about the same six items in RA2 as in RA1. Data were exported, sorted, and screened for exclusion criteria on Microsoft © Excel. Demand curves were generated using the template for the Zero-Bounded Exponential Model of Demand (https://ibrinc.org/behavioral-economics-tools/) using GraphPad Prism version 9.0 (GraphPad Software, Inc., La Jolla, CA, USA). P_{max} was calculated using the P_{max} calculator retrieved from the Institutes for Behavioral Resources, Inc. website.

Procedure

Procedures in RA2 were identical to procedures in RA1, except that three different time and quantity restrictions were evaluated. Because the restrictions included in RA1 did not result in significantly different curve fits, a wider range of quantities and times were used. The three quantities used were one hundred, ten thousand, and one hundred thousand. The three times were 1 month, 6 months, and 1 year. Table 4 displays the order of conditions assigned in RA2.

Table 4

Order of conditions and items presented during Restriction Assessment 2.

Batch A (*n*=12)	
Condition Sequence	Quantities: 100, 10,000, 100,000; Times: 1 mo., 6 mos., 1 yr.
Item Sequence	underwear, dining furniture, bread, toilet paper, socks, sheets
Batch B (*n*=13)	
Condition Sequence	Quantities: 100,000, 10,000, 100; Times: 1 yr., 6 mos., 1 mo.
Item Sequence	bread, underwear, toilet paper, socks, dining furniture, sheets
Batch C (*n*=12)	
Condition Sequence	Times: 1 mo., 6 mos., 1 yr.; Quantities: 100, 10,000, 100,000
Item Sequence	toilet paper, underwear, sheets, bread, socks, dining furniture
Batch D (*n*=13)	
Condition Sequence	Times: 1 yr., 6 mos., 1 mo.; Quantities: 100,000, 10,000, 100
Item Sequence	sheets, bread, socks, toilet paper, dining furniture, underwear

Data Analysis

Data were graphed using the ZBEn model of demand. Model fit (R^2) was calculated to assess the fit of demand curves to the data. To determine whether there were statistically significant differences between demand curves across conditions and to determine whether the elasticity rate parameter (α) and Q_0 were significantly different between data sets, extra-sum-of-squares *F* tests were run. Dependent samples *t* tests were conducted to identify exact differences between curve parameters.

Restriction Assessment 2 Results

Table 5 displays demographic data for RA2 participants. Participants were mostly White or Caucasian and ages 35-44. An equal number of males and females participated in the study.

Table 5

Demographic data for Restriction Assessment 2 participants.

Participant Demographics $N = 26$		
Variable	Category	Percent (%)
Gender	Male	50
	Female	50
	Other	0
Age	18-24 years	3.84
	25-34 years	23.08
	35-44 years	42.31
	45-54 years	23.08
	55-64 years	7.69
	65 or older	0
Ethnicity	White or Caucasian	80.77
	Black or African American	7.69
	Asian or Pacific Islander	3.84
	Hispanic or Latino	7.69
	Native American or American Indian	0
	Other	0
Education	High School or GED	23.08
	Some College	15.38
	2 Year Degree	23.08
	4 Year Degree	26.92
	Professional Degree	7.69
	Master's Degree	0
	Doctorate	3.84
Occupation	Student	0
	Business/Marketing/Accounting	7.69
	Communications/Media	3.84
	Engineering	0
	Biology	0
	Computer Science/Technology	11.54
	Health Sciences/Medicine/Nursing	11.54
	Education	0
	Retail	11.54
	Arts and Entertainment	15.38
	Skilled Trade	0
	Psychology (research)	0
	Food Service	0
	Hospitality/Tourism	0
	Law	0
	Political Science/Government	0

Table 5 Continued

	English Language and Literature	0
	Other	34.62
Income	<$25,000	7.69
	>$25,000 to <$50,000	46.15
	>$50,000 to <75,000	19.23
	>75,000 to <$100,000	11.54
	>$100,000 to <$125,000	7.69
	>$125,000 to <$150,000	7.69
	>$150,000	3.84

Demand

Table 4 displays Q_0, a, EV, P_{max}, and R^2 values for all commodities under all conditions. Demand curves fit the data well (Median R^2 = 0.989, [range = 0.968-0.995]). Demand curves were generated using the ZBEn model of demand. Figure 14 displays demand curves for grocery items under the three quantity (one hundred, ten thousand, one hundred thousand) and three time (1 month, 6 months, 1 year) restriction conditions. Extra-sum-of-squares F tests with alpha set to .05 were run to identify differences in the rate elasticity parameter (a) and Q_0 between curves. A significant difference between the rate elasticity parameter (a) was detected between curve fits for toilet paper quantity conditions, $F(2, 27) = 8.64$, $p = .0013$.

Table 6

Restriction Assessment 2 demand parameters.

		Baseline	Quantities			Times		
			One Hundred	Ten Thousand	One Hundred Thousand	1 Month	6 Months	1 Year
Toilet Paper (G)	Q_0	122	106	110	109	106	109	111
	a	.000674	0.000419	0.000628	0.000679	0.000473	0.000577	0.000653
	EV	15.5	23.8	15.9	14.7	21.1	17.3	15.3
	P_{max}	6.93	12.97	8.32	7.77	11.49	9.14	7.92
	R^2	0.987	0.992	0.991	0.992	0.976	0.992	0.989
Bread (G)	Q_0	119	95.8	95.8	97.3	91.2	96.8	99.3
	a	0.00206	.000771	.000111	.000913	0.00198	0.00231	0.00242
	EV	4.86	6.54	4.55	5.51	5.04	4.34	4.13
	P_{max}	2.33	7.87	54.64	6.53	3.23	2.59	2.41
	R^2	0.984	0.982	0.986	0.988	0.991	0.992	0.991
Underwear (R)	Q_0	108	90.3	102	99.6	101	101	102
	a	.00116	0.000735	0.000917	0.000975	0.000883	0.000939	0.00102
	EV	8.61	13.6	10.9	10.3	11.3	10.7	9.77
	P_{max}	4.59	8.80	6.18	5.96	6.49	6.10	5.56
	R^2	0.995	0.971	0.987	0.989	0.977	0.981	0.989
Socks (R)	Q_0	111	95.8	98.1	98.1	99.0	96.6	104
	a	0.00104	0.000757	0.000856	0.000916	0.000786	0.000846	0.000999
	EV	9.62	13.2	11.7	10.9	12.7	11.8	10.0
	P_{max}	4.97	8.01	6.90	6.45	7.45	7.10	5.55
	R^2	0.994	0.974	0.987	0.990	0.983	0.982	0.994
Dining Furniture (L)	Q_0	88.6	74.8	76.9	83.1	74.3	74.7	79.5
	a	.0000291	.0000168	.0000195	.0000224	.0000182	.0000176	.0000195
	EV	344	597	514	447	550	568	513
	P_{max}	226.86	472.70	395.13	316.05	439.49	451.81	380.99
	R^2	0.990	0.981	0.982	0.991	0.968	0.974	0.989
500 Thread Ct Cotton Sheets (L)	Q_0	107	106	103	101	101	98.9	113
	a	0.000172	0.000135	0.000173	0.000176	0.000149	0.000143	0.000178
	EV	58.0	74.2	58.0	56.7	66.9	69.9	56.2
	P_{max}	31.28	40.26	32.41	32.54	38.43	40.97	28.50
	R^2	0.994	0.988	0.991	0.989	0.989	0.974	0.992

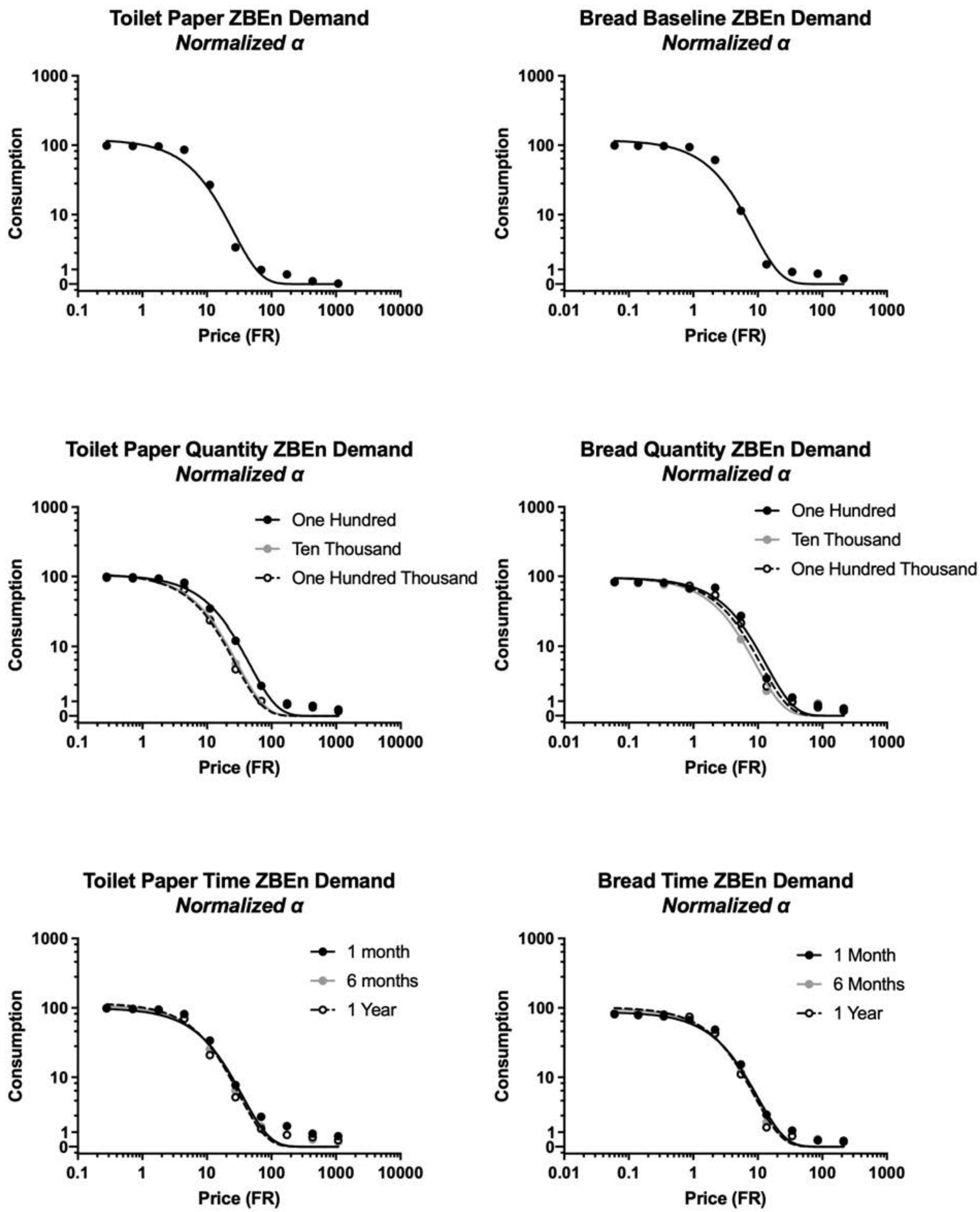


Figure 14. RA2 baseline, restricted quantity, and restricted time demand for grocery items.

Paired samples t-tests were run to identify the rate elasticity parameter(s) that differed significantly from the others. Significant differences were detected between rate elasticity parameters for conditions One Hundred vs. Ten Thousand [$t(10) = 2.245$, $p < .05$] and between One Hundred vs. One Hundred Thousand [$t(10) = 2.385$, $p < .05$]. No other significant differences were detected between parameters for toilet paper or bread demand curves. EVs for toilet paper increased as restriction increased. For bread, EVs increased as restriction increased under the restricted time conditions. However, EV was highest under the most restricted quantity condition and lowest under the middle quantity restriction.

Figure 15 displays demand curves for retail items. Extra-sum-of-squares *F* tests were run to detect differences between rate elasticity (a) and Q_0 parameters between demand curves under quantity restricted and time restricted conditions. No significant differences between parameters were detected between the three quantity conditions or three time conditions. Although no differences were detected, EVs for both underwear and socks increased as restriction increased under quantity and time conditions.

Demand curves for luxury items are displayed in Figure 16. Extra-sum-of-squares *F* tests revealed no significant differences between the rate elasticity (a) and Q_0 parameters for any of the quantity or time restrictions. EVs under quantity restriction conditions increased as restriction increased. For time restriction conditions, EVs for both dining furniture and 500 thread-count cotton sheets was highest under the middle restriction condition and lowest in the least restricted condition.

Combined Results

Following analyses of RA2 data, data for RA1 and RA2 were combined to assess differences between all quantity and all time demand curves. Extra-sum-of-squares *F* tests were

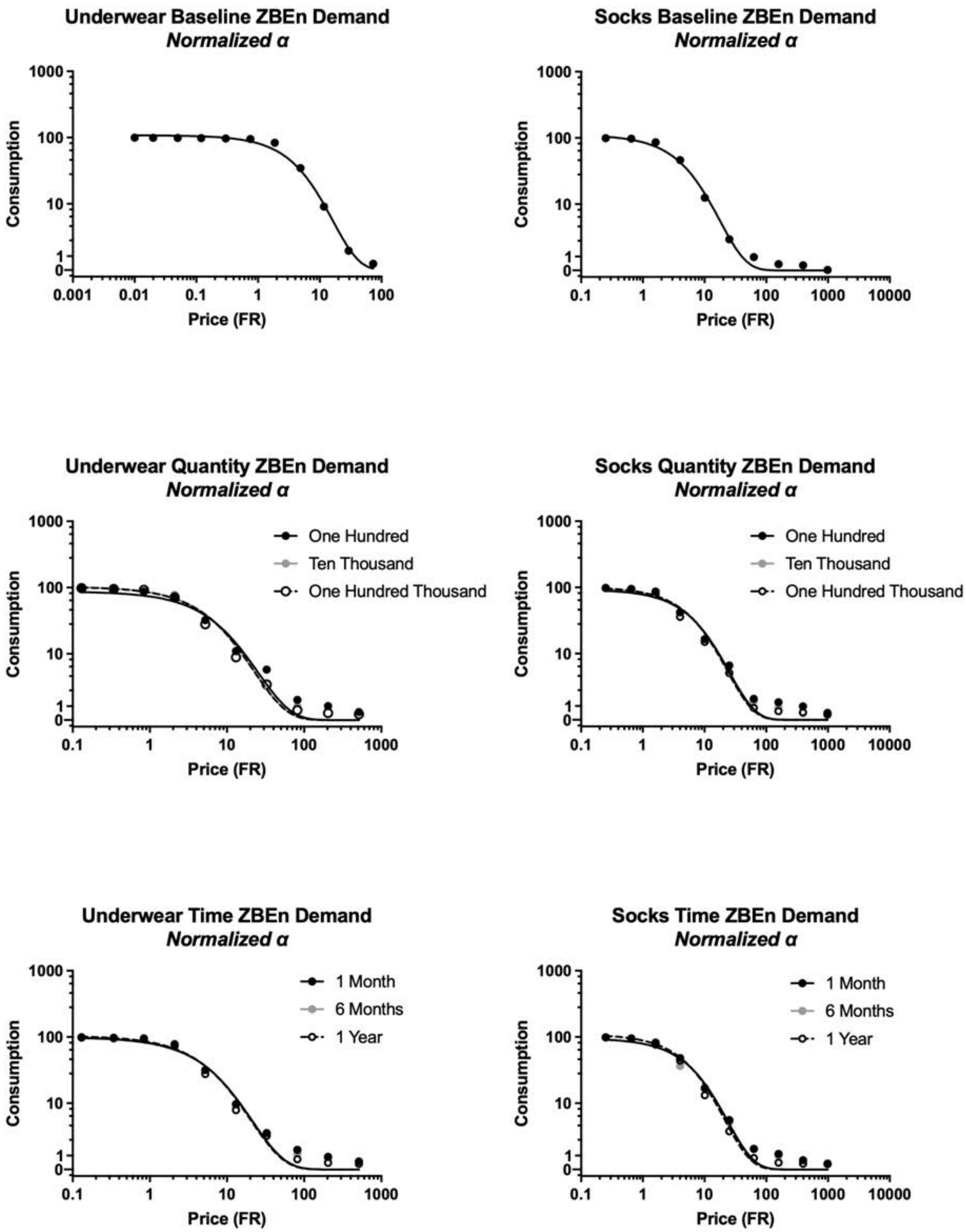


Figure 15. RA2 baseline, restricted quantity, and restricted time demand for retail items.

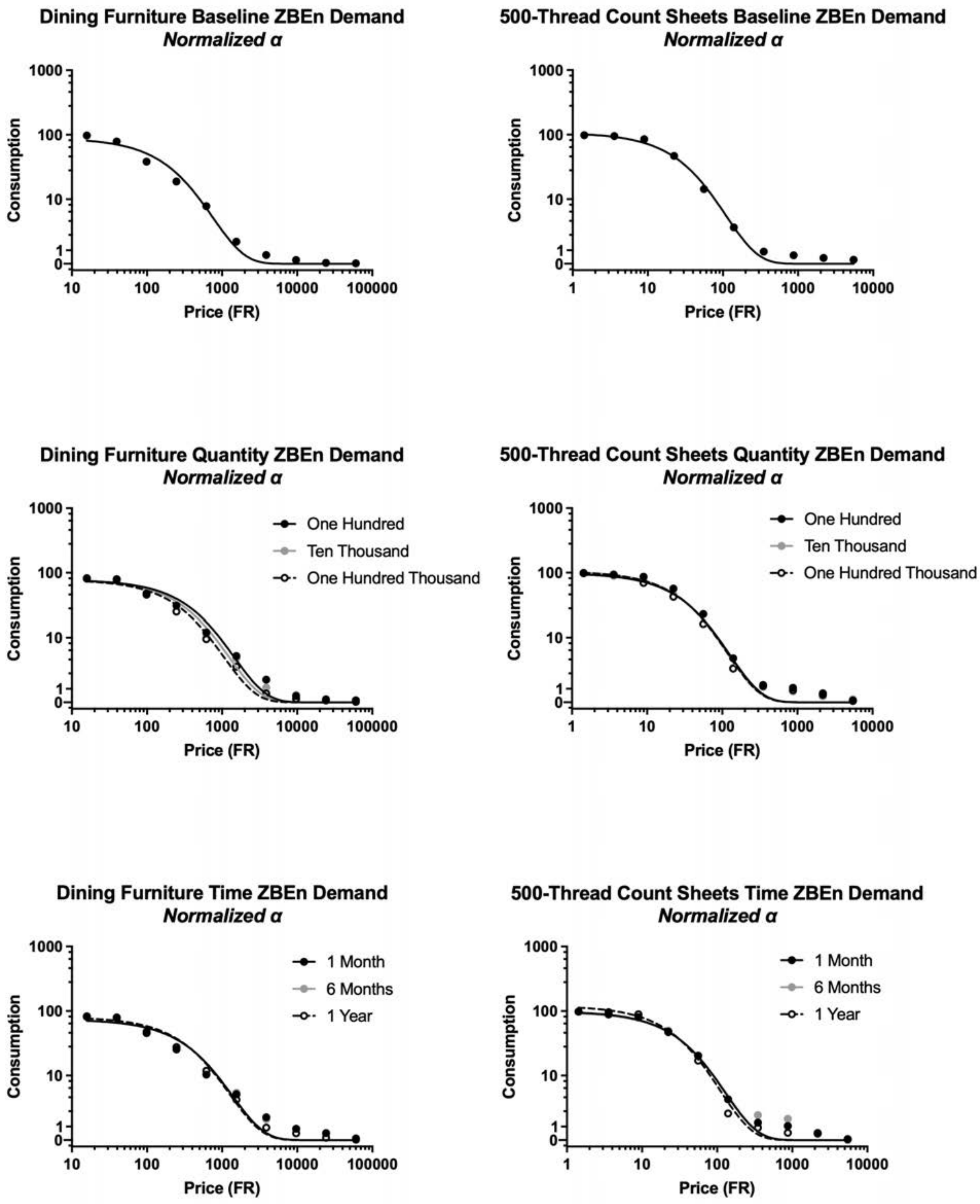


Figure 16. RA2 baseline, restricted quantity, and restricted time demand for luxury items.

run to check for consistency among baseline measures, assess differences between demand curves for quantity restrictions, and assess differences between demand curves for time restrictions. Baseline measures of the rate elasticity parameter, *a*, for underwear significantly differed [$F(1, 18) = 61.1$, $p < .0001$]. Baseline measures for dining furniture were also significantly different [$F(1, 18) = 4.48$, $p = 0.0484$].

Extra-sum-of-squares *F* tests revealed significant differences between the rate elasticity (*a*) parameters for toilet paper quantity restricted conditions [$F(5, 54) = 3.67$, $p = 0.0062$]. Significant differences between *a* parameters for bread time restricted conditions were also detected [$F(5, 54) = 4.31$, $p = 0.0023$]. Dependent samples *t*-tests were run to identify significant differences between *a* parameters between curves. Significant differences in *a* for toilet paper quantity conditions were detected between one vs. ten thousand [$t(10) = 3.073$, $p < .05$], one vs. one hundred thousand [$t(10) = 3.073$, $p < .05$], ten vs. ten thousand [$t(10) = 3.391$, $p < .01$], ten vs. one hundred thousand [$t(10) = 3.724$, $p < .01$], fifty vs. ten thousand [$t(10) = 4.353$, $p < .01$], fifty vs. one hundred thousand [$t(10) = 4.969$, $p < .001$], one hundred vs. ten thousand [$t(10) = 2.245$, $p < .05$], and one hundred vs. one hundred thousand [$t(10) = 2.385$, $p < .05$].

Dependent samples *t*-tests were run to identify significant differences between *a* parameters between bread time restriction demand curves. Significant differences were found between *a* parameters for all RA1 times against all RA2 times (one hour vs. one month [$t(10) = 4.113$, $p < .01$], one hour vs. six months [$t(10) = 3.308$, $p < .01$], one hour vs. one year [$t(10) = 3.121$, $p < .05$], one day vs. one month [$t(10) = 5.779$, $p < .001$], one day vs. six months [$t(10) = 4.142$, $p < .01$], one day vs. one year [$t(10) = 3.835$, $p < .01$], one week vs. one month [$t(10) = 6.359$, $p < .0001$], one week vs. six months [$t(10) = 4.629$, $p < .001$], and one week vs. one year [$t(10) = 4.445$, $p < .01$]).

Prior to selecting the conditions for use in the final study, a Spearman's Rank Order Correlation was conducted to assess correspondence between condition and EV. Conditions were assigned a rank from 1 to 6, with the most restrictive time and quantity restrictions ranked as 1, and the least restrictive time and quantity conditions ranked as 6. All EVs for all six items were converted to ranks, where rank 1 indicated the highest EV and rank 6 indicated the lowest EV. Figure 17 displays correlations between quantity condition and EV rank. These data show that as the number of items available increased, EV decreased. Spearman's rho correlation coefficients between quantity condition and EV equaled 0.9429 for toilet paper, 0.9429 for bread, 0.9429 for underwear, 1.0 for socks, 1.0 for dining furniture, and 0.8286 for cotton sheets. These data show that there was a strong positive correlation between EV rank and quantity rank for toilet paper, bread, underwear, socks, dining furniture, and cotton sheets.

Figure 18 displays the correlation between time condition and EV rank. These data show that as the time available to purchase items increased, EV decreased. Spearman's rho correlation coefficients between time condition and EV were 1.0 for toilet paper, 0.9429 for bread, 1.0 for underwear, 1.0 for socks, 0.9429 for dining furniture, and 0.6 for cotton sheets. There was a strong positive correlation between EV and time restriction ranks for toilet paper, bread, underwear, socks, and dining furniture. A moderate correlation was detected between EV and time restriction ranks for cotton sheets.

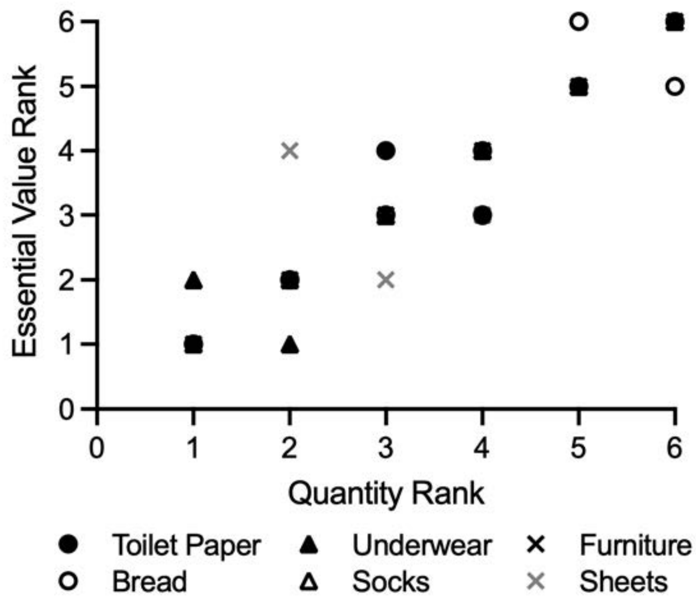


Figure 17. Essential value vs. quantity correlation.

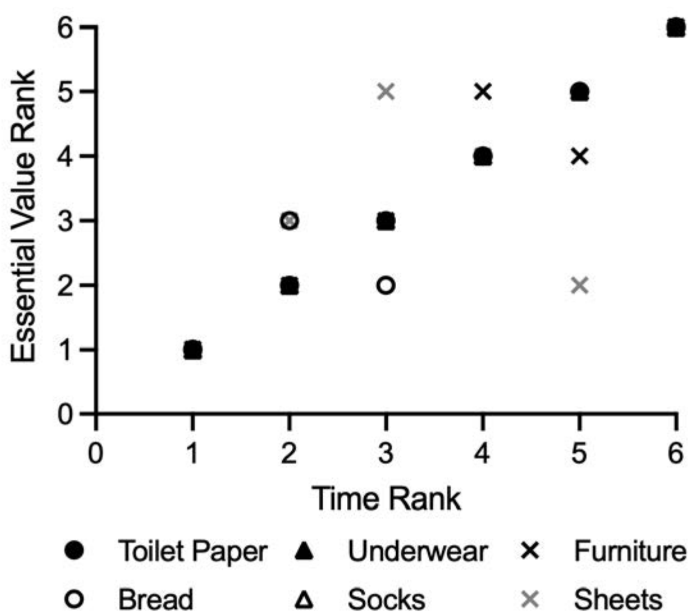


Figure 18. Essential value vs. time correlation.

Restriction Assessment 2 Discussion

RA2 was conducted to assess three additional time and three additional quantity conditions for use in the final study. Results of RA2 revealed significant differences between rate elasticity parameters between quantity restricted demand curves for toilet paper. Differences between demand curves were detected when toilet paper was restricted to 100 units. A significant difference was found between 100 units and 10,000 units, and 100 units and 100,000 units. No other significant differences were detected between demand curves for any other commodities or conditions. Although no other differences were detected, the data for RA2 demonstrated an inverse relationship between EV and restrictedness of a commodity. That is, when each commodity was further restricted, EV increased.

Before selecting conditions that would be used in the final study, data for RA1 and RA2 were combined to detect overall differences in parameters across all conditions. Significant differences in rate elasticity parameters were detected between quantity restricted demand curves for toilet paper. Significant differences in rate elasticity parameters were also detected between time restricted demand curves for bread. Differences in rate elasticity for toilet paper quantities existed between all RA1 conditions (i.e., 1, 10, or 50 units available) versus 10,000 and 100,000 units available. As stated above, significant differences were also detected between 100 units of toilet paper versus 10,000 and 100,000 units.

For bread time restricted conditions, significant differences existed between all RA1 time restrictions (i.e., 1 hour, 1 day, or 1 week available) versus all RA2 time restrictions (i.e., 1 month, 6 months, or 1 year available). A Spearman's Rank Order Correlation was run to assess the direction of the relationship between EV and restriction. It revealed that as the condition was more restricted, the EV for each item increased. This relationship was expected, as previous research on scarcity framing has revealed that scarcity increases demand for commodities (Shi et al., 2020, Inman et al., 1997).

Taken together, these data show that as commodities are more restricted, demand for them increases. Even after combining data from the two groups, EV ranks consistently increased as restriction increased. This is an interesting finding, as these data come from two different groups of participants. However, because these groups consisted of different sample sizes and the conditions in RA1 and RA2 were never directly compared within participants, it is important to conduct the final analysis of demand under restriction to confirm that these patterns were not due to chance.

The range of conditions selected in RA1 and RA2 show promise for use in the final study. A significant difference was detected between the smallest (one) and largest (one hundred thousand) quantity conditions. These conditions should represent a wide enough range to detect differentiated responding for items in the final study. In RA2, differences were detected between demand curves when toilet paper was restricted to one hundred units versus the two less restricted toilet paper quantity conditions. Thus, the restriction to one hundred units shows promise for use in the final study. For the final analysis of demand under restriction, the quantity conditions selected were one, one hundred, and one hundred thousand.

A significant difference was detected between the smallest (one hour) and largest (one year) time conditions for bread. Therefore, these conditions should lead to differentiated responding in the final study and were selected. Although there were no significant differences between RA1 demand curves when compared against each other, or RA2 curves when compared against each other, there was a significant difference between all the RA1 values and the smallest RA2 value (one month). Therefore, one month was selected as the middle condition used in the final study. Altogether, the time restrictions selected for use in the final study were one hour, one month, and one year.

One important limitation to the restriction assessments that should be addressed during the final study was that there was a difference in prices offered in the underwear baseline conditions compared to the prices in all other underwear conditions. This error was not caught until after RA2. However, this error in baseline prices offered was consistent across RA1 and RA2, which made it possible to compare the baselines to each other for consistency. A significant difference between the rate elasticity parameters for baselines in RA1 and RA2 was detected. As a result, the EV for underwear in RA1, which was 2.16, was substantially lower than the EV for RA2, which was 8.61. It is unclear why this difference was so robust. However, it should also be noted that the sample sizes were different, which could have resulted in overweighting of more extreme data in RA2. In addition to inconsistent baseline measures for underwear, a significant difference in baselines was detected for dining furniture. However, the difference just achieved significance at $p = 0.0484$. Despite that baseline measures significantly differed between Restriction Assessments for underwear and dining furniture, no other significant differences were detected between the other tested conditions for those items. Data for underwear and dining furniture should be interpreted with caution.

Another limitation to the Restriction Assessments was the small sample sizes. Although the Restriction Assessments provided important preliminary information, they were not powered to detect significant effects between demand curves. Therefore, a larger sample size should be used in the final analysis of demand under restriction. For the final study, a power analysis will determine the appropriate sample size needed to detect an effect.

Altogether, the data obtained from RA1 and RA2 provide evidence that as commodities are restricted, demand increases. Given the orderliness of the current data, it is hypothesized that as restriction is increased in the final study, demand for each of the six items will increase.

Analysis of Demand Under Restriction Methods

Participants. The final study was the Analysis of Demand Under Restriction (ADR). An a priori power analysis for repeated measures, within subjects, was conducted using G*Power software version 3.1.9.6 (retrieved from https://www.psychologie.hhu.de/arbeitsgruppen/allgemeine-psychologie-und-arbeitspsychologie/gpower). The targeted effect size was $f = 0.1$ (small effect size; Cohen, 1992) with 80% power and a type 1 error rate of $\alpha = 0.05$. The results of the power analysis determined that a sample size of 161 participants was required to detect a small effect size. A total of 255 participants were recruited. Two-hundred forty-four participants were recruited from Amazon MTurk. Ninety-two participants were excluded due to nonsystematic data (Stein et al., 2015). This was equivalent to an exclusion rate of approximately 37.7%. To save on costs incurred from recruiting through Amazon MTurk, the remaining participants were recruited from a large Midwestern university. In total, 161 participants were included in the study.

Setting and Materials. Participants were recruited through Amazon MTurk and through in-class recruitment at a large Midwestern university. All surveys were administered through Qualtrics. Data were analyzed using Microsoft © Excel software and GraphPad Prism 9 (GraphPad Software, Inc., La Jolla, CA, USA). The ZBEn model of demand template and P_{max} calculator were retrieved from the Institutes for Behavioral Resources, Inc. website (https://ibrinc.org/behavioral-economics-tools/).

Procedure

The ADR included four conditions: baseline, quantity restriction, time restriction, and prices anchored.

Table 7 displays the order of conditions for participants. Participants were randomly assigned to one of four batches to reduce sequencing effects. Participants received conditions in either ascending (least to most restrictive) or descending (most to least restrictive) order. Some participants received quantity restriction conditions first and some received time restriction conditions first. Data from RA1 and RA2 were used to determine the time and quantity restrictions included in the ADR. The time restrictions were one hour, one month, and one year. The quantity restrictions were one, one hundred, and one hundred thousand.

Table 7

Order of conditions and items presented for Analysis of Demand Under Restriction.

Batch A (*n*=65)	
Condition Sequence	Quantities: 1, 100, 100,000; Times: 1 hr., 1 mo., 1 yr.
Item Sequence	underwear, dining furniture, bread, toilet paper, socks, sheets
Batch B (*n*=63)	
Condition Sequence	Quantities: 100,000, 100, 1; Times: 1 yr., 1 mo., 1 hr.
Item Sequence	bread, underwear, toilet paper, socks, dining furniture, sheets
Batch C (*n*=63)	
Condition Sequence	Times: 1 hr., 1 mo., 1 yr.; Quantities: 1, 100, 100,000
Item Sequence	toilet paper, underwear, sheets, bread, socks, dining furniture
Batch D (*n*=64)	
Condition Sequence	Times: 1 yr., 1 mo., 1 hr.; Quantities: 100,000, 100, 1
Item Sequence	sheets, bread, socks, toilet paper, dining furniture, underwear

Assessment of understanding. Participants were given the same Assessment of Understanding in the ADR as in RA1 and RA2, with correct answers changed to reflect the selected procedures. The assessments ensured that participants understood how to use the survey functions and that they correctly understood the questions being asked (see Appendix C).

Baseline. Baseline procedures were identical to RA1 and RA2. Assumptions to include with each scenario were identical to those finalized after RA1 and RA2. The assumptions included that 1) all items will be delivered the next day; 2) the item is the same brand you are familiar with, and the quality is exactly the same at every price; 3) you have the same income and savings as you have today; and 4) the item is the only one available to you and only for you. It must be purchased for personal use, not to save or sell for profit later.

Framing manipulations. The structure of the decision framing HPTs was be identical to RA1 and RA2. The specific quantity restrictions were one, one hundred, and one hundred thousand. The specific time restrictions were one hour, one month, and one year.

Anchor prices revealed. During the final HPT in the ADR, participants were presented with each item and told the anchor (true market) price of the item. As in Baseline and Framing Manipulations, participants were asked to indicate the probability that they would purchase one of each item at each price point. The anchor was revealed to participants to determine how participants' knowledge of the true price affected demand. The following script was presented to participants:

Please read and consider the following scenario.

Suppose you are planning to purchase ***[item]*** *from an internet retailer. The* ***average market price*** of one [item] is ***$[price]***.

What is the probability you would purchase ***one [item]*** **right now** *if it was being offered* *at the following prices?*

Assumptions:

- All items will be delivered the next day.

- The item is the same brand you are familiar with, and the quality is exactly the same at every price.

- You have the same income and savings as you have today.

- The item is the only one available to you and only for you. It must be purchased for personal use, not to save or sell for profit later.

There are no right or wrong answers. Using the sliding scale below, please answer honestly and to the best of your ability, as if you were actually in this situation.

Debrief survey. A debrief was included to identify extraneous variables that impacted performance in the HPTs (see Appendix D).

Demographics survey. Following the demand analysis, participants were asked to report demographic information including gender, age, ethnicity, highest education, profession, and income.

Data Analysis

The ZBEn model of demand was used to graph data. Model fit (R^2) was calculated to assess the fit of demand curves to the data. Extra-sum-of-squares F tests were run to determine whether there were statistically significant differences between elasticity rate parameter (α) and demand intensity (Q_0) between data sets. Dependent samples t tests were conducted to identify exact differences between curve parameters.

Analysis of Demand Under Restriction Results

Table 8 displays demographic data for all ADR participants. Overall, 161 participants were included. Participants were mostly White or Caucasian. Approximately 59% of participants were female. A majority of participants had a 4 year college degree and were between the ages of 25 and 44 years old.

Table 8

Demographics data for all Analysis of Demand Under Restriction participants.

Participant Demographics $N = 161$		
Variable	Category	Percent (%)
Gender	Male	40.37
	Female	59.0
	Other	0.62
Age	18-24 years	8.69
	25-34 years	40.37
	35-44 years	27.95
	45-54 years	15.53
	55-64 years	5.59
	65 or older	1.24
Ethnicity	White or Caucasian	65.22
	Black or African American	20.49
	Asian or Pacific Islander	9.32
	Hispanic or Latino	3.73
	Native American or American Indian	0.62
	Other	0.62
Education	High School or GED	10.56
	Some College	14.29
	2 Year Degree	11.18
	4 Year Degree	44.72
	Professional Degree	18.63
	Master's Degree	0
	Doctorate	0
Occupation	Student	3.73
	Business/Marketing/Accounting	21.12
	Communications/Media	2.48
	Engineering	2.48
	Biology	0
	Computer Science/Technology	25.47

Table 8 Continued

	Health Sciences/Medicine/Nursing	2.48
	Education	3.73
	Retail	8.07
	Arts and Entertainment	3.11
	Skilled Trade	5.59
	Psychology (research)	1.86
	Food Service	2.48
	Hospitality/Tourism	0
	Law	1.24
	Political Science/Government	0
	English Language and Literature	0.62
	Other	15.53
Income	<$25,000	15.53
	>$25,000 to <$50,000	27.33
	>$50,000 to <75,000	24.48
	>75,000 to <$100,000	21.74
	>$100,000 to <$125,000	4.35
	>$125,000 to <$150,000	3.11
	>$150,000	3.11

Baseline vs. Quantity and Time Restrictions

Table 9 displays data for demand intensity, rate of change in elasticity (*a*), EV, P_{max}, and R^2 for all items across all conditions. Demand curves were generated using the ZBEn model of demand. Demand curves fit the data well with a median R^2 of 0.975 (range = 0.963-0.986). Figure 19 displays demand curves for grocery items under time and quantity restriction conditions. Extra-sum-of-squares *F* tests were conducted to identify differences in rate elasticity and demand intensity parameters between demand curve fits for grocery items. No significant differences were detected. EVs for toilet paper quantity curves were highest when toilet paper was most restricted (one available; EV = 33.3) and lowest when commodities were least restricted (one hundred thousand available; EV = 24.8). Toilet paper baseline EV was slightly higher than the EV for the least restricted quantity condition. Under quantity conditions for bread, the lowest EV was obtained from baseline (EV = 7.7) and the highest EV was in the most restricted quantity condition (EV = 10.4).

EVs for toilet paper time conditions were highest when time to purchase was most restricted (EV = 30.6) and lowest when time was least restricted (EV = 24.4). The EV for the least restricted time condition was lower that the baseline EV. EVs for bread time conditions were highest when time was most restricted (EV = 9.4) and lowest when the time was least restricted (EV = 7.44). Baseline EV for bread was slightly higher than the EV for the least restricted time condition. Although baseline EVs were sometimes higher than EVs in the least restrictive time and quantity conditions, all EVs increased as restriction increased across the three test time and three tested quantity conditions. These data provide some evidence supporting that increasing the restriction on the tested grocery items leads to increased value.

P_{max}, the point at which the commodity changes from inelastic to elastic, was highest for toilet paper when the quantity available for purchase was most restricted (P_{max} = 20.13) and lowest when the toilet paper quantity was least restricted (P_{max} = 15.05). P_{max} was highest when the toilet paper time condition was most restricted (P_{max} = 19.33) and lowest when the time was least restricted (P_{max} = 13.82). P_{max} was highest when the bread time condition was most restricted (P_{max} = 6.83) and lowest during baseline (P_{max} = 4.97). Across all tested time and quantity conditions, P_{max} increased as restriction increased. However, baseline P_{max} was sometimes higher than the P_{max} in the least restrictive conditions. Altogether, the probability of purchasing these items at higher prices was greater when the items were more restricted.

Table 9

Intensity, rate of change in elasticity, EV, P_{max}, and R^2 for all items across all conditions.

		Q_0	a	EV	P_{max}	R^2
Toilet Paper	Baseline	96.2	0.000399	25.1	15.13	0.974
	Anchor	107	0.000338	29.6	15.92	0.970
	Quantity 1	96.2	0.000300	33.3	20.13	0.982
	Quantity 2	98.1	0.000320	31.2	18.47	0.980
	Quantity 3	95.8	0.000403	24.8	15.05	0.980
	Time 1	92.5	0.000326	30.6	19.33	0.981
	Time 2	98.1	0.000366	27.4	16.15	0.978
	Time 3	102	0.000410	24.4	13.82	0.978
Bread	Baseline	90.4	0.00130	7.7	4.97	0.969
	Anchor	93.4	0.00140	7.12	4.45	0.973
	Quantity 1	76.1	0.000960	10.4	8.12	0.973
	Quantity 2	81.6	0.00101	9.92	7.15	0.972
	Quantity 3	81.2	0.00120	8.30	6.05	0.972
	Time 1	81.4	0.00106	9.40	6.83	0.973
	Time 2	83.2	0.00122	8.22	5.79	0.976
	Time 3	84.3	0.00134	7.44	5.20	0.966
Underwear	Baseline	84.7	0.000602	16.6	11.52	0.978
	Anchor	96.2	0.000654	15.3	9.23	0.977
	Quantity 1	83.5	0.000452	22.1	15.58	0.973
	Quantity 2	86.1	0.000508	19.7	13.40	0.983
	Quantity 3	86.3	0.000585	17.1	11.61	0.980
	Time 1	82.5	0.000553	18.1	12.90	0.971
	Time 2	87.6	0.000584	17.1	11.44	0.980
	Time 3	86.3	0.000679	14.7	10.01	0.974
Socks	Baseline	85.0	0.000537	18.6	12.86	0.979
	Anchor	99.0	0.000428	15.0	13.67	0.977
	Quantity 1	81.3	0.000478	20.9	15.17	0.974
	Quantity 2	83.2	0.000511	19.6	13.83	0.978
	Quantity 3	86.7	0.000581	17.2	11.63	0.977
	Time 1	83.9	0.000500	20.0	14.01	0.980
	Time 2	87.2	0.000507	19.7	13.25	0.978
	Time 3	88.7	0.000592	16.9	11.14	0.985
Dining Furniture	Baseline	76.5	0.0000152	658	509.86	0.972
	Anchor	88.1	0.00000973	1028	682.60	0.986
	Quantity 1	78.2	0.0000123	816	614.88	0.972

Table 9 Continued

	Quantity 2	78.5	0.0000138	726	545.77	0.973
	Quantity 3	82.0	0.0000148	677	485.28	0.980
	Time 1	72.4	0.0000135	741	609.95	0.971
	Time 2	81.3	0.0000132	760	549.27	0.978
	Time 3	80.3	0.0000141	707	521.35	0.979
Sheets	Baseline	81.3	0.000116	86.5	62.49	0.970
	Anchor	101	0.0000849	118	67.46	0.980
	Quantity 1	90.2	.0000865	116	74.84	0.970
	Quantity 2	88.8	.0000918	109	71.72	0.963
	Quantity 3	89.4	0.000104	96	62.86	0.969
	Time 1	90.9	0.0000918	109	69.93	0.969
	Time 2	90.3	0.0000935	107	69.15	0.970
	Time 3	88.8	0.000103	96.9	63.94	0.974

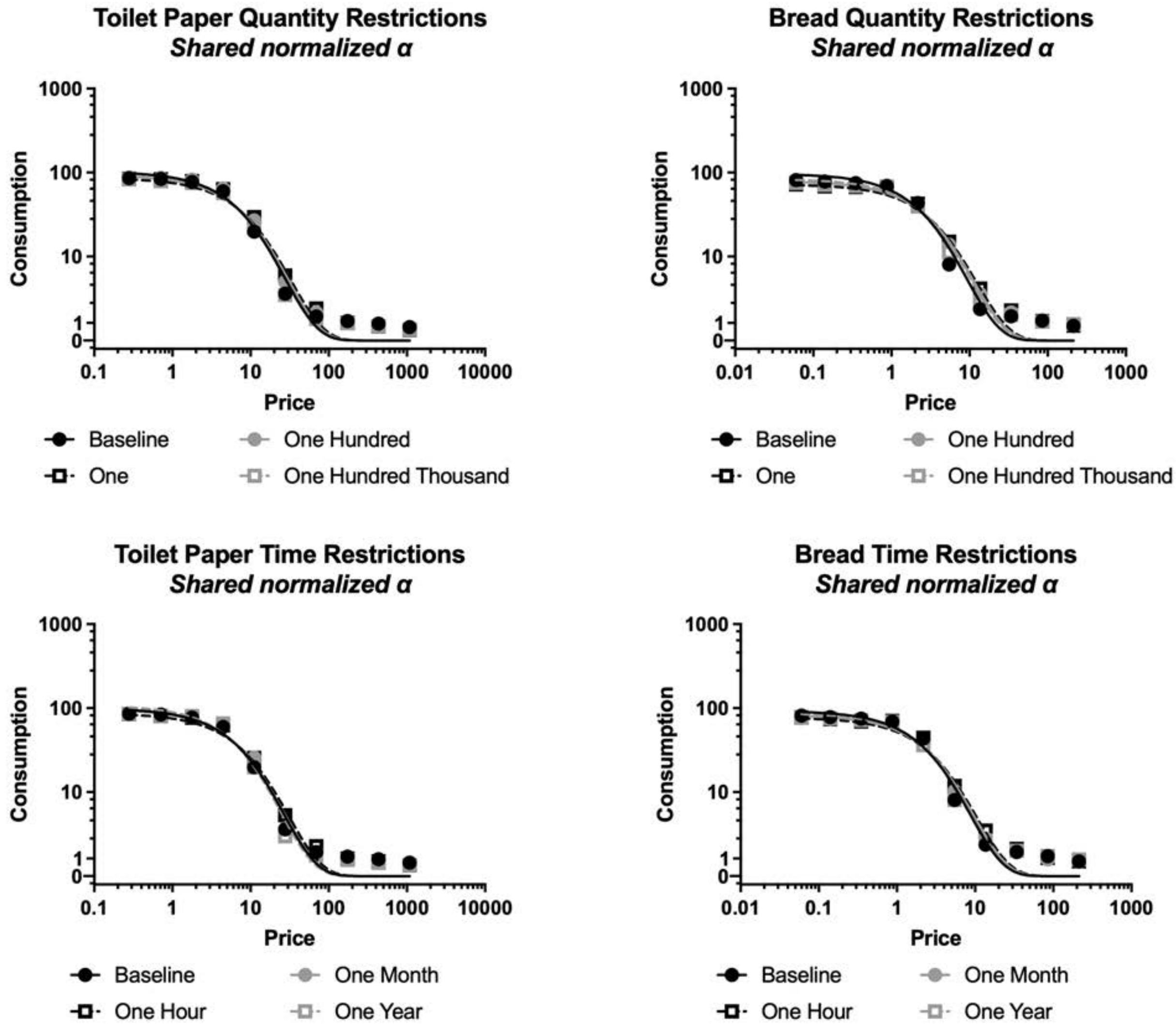


Figure 19. Demand for grocery items under time and quantity conditions compared to baseline.

Figure 20 displays demand curves for retail items under time and quantity restriction conditions. Extra-sum-of-squares *F* tests were conducted to identify differences between rate elasticity and demand intensity parameters on curve fits. No differences were detected. Under quantity restriction conditions, EVs were highest for underwear when the quantity was most restricted (EV = 22.1). EV was lowest under baseline conditions for underwear (EV = 16.6). Overall, EVs for quantity conditions decreased as restriction increased.

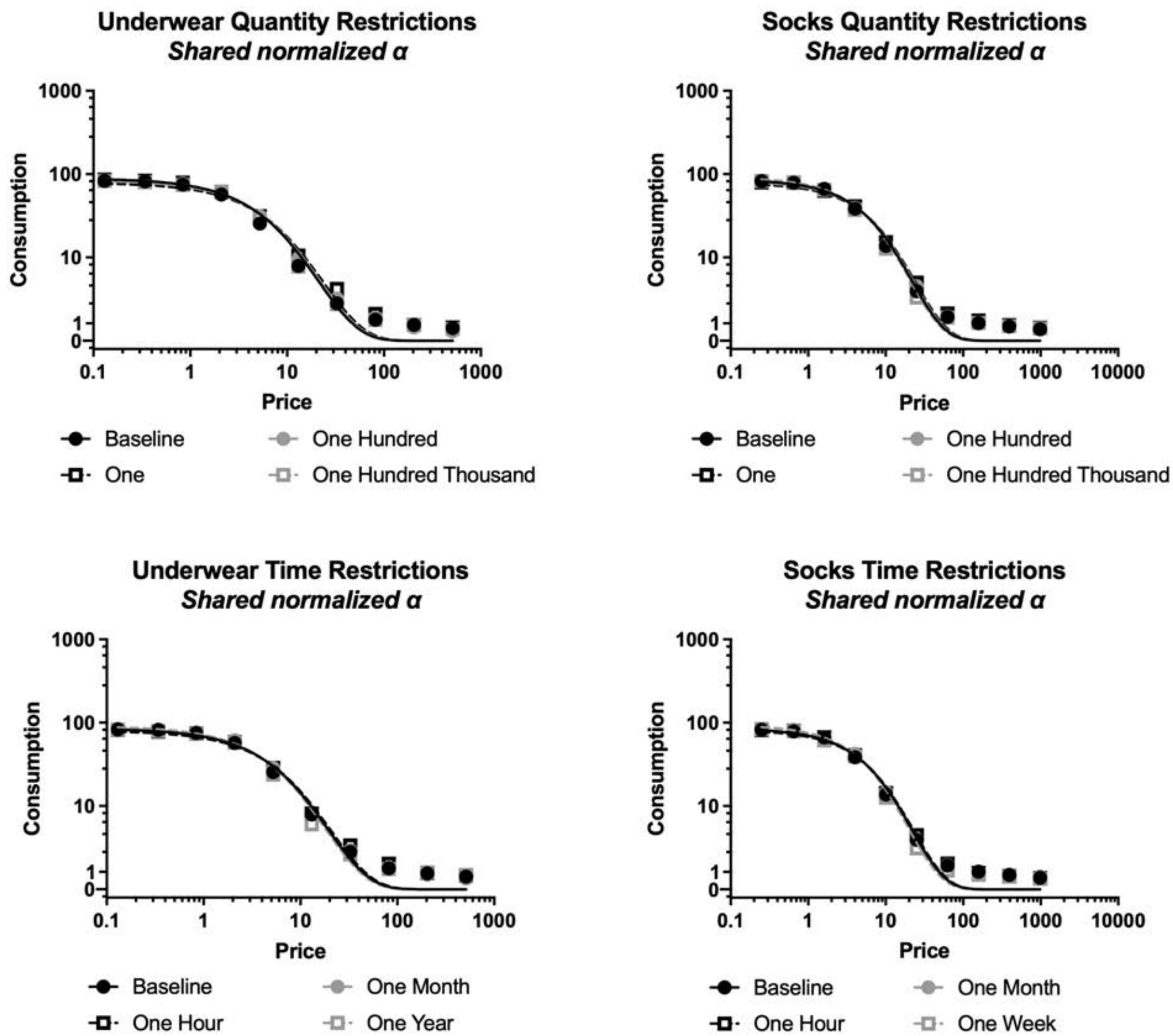


Figure 20. Demand for retail items under time and quantity conditions compared to baseline.

EVs were highest for socks when the quantity was most restricted (EV = 20.9) and lowest when quantity was least restricted (EV = 17.7). The baseline EV for socks was higher than the EV for the least restrictive quantity condition. Across the three tested quantity conditions, EV decreased as quantity restriction increased. EVs for underwear under time conditions were highest when underwear were most restricted (EV = 18.1) and lowest when underwear were least restricted (EV = 14.7). EVs for socks under time conditions were highest when socks were most restricted (EV = 20) and lowest when socks were least restricted (EV = 16.9). Across all time conditions for both items, EV increased as time restriction increased, providing additional evidence that as restriction increases, demand increases.

P_{max} values under quantity restriction conditions for underwear decreased as restriction decreased, with the highest P_{max} for the most restricted condition (P_{max} = 15.58) and the lowest P_{max} for observed during baseline (P_{max} = 11.52). Under time conditions, P_{max} for underwear was highest during the most restrictive time condition (P_{max} = 12.9) and lowest during the least restrictive time condition (P_{max} = 10.01). Under quantity conditions for socks, P_{max} was highest under the most restrictive condition (P_{max} = 15.17) and lowest under the least restrictive quantity condition (P_{max} = 11.63). P_{max} was highest under the most restrictive time condition for socks (P_{max} = 14.01) and lowest under the least restricted time condition (P_{max} = 11.14). These data provide evidence that participants are more likely to purchase these items at higher prices when the quantity is more restricted.

Figure 21 displays demand curves for luxury items under baseline, quantity restriction, and time restriction conditions. Extra-sum-of-squares *F* tests were conducted to identify differences between the rate elasticity and demand intensity parameters. No significant differences were detected. EVs for dining furniture under quantity conditions were greatest for the most restricted condition (EV = 816) and lowest under the baseline condition (EV = 658). The EVs for cotton sheets under quantity conditions were highest when the quantity was most restricted (EV = 116) and lowest during baseline (EV = 86.5). Overall, EV increased as quantity restriction increased for both dining furniture and cotton sheets.

The EV for dining furniture under time conditions was highest when the time was moderately restricted (EV = 760) and lowest during baseline (EV = 658). The EV for cotton sheets under time conditions was highest when the time was most restricted (EV = 109) and lowest during baseline (EV = 62.49). The inflated EV for the moderate time restriction on purchase dining furniture was the only time during the ADR when EV did not increase as restriction increased across conditions. Thus, EVs increased as quantity available decreased in six out of six items in the study. EVs increased as time available for purchase decreased in five out of six items in the study.

For luxury items, P_{max} was highest under dining furniture quantity restricted conditions when the quantity was most restricted (P_{max} = 614.88) and lowest when quantity was least restricted (P_{max} = 485.28). P_{max} was highest under dining furniture time restricted conditions when time available for purchase was most restricted (P_{max} = 609.95) and lowest during baseline (P_{max} = 509.96). For sheets, P_{max} was highest under the most restricted quantity (P_{max} = 74.84) and most restricted time (P_{max} = 69.93) conditions. P_{max} was lowest during baseline for sheets (P_{max} = 62.49). These data support that the probability of purchasing items is remains higher at higher prices when availability is restricted.

Baseline vs. True Price Anchor

In addition to examining demand under time and quantity restrictions, demand was assessed for items after the true market price was revealed. This analysis was conducted to assess whether knowledge of the true price of a commodity would impact rate of change in elasticity and demand intensity. Figure 22 displays baseline and true price “anchor” demand curves for grocery items. Extra-sum-of-squares *F* tests were conducted to identify differences in the rate elasticity and demand intensity parameters for the best fit curves. No significant differences between baseline and anchor demand curve parameters were detected.

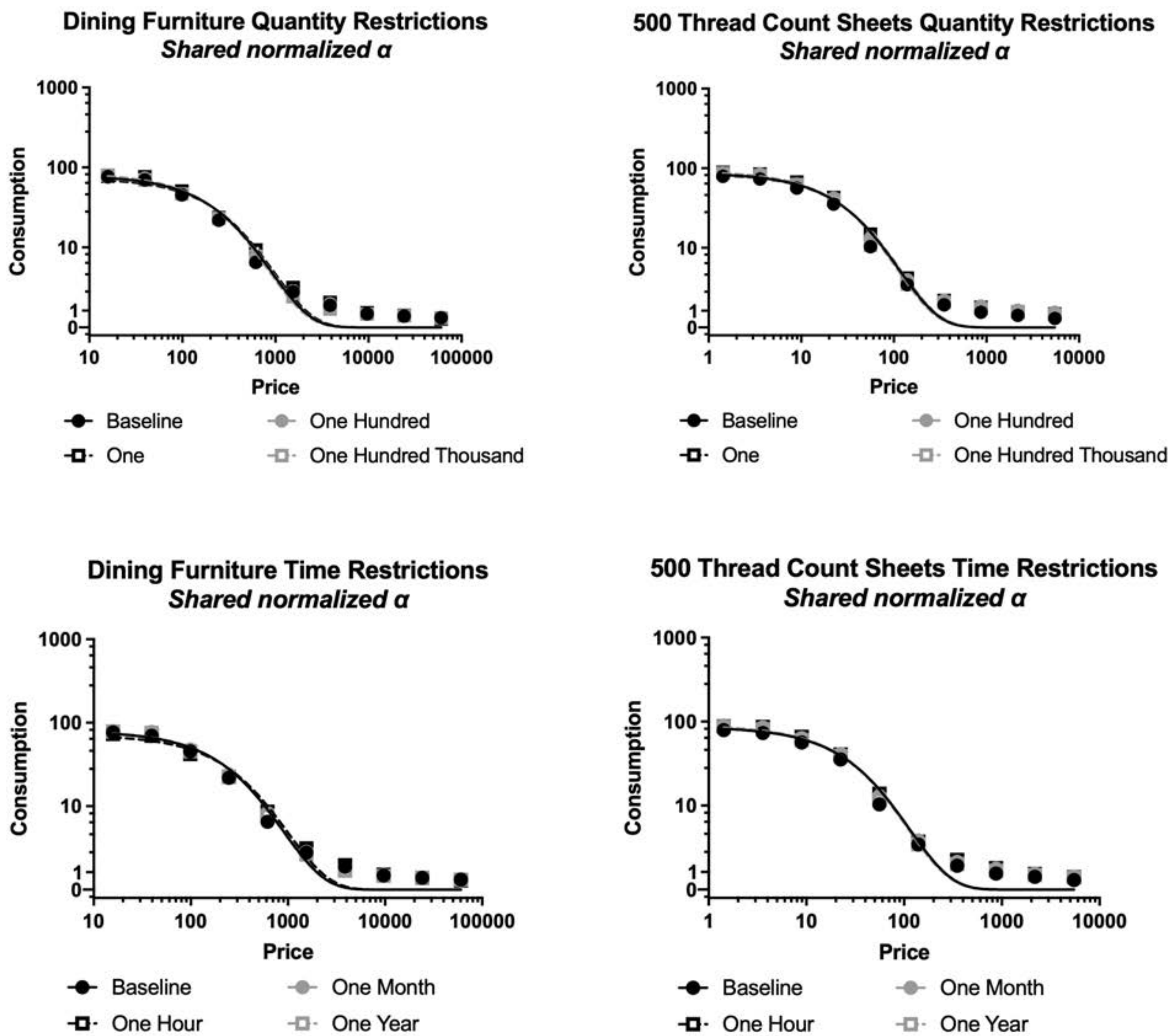
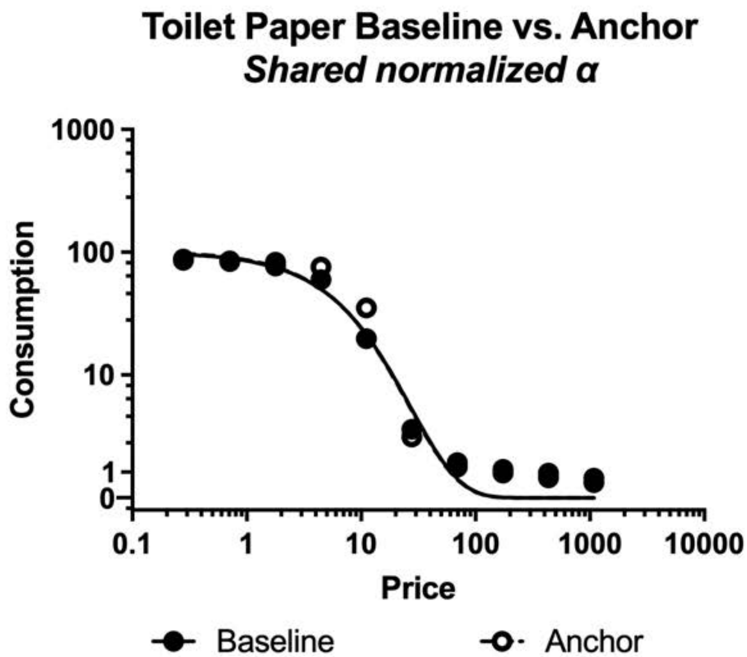


Figure 21. Demand for luxury items under time and quantity conditions compared to baseline.

EVs for baseline and anchor demand curves were compared. EV for toilet paper was higher during the anchor condition (EV = 29.6) than the baseline condition (EV = 25.1). That is, EV was higher after the participants learned the true market price of toilet paper. For bread, EV was slightly higher during baseline (EV = 7.7) than after the true market price was revealed (EV = 7.12). Participants were asked to indicate their estimate of the true market value prior to learning the true price. The average price participants estimated for a 12-pack of toilet paper was $12.20. The actual average market price was $11.10.



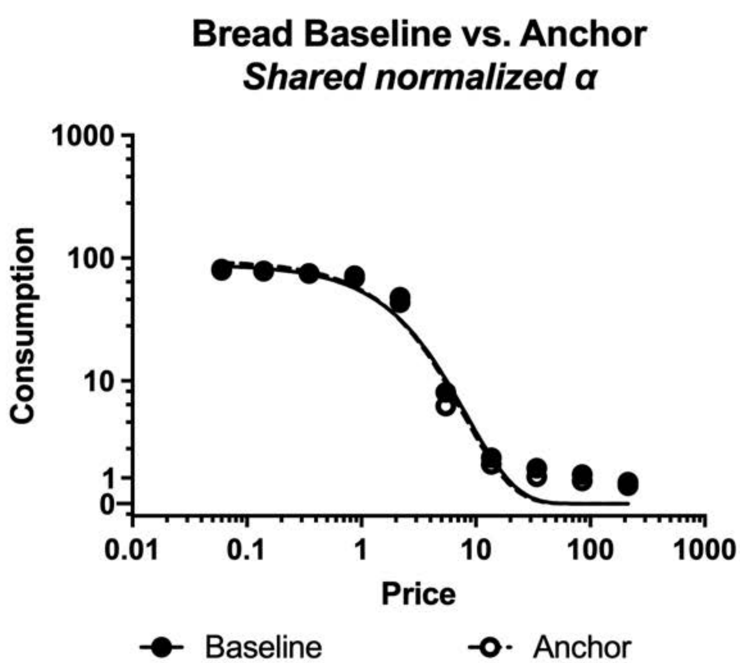


Figure 22. Demand curves for baseline and anchor conditions for grocery items.

The P_{max} value for toilet paper was higher under the anchor condition (P_{max} = 15.92) than under baseline (P_{max} = 15.13). P_{max} for bread was higher under baseline (P_{max} = 4.97) than under the anchor condition (P_{max} = 4.45). The differences in P_{max} between conditions were slight. However, it is interesting that EV and P_{max} for toilet paper increased under the anchor condition although the true price revealed was lower than the average estimated price of toilet paper.

The estimated true price of bread was $5.40. The actual average market price of bread was $2.18. The direction of the change in EV and P_{max} for bread matched the direction of the change in anchor price, with P_{max} and EV decreasing when the anchor price was revealed. Figure 23 displays the relationship between P_{max} during baseline and after the true price was revealed, and the average estimated price and actual market price. Timepoint 1 on the graph displays the estimated price of each commodity and the baseline P_{max}. Timepoint 2 displays the true price of each commodity and the P_{max} after the true price was revealed. For toilet paper, the decrease in the anchored price did not result in a decrease in P_{max}. In fact, it led to a slight increase. However, for bread, the decrease in the anchored price led to a slight decrease in P_{max}.

Figure 24 displays demand curves for retail items in baseline versus anchored true price conditions. Extra-sum-of-squares *F* tests revealed no significant differences between rate elasticity or demand intensity parameters for best fit baseline or anchor demand curves. EV was higher for the underwear baseline condition (EV = 16.6) than under the anchor condition (EV = 15.3). EV was also higher under the baseline condition for socks (EV = 18.6) than under the anchor condition (EV = 15).

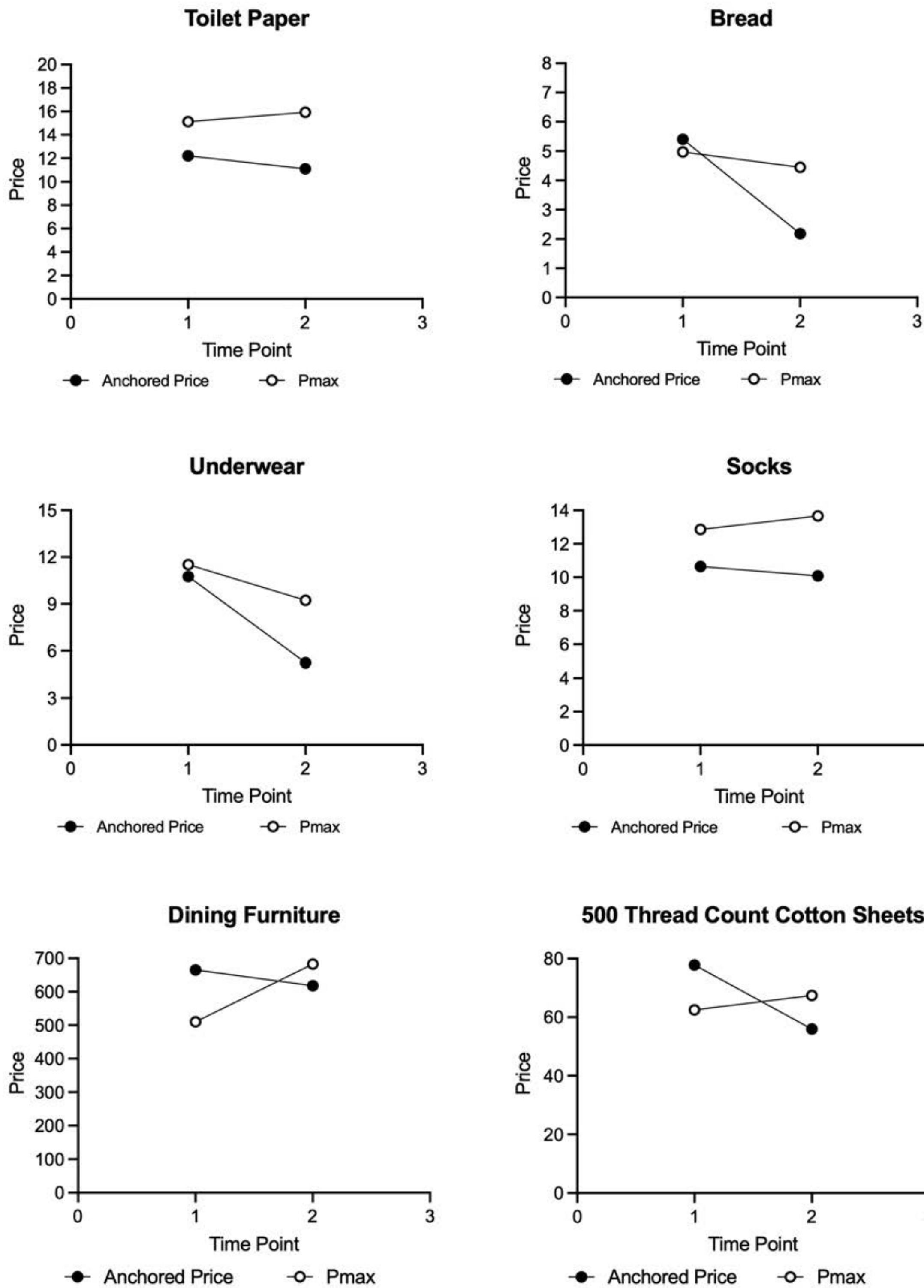


Figure 23. Relationship between anchored price and P_{max} during baseline and true price anchored conditions.

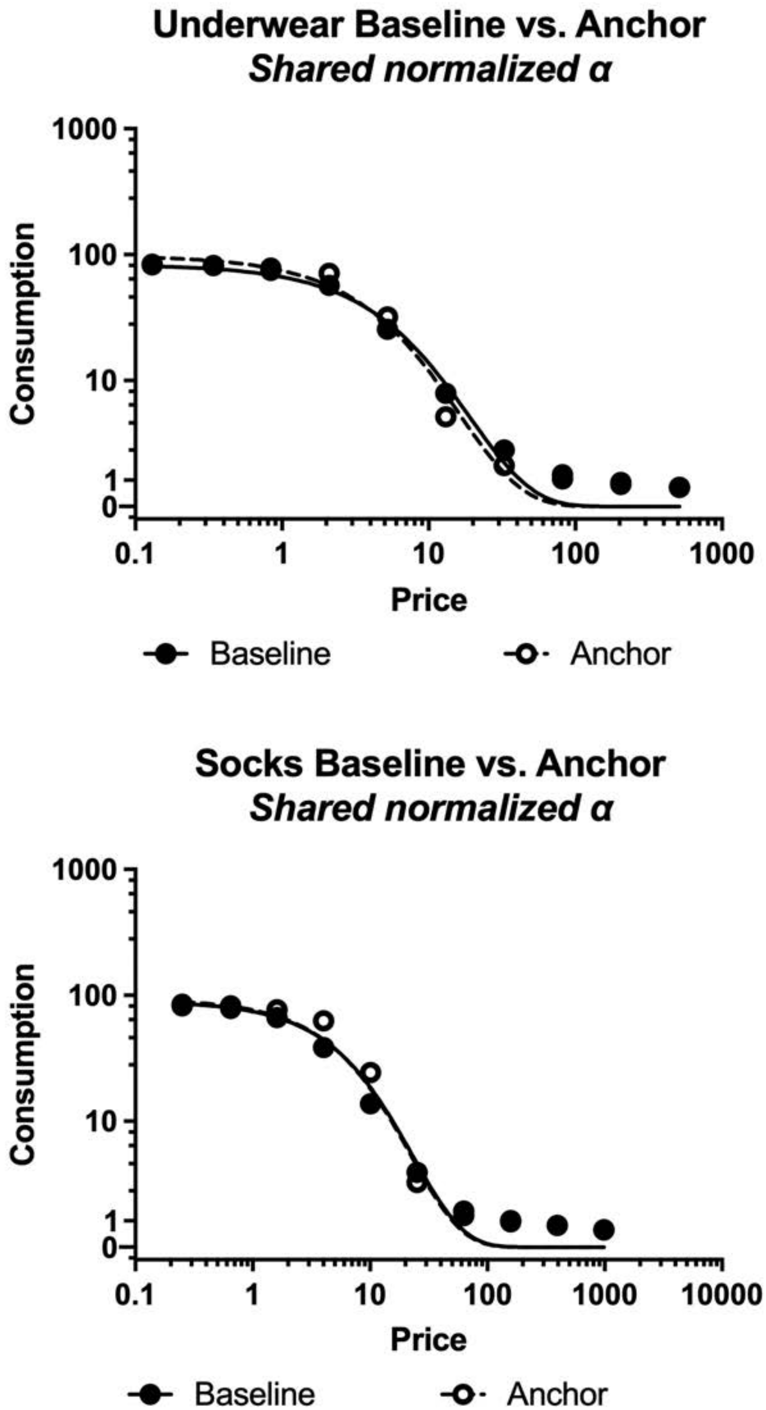
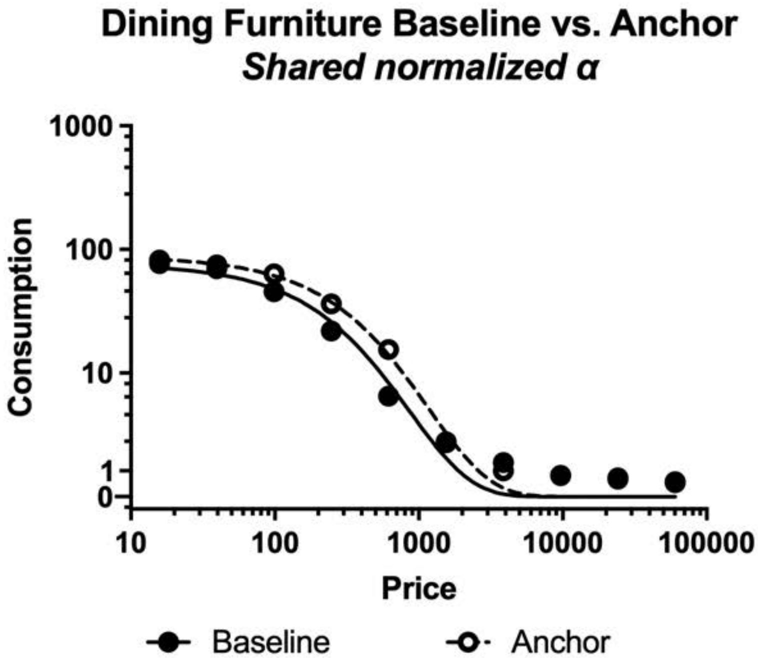


Figure 24. Demand curves for baseline and anchor conditions for retail items.

P_{max} was higher for underwear under the baseline condition (P_{max} = 11.52) than anchor (P_{max} = 9.23). The average estimated price of underwear was \$10.75. The actual price of \$5.24. P_{max} decreased when the anchor was revealed. Figure 23 graphically displays this relationship. P_{max} was higher for socks under the anchor condition (P_{max} = 13.67) than baseline (P_{max} = 12.86). The estimated price of socks was \$10.65. The actual price revealed during the true price anchor condition was \$10.08. Although the true price was slightly higher than the estimated price, P_{max} decreased after the presentation of the anchor.

Demand curves were generated comparing baseline for luxury items to true price anchor conditions. Extra-sum-of-squares *F* tests revealed a significant difference in the rate elasticity parameter for dining furniture ($F(1, 18) = 4.55$, $p = 0.0469$). EV for the anchor condition (EV = 1028) was greater than the EV for the baseline condition (EV = 658). No other significant differences between rate elasticity or demand intensity were identified for luxury items. EV was higher for the cotton sheets under the anchor condition (EV = 118) than baseline (EV = 86.5).

Pmax was greater under the anchor condition (P_{max} = 682.6) for dining furniture than baseline (P_{max} = 509.86). The estimated price of dining furniture was \$665.11. The true market price of dining furniture was \$618.09. The relationship between price and P_{max} is displayed in Figure 23. P_{max} increased during the true price anchor condition, although the anchored true price was lower than the estimated price. P_{max} for cotton sheets was higher under the anchor condition (P_{max} = 67.46) than baseline (P_{max} = 62.49). The estimated true price of cotton sheets was \$77.87. The true market price of sheets was \$55.99. Similar to dining furniture, P_{max} was higher during baseline when the anchored estimate was lower, and higher when the anchored true price was lower. Figure 23 displays this relationship.



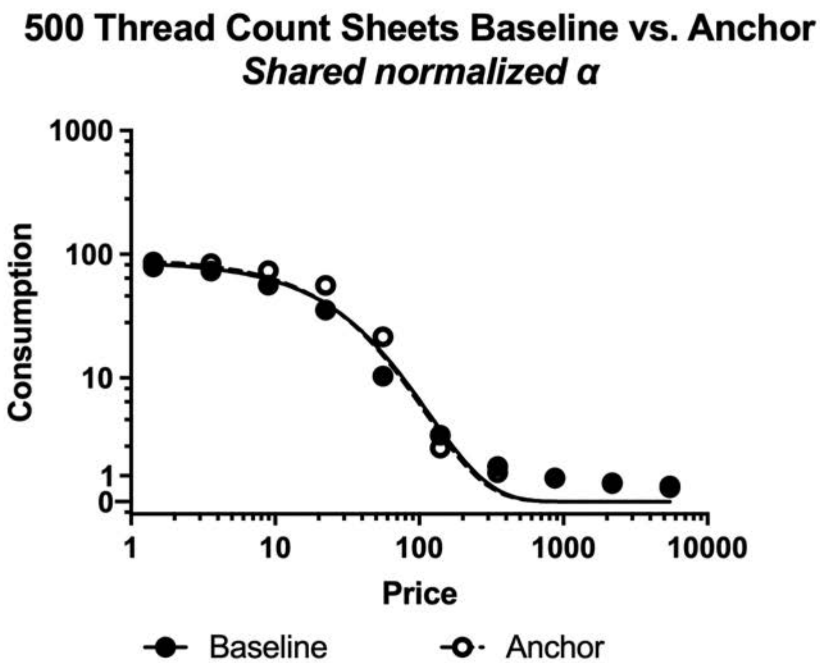


Figure 25. Demand curves for baseline and anchor conditions for luxury items.

In a final analysis, the EVs produced during the Restriction Assessments were compared to the EVs produced in the ADR. This analysis was conducted to assess whether the data collected in the ADR was consistent with the data collected in RA1 and RA2. Figure 26 displays EVs obtained during the ADR compared to the Restriction Assessments for each of the six items. Baseline EVs for RA1 and RA2 were averaged and a single value was included in the graph. Across all items and all conditions, EVs were higher in the ADR than in either of the Restriction Assessments. It should be noted that the baseline for underwear in the Restriction Assessments is substantially lower than the EV in the ADR. This could be due, in part, to the fact that different prices were used in the Restriction Assessment baselines than in the ADR baseline. Despite that EVs in the ADR were inflated compared to the Restriction Assessments, EV consistently decreased as restriction decreased in all three components of the study.

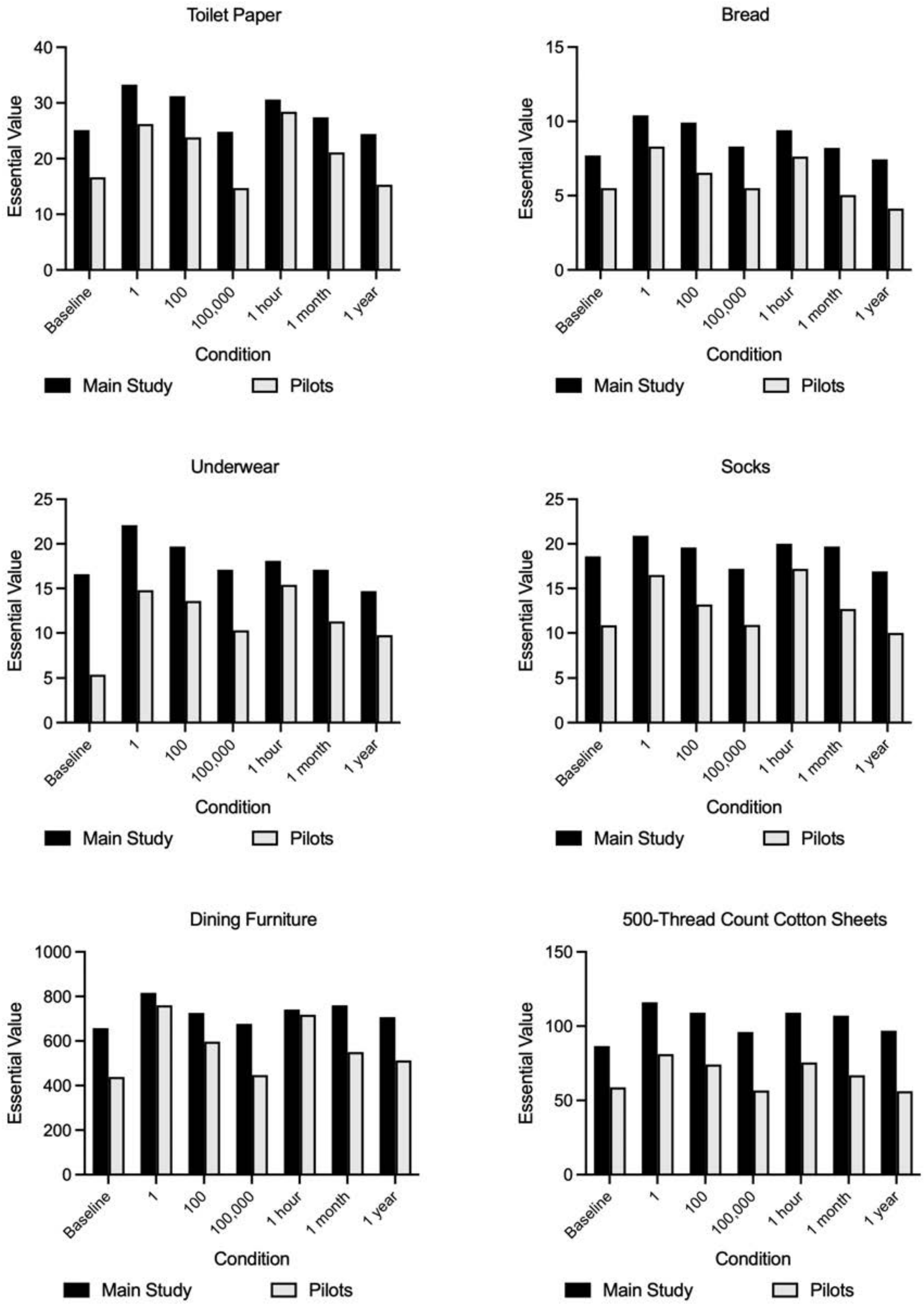


Figure 26. EVs obtained in the ADR compared to EVs obtained in RA1 and RA2.

Analysis of Demand Under Restriction Discussion

The ADR was conducted to assess whether demand for items increases when restriction is increased. Demand under three time and three quantity restrictions was assessed. Results of the ADR revealed no significant differences between rate of change in elasticity or demand intensity for the best fit curves for each item. It is unclear why significant differences were not obtained given that the ADR was powered to detect a small effect size, and RA1 and RA2 were not. Significant differences were, however, detected in the Restriction Assessments. There are a few possible explanations. First, it is possible that the small sample sizes used in RA1 and RA2 studies resulted in overweighting of extreme data. Fewer participants were included in the Restriction Assessments, especially RA2. Therefore, extreme data had more power to influence the average rate of change in elasticity and demand intensity parameters. A second possible explanation for the non-significant effect is that the survey itself served as context for participants as they made purchasing decisions in the HPTs. That is, participants' responding on HPTs may have been controlled by their previous responses on other HPTs within the survey. Participants' responses on previous HPTs may have served as an anchor that participants referenced while making decisions on future HPTs for the same item.

It is interesting that when RA1 and RA2 were combined, EVs remained orderly, in that EVs increased as restriction increased. The EVs obtained in the ADR were consistently higher than those obtained in either of the Restriction Assessments. Despite that EVs obtained in the ADR were inflated compared to RA1 and RA2, there was a clear pattern in the EVs for all study components that suggests that the value of items does increase when availability decreases.

Values for P_{max} obtained in the ADR consistently increased as items were more restricted. Thus, responding was maintained at higher prices when items were more restricted. These data in combination with the obtained EVs favor the hypothesis that decreasing the availability of items increases demand for them. However, these are only preliminary investigations.

In addition to baseline and restriction conditions, demand for items was also assessed after the true price was revealed. This condition was called the “anchor” condition, because it included a price that was expected to be used as a reference point in responding for participants. It was expected that responding would drop off at prices higher than the true price. No restrictions were imposed in the anchor HPTs. One significant difference was detected between the rate of change in elasticity parameter for the anchor condition compared to baseline. This difference occurred when comparing baseline demand curves for dining furniture to the anchor. This was an interesting finding, as the difference in price between the participants’ average estimate and the true market price was proportionally small. The estimated price was higher than the true price but P_{max} was higher during the anchor condition. Participants’ responding was maintained across a wider range of prices during the anchor condition, despite that the estimated price of dining furniture was lower than the anchor.

Overall, no consistent patterns were observed in the relationship between the anchored price and P_{max}. P_{max} did not consistently decrease when the true price was less than the average estimated price. Likewise, P_{max} did not always increase when the true price was greater than the average estimate. Some potential explanations for this include that the anchored true price did not exert stimulus control over responding. Participants may not have been attending to the true price when making decisions about their probability of purchasing the items in the anchor condition. Alternatively, it is possible that the true price exerted stimulus control before it had been revealed to participants. The average estimated prices for most items were not drastically different from the anchored price. In situations where the true price was approximately 50 percent of the estimate, such as for bread and underwear, the direction of change in P_{max} followed the direction of the change in the price. The items selected for the ADR were all items that participants in the IPA had reported familiarity with. Therefore, it is possible that participants were already aware of the approximate price of these items and this could have controlled responding during baseline. It is possible that the increases and decreases in P_{max} may be variability due to error.

General Discussion

This study was conducted to evaluate whether limiting the quantity and time available to purchase items increases demand for them. The results of the current study provide preliminary evidence that as access to items is more restricted, demand for those items increases. A secondary purpose of this study was to provide a behavioral analysis of the traditional behavioral economic concept, decision framing. The current study provides an example of a successful integration of TBE and MAB.

Although significant differences in demand curve parameters between restriction conditions were not achieved for any of the tested items in the ADR, these data still support that increasing scarcity increases value. Aggarwal and colleagues conducted a study examining time and quantity restriction and its effect on participants' intentions to purchase items in the future (Aggarwal et al., 2013). They found that intention to purchase was greater when restriction was imposed compared to unrestricted conditions (Aggarwal et al., 2013). The current study supports these findings and improves upon them. It supports these findings in that essential value increased as restriction increased, consistent with the obtained results. It improves upon the findings because it removes the hypothetical construct, "intention" and quantifies the value of the items under restriction conditions objectively. Through the use of the demand analysis, an essential value could be obtained for each of the items under each of the tested conditions. This value allowed for objective comparisons between conditions. The demand analysis procedure also allowed for the prediction of demand and rate of change in responding across different prices, which was not possible with the procedures used in Aggarwal's study.

The current study also improved on previous research by including multiple quantity and time manipulations to decision frames. These frames likely served as contextual cues. Leigland outlined two types of augmental rules: formative and motivative (Leigland, 2005), both of which serve as contextual cues. The frames in this study likely served as motivative augmental rules, as they did not *establish* reinforcers, but they did change the value of them. As part of the debrief for each item, participants were asked to indicate whether they would have been more likely to purchase an item if they could sell or give it away later. Some participants indicated that they would be more likely to purchase the item under those circumstances. Participants sometimes stated that they would be likely to sell the item if it had value to collectors. It is possible that if participants had been allowed to hypothetically sell or give items away, the frames could have served as a formative augmental rule for participants who otherwise exhibited no demand for the item.

As a motivative augmental rule, the quantity and time restriction frames served as contextual cues. Each word in the phrasing of the frames was important for setting the context. Although no significant differences were detected between demand curve parameters, value increased with restriction. Within each frame, the only manipulation to phrasing was the restriction. By only manipulating the restriction, we found evidence that the restriction was impacting responding. Using frames that included minimal variation and minimal contextual information was helpful for observing an effect. However, these frames may have lacked in external validity and this may be the reason that results were not robust. Specific wording was carefully selected for the frames to reduce the impact of potential extraneous variables.

Although orderly data was obtained, it is possible that differences in demand curve parameters did not reach significance because the frames lacked external validity. Nuance may be an important feature of a decision frame. Each frame was scaled back to the minimum amount of information needed to make decisions about purchasing. Compared to a real-world online purchasing situation, these frames were fairly diluted. For example, online retail websites like Amazon © and Etsy © feature images of products. Scarcity frames are often used on these sites to increase the likelihood of making a purchase, but these frames differ in many important ways including the phrasing, length, color, and location of the message relative to other information. It was advantageous in this study to scale frames back to ensure that the restriction was the component of the frame exerting an effect. Extensions of this research should include the use of images and manipulation to the words included in the frame. Phrasing, in particular, may be of importance.

The phrasing included in a scarcity frame is important in a few ways. First, it can evoke differential responding based on how the words, images, colors, and location participate within frames of coordination with other contextual cues that have been previously associated with reinforcement or punishement. The phrasing chosen for the decision frames in this study was carefully considered to reduce variability in responding. No specific brands of items were selected because these could have evoked differential responding based on participants' history with the items and preference for them. If brands had been used, participants who were familiar with the brands or had favorable opinions of them may have responded differently to the framing scenario than participants who did not have a history with the brands or had a negative opinions of them. For example, if the dining furniture included was Bentley © Home Collection, which is a luxury furniture brand, participants familiar with this brand may be willing to pay more for it than participants who have not heard of this brand or who find the Bentley © brand aversive.

Rather than using specific brands, one of the assumptions included in the demand tasks was that these items were “the same brand you are familiar with.” This phrasing was selected to standardize the way participants responded to each of the objects. It was limited in that the brands that participants were familiar with likely varied from participant to participant. It is still possible that participants differentially responded to frames based on the brand they were familiar with, but by not including the brand, no participants were alienated from the task. By using “the same brand you are familiar with”, variability due to branding was reduced. Future studies should focus on how quality and brand reputation impact demand under restriction conditions.

In addition to limiting information about the brand, the restriction itself was carefully phrased so that it contained no implications about why there was a limited number or time available for purchasing the items. As part of the debrief, participants were asked to indicate whether they would be more likely to purchase each item if they were allowed to sell it or give it away later. Several participants, especially under toilet paper conditions, stated that they would be more likely to purchase the item if there was a shortage of the item and they could make a profit by selling it to others. For example, one participant stated, “If I could sell it in the future when there may be a shortage of toilet paper in stores I would definitely buy it at a higher price than I usually would in hopes of making a profit.” Thus, including the assumption that there was a shortage would likely have evoked different behavior. The word “shortage” has likely been associated with other words that have an evocative effect on behavior. Some words that were included in descriptive comments in the debrief that may be associated with “shortage” included pandemic, panic, lockdown, and profit. These words would likely affect behavior differently than the wording included in the current frames.

In the current frames, items were listed as *unavailable* once the supply depleted or timeframe expired. In a study conducted by Peterson and colleagues in 2019, researchers investigated the effects of scarcity frames. The depletion of products was phrased as either “out-of-stock”, “unavailable”, or “sold out” and intention to purchase and perception of the retailer were measured. Peterson et al. found that intention to purchase did not differ across conditions. However, participants reported different perceptions of products based on the frame. Participants’ perception of the online retailer and brand remained highest when the items were framed as “sold out” and lowest when framed as “out-of-stock” (Peterson et al., 2019). Peterson et al. suggest that listing an item as “unavailable” is ambiguous to consumers and may lead to negative perceptions of the items and retailer. Each of the different frames used in the Peterson study likely evokes different behavior based on how each phrase has been associated with other phrases and outcomes. Indeed, each phrase likely participates in a different frame of coordination from the others. Therefore, these frames may have been differentially associated with reinforcing or punishing outcomes. Further research is needed to determine whether demand is differentially affected by the phrasing of scarcity frames.

Phrasing can also impact responding by signaling competition in the marketplace. It is possible that significant differences in demand curve fits would have been detected if the marketplace in the study was competitive. Aggarwal et al. found that consumer competition mediated the relationship between scarcity and consumers’ intention to purchase items (Aggarwal et al., 2013). Competition in the marketplace is commonplace. Some online retailers capitalize on this. For example, the online retailer, Etsy ©, often includes a message on low stock items that states the number of people who currently have the item in their cart. There is reason to believe that framing scarcity in terms of consumer competition would further drive up demand.

Demand in a competitive marketplace may be especially evident when the items included are limited edition and collector's items. Some participants in the current study indicated that they would be more likely to purchase the items if they could sell them later. Reasoning given for this included that they could make a profit selling the items if they were rare or collectible. Future extensions of this research should examine demand in a competitive marketplace.

The phrasing manipulations listed above are only a few examples of the ways that frames may be manipulated to further drive up demand. Although these tactics have not been well studied by behavior analysts, companies use these tactics frequently when marketing products. It has been shown that manipulating phrasing and introducing competition increases demand for items. The question, then, is what do behavior analysts add to the analysis of decision frames? Behavior analysts add precision through the careful analysis of verbal behavior. Frames are verbal statements that serve as contextual cues and establish or modify the effectiveness of other stimuli as reinforcers or punishers. Behavior analysts also add precision through analysis of the three term contingency, the application of single subject designs, and the operant selectionist perspective. Behavior analysts are well trained to assess how environmental relations and behavioral history impact the probability of a response. Through analyzing environmental relations, several procedures have emerged to precisely measure the functional relationship between antecedents, behaviors, and consequences. Through the procedures and principles of behavior analysis, prediction of future behavior is possible. Behavior analysis includes an objective analysis of environmental relations, therefore removing hypothetical constructs in the analysis of past, present, and future behavior.

Limitations

This study was limited in several ways. First, there were few exclusion criteria for participants in the IPA and the exclusion criteria for RA1, RA2, and the ADR may have been too strict. In the IPA, participants were included if they were located in the United States, had a HIT approval rate of over 95%, and over 100 approved HITS. There were no other exclusion criteria aimed at improving the quality of the obtained data. Therefore, it is possible that some participants rushed through the task and did not provide reliable data. It is possible that different items may have been identified from the IPA if there were more quality controls in place.

RA1, RA2, and the ADR had exclusion rates of over 30% on average. This was problematic for two reasons. First, this exclusion rate led to increased costs of the study. The cost per participant on MTurk is up to 40% of compensation. In order to obtain a sample size large enough to detect an effect, 255 participants were recruited for the ADR to obtain data from 161. Because the exclusion rate was so high, eleven of these participants were recruited from a Midwestern university to minimize additional costs. A second limitation to the exclusion rate was that the sample sizes included in RA1 and RA2 were small. This was especially evident in RA2, wherein 26 out of 50 participants' data were used in the final analysis. Because the sample sizes were small, extreme data may have been overweighted. This made comparisons between Restriction Assessment data and ADR data difficult.

Data were excluded by applying algorithms for identifying nonsystematic data (see Stein et al., 2015). The algorithms should be used as a guideline for exclusion but should be used with discretion. In the current study, data were excluded if two or more demand curves met criteria for exclusion based on trend, bounce, or reversals from zero. Further easing exclusion based on these criteria may have led to a small increase in sample size. However, several participants appeared to be responding randomly. It is important to investigate reasons why so many participants' data were nonsystematic.

One potential reason for nonsystematic data, and a second limitation to the current study, was that the survey was lengthy. Completing the survey was estimated to take between 30 minutes and 2 hours. Most participants completed the task in about an hour. In addition to being long, the task was quite repetitive. It is possible that participants were becoming bored and fatigued throughout the study, and therefore began responding randomly. It is also possible that the frames were not exerting stimulus control over participants' responding. Perhaps instructions were unclear or too lengthy.

Another possible explanation for random responding may be due to the rate of compensation. The average compensation for an MTurk worker is approximately $2 per hour (Hara et al., 2018). Compensation for the current task was just above minimum wage, substantially higher than the average. It is possible that some participants took the survey quickly in attempt to maximize earnings while minimizing effort. Future investigations should be conducted to examine the factors that lead to nonsystematic data in behavioral tasks on MTurk.

Another limitation of this study was that it included the analysis of only aggregate data. This means that important individual differences may have been lost due to averaging. Implementing a single subject design may lead to better explanations about what the important features of scarcity frames are. Using a single subject design, important information about behavioral history can be assessed. A single subject design is more amenable to testing the theories underlying demand under scarcity, such as those outlined by Shi et al. (2020). Shi et al.

outlined four possible theories to explain why scarcity leads to increased demand. These theories included the commodity theory (participants value an item to the extent that it is rare or scarce), conformity theory (participants value an item because others value it), regret theory (demand increases because participants are avoiding opportunity costs), and reactant theory (demand increases in response to the perception that freedom to purchase is being removed) (Shi et al., 2020). Each of these theories represents a potential antecedent condition that could lead to increased demand. In fact, frames could be derived from all of these theories and included in future demand analyses. Assessing participants' behavioral history could explain why these frames are more effective at controlling behavior in some participants compared to others. The frames derived from these theories could be assessed in a group design, but differences in the effectiveness of each type of frame could be more difficult to detect if individual differences are not considered.

A final limitation to this study is that it may lack in external validity. Some ways that external validity was sacrificed for internal validity have been identified above, including that the frames were scaled back to reduce variability in data and that participants' purchasing decisions may have been limited to the context of the other HPTs. Another way that the frames may lack in external validity is that the restrictions included may not affect purchasing for all the items in the same way. For example, it is possible that a limit of 100 loaves of bread evokes different responding than limiting dining furniture to 100 sets. The nature of the commodity and typical patterns of purchasing are important to consider. In this study, a probability of purchase task was used instead of a quantity of purchase task to mitigate variability due to the nature of purchasing each of the items. However, it is possible that different levels of restriction could lead to different types of responding across items. In the future, researchers should consider tailoring the restrictions to the commodity.

Future Directions

The current study provides preliminary evidence that framing an item as scarce leads to increased behavioral demand. However, there is still much to be learned about how decision frames influence demand. The task used in this experiment was a demand analysis of participants' probability of purchasing items under various restriction conditions. Roma and colleagues found that when comparing probability and quantity of purchasing tasks, the value ranks of items remained consistent across task types. Roma et al. found that probability tasks led to greater item values than quantity (Roma et al., 2016). However, given that this experiment included scarcity frames with a maximum quantity indicated, it may be useful to replicate this study using quantity of purchase tasks instead of probability to investigate the conditions under which participants will maximize purchasing when items are scarce. Given that demand intensity would likely differ across demand curves due to different quantities available in the tasks, P_{max} would probably need to be used as a main measure of value.

Another procedural variation to consider in future demand tasks is the inclusion of direct comparisons of commodities offered at different levels of scarcity. It would be interesting to investigate whether demand for scarce items is still increased when an alternative, freely available item is made available concurrently. Rather than using two HPTs to analyze demand for freely available items versus restricted items, one HPT would be used with the price of baseline held constant. In doing this, the baseline condition in the current study would be directly compared to the restriction condition. Analyzing the conditions together may improve external validity, as there are often alternative choices available for purchase. By making direct comparisons, substitability and complementarity could be assessed. For example, a participant may prefer the scarce item over the freely available item across a range of prices. As price increases, the participant's preference for the scarce item may equal or drop below preference for the freely available item at some point. Thus, the freely available item would substitute for the restricted item when the restricted item reached that price.

Making alternative commodities available would shift the experiment from a closed economy to a somewhat open economy. Demand curves in this experiment were not differentiated from each other. It is possible that using a closed economy, with the assumption that the only access to these items was in the context of purchasing them in the task, drove up demand across all conditions. Some of the items included in the study were essential (e.g., toilet paper, underwear, socks). Thus, demand for them was likely high for that reason. Using a closed economy was useful in that it helped control motivation to obtain the commodities. However, it is possible that allowing some access to the commodities outside of the purchasing scenario could have led to differentiation between curves. Future researchers should consider how availability of the items outside of the purchasing context could influence demand under restriction conditions.

In the future, researchers should continue investigating how framing manipulations influence demand. One possible manipulation to the current study would be to include generic images of the items to see if that leads to differences in demand or attending to the task. Specific phrasing changes could also lead to differentiated demand. A careful analysis of phrasing may help to improve the scenarios presented in HPTs. For example, the word "unavailable" could be replaced with phrases like, "out-of-stock" or "discontinued." The phrasing of the scarcity frame could also be manipulated to include words like, "rare" or "special" to see if qualifying the item in different ways impacts demand. Investigating nuanced versus scaled back framing scenarios may help to further identify the important components of HPT scenarios.

In addition to the demand analysis, delay discounting tasks may provide important information about the value of restricted commodities. Future studies should include investigating whether steeper discounting curves are generated with more or less restricted commodities. Delay discounting tasks could be implemented in combination with demand analyses to fully characterize the value of commodities under different levels of restriction. Delay discounting tasks could also be used to identify response patterns in participants. It would be interesting to investigate how participants who exhibit steeper discounting curves value commodities in a restricted commodity demand task compared to those with less steep discounting curves.

Another worthwhile direction for future research is to investigate how decision frames impact demand for clinically relevant commodities. One important extension of this research is to investigate drug legalization. For example, as cannabis becomes legalized across more of the United States, it becomes important to consider whether the wide availability of cannabis drives demand down compared to demand under conditions where cannabis is not legal. The direction of the change in demand may have implications for policy making. Variations in HPTs for assessing drug demand could include examining how demand for drugs supplied from a dealer changes when substitutes are available. This could provide important information about how street dealing is affected by the accessibility of dispensaries.

While drug legalization is an important issue, it is not a straightforward issue thus necessitating additional investigations of decision frames. For example, drug purity adds an additional layer to the analysis of demand for restricted drugs. Dolan and Johnson conducted a study investigating demand for ecstasy (Dolan & Johnson, 2020). Participants completed an Ecstasy Purity Discounting Task and a hypothetical ecstasy purchasing task. Participants' likelihood of using ecstasy decreased when ecstasy contained impurities (Dolan & Johnson, 2020). Legalizing and regulating drugs increases the likelihood that they will be pure and safe, which could lead to increased demand under less restricted conditions, counterintuitive to current investigations. Future research should include investigating how restriction and related frames impact demand for drugs.

Conclusion

The current study provided evidence that as the availability of commodities is restricted, demand for them increases. Although there were not significant differences in demand curve parameters, the EV of commodities reliably increased as restriction increased. Additional investigations of framing effects are needed to further assess the conditions under which restriction decision frames impact demand. Nevertheless, the results of the current experiment provide promising data that can be used to improve the demand analysis. As the demand analysis advances as a tool for investigating value, it will be important to investigate how the phrasing in decision frames and therefore, HPT scenarios, influences demand for items. Behavior analysts are well trained in procedures for investigating framing effects. Behavior analysts should continue pushing for the inclusion of behavior analytic techniques in traditional behavioral economic investigations. Behavior analysts still have much to add to the field of behavioral economics. Future integrations of traditional behavioral economics and behavior analysis will lead to a more precise science of decision making.

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Appendix A

Item Purchase Assessment: List of Items

Grocery/Consumables:

1. Bananas
2. Salted Peanuts
3. Toilet paper
4. Bread
5. Milk
6. Cheese
7. Ground beef
8. Hand soap
9. Shampoo
10. Chocolate chip cookies
11. Pasta
12. Potato chips
13. Cereal
14. Ice cream
15. Eggs
16. Yogurt
17. Orange juice
18. Canned corn
19. Frozen pizza
20. Bagels
21. Chicken breasts
22. Toothbrush
23. Toothpaste
24. All purpose cleaner
25. Coffee

Non-grocery/Non-luxury:

1. Sneakers
2. Cotton t-shirt
3. Standard ink pens
4. Printer paper
5. Spiral notebook
6. Blue jeans
7. Sunglasses
8. Baseball cap
9. Lightbulb
10. Coffee mug
11. Wine glass
12. Underwear
13. Socks
14. Bath towels
15. General admission concert tickets to preferred show
16. Movie pass to preferred movie
17. Workout shorts
18. Spatula
19. Bath mat
20. Umbrella
21. Fleece blanket
22. Decorative keychain
23. Resuable water bottle
24. Single wick scented candle in preferred scent
25. Fingernail clippers

Luxury:

1. New luxury sedan
2. Designer brand watch
3. Designer brand dress shoes/heels
4. Designer brand purse
5. Designer brand wallet
6. Designer brand armchair
7. Original wall art
8. Designer brand perfume/cologne
9. 14k gold necklace chain
10. Porcelain china dining set
11. Diamond (1 ct, VS1 clarity, D color)
12. Gourmet chocolate truffle box (30 pieces)
13. Reservation at fine dining restaurant (5 star restaurant)
14. Backstage pass to preferred concert
15. New pontoon boat
16. 1 year country club membership
17. New golf clubs
18. Dining furniture
19. Fine wine
20. Luggage set
21. 1 week all inclusive vacation

22. First class flight
23. 500 thread count cotton bed sheets
24. Designer brand jacket
25. Designer brand jeans

Appendix B

Item Purchase Assessment Questions

Consider your real life purchasing history for the following:

[item]

Answer the following questions about previous and future purchases. Please answer honestly, thoughtfully, and to the best of your ability.

1. Have you ever purchased [this item]?
    a. Yes
    b. No (skip to #5)

2. If yes, when did you most recently purchase [this item]?
    a. Within the last week
    b. Within the last month
    c. Within the last 6 months
    d. Within the last year
    e. Within the last 5 years
    f. Over 5 years ago but within my lifetime

3. How many of [this item] do you typically purchase at one time?

[insert number]

4. Which best describes how frequently you purchase [this item]?
    a. Once a week
    b. Once a month
    c. Once every 6 months
    d. Once a year
    e. Once every 5 years
    f. Less frequently than every 5 years

5. Using the slider, please indicate how likely are you to purchase [this item] in the future.

    0% 25% 50% 75% 100%

    |------------------|------------------[]-----------------|------------------|

6. Please leave any additional comments or explanations, especially related to why you would or would not purchase this item in the future.

    [text box]

Appendix C

Assessment of Understanding

Please read and consider the following scenario.

[scenario]

What is the probability that you would purchase one [item] if it was being offered at the following prices?

Assumptions:

- All items will be delivered the next day.
- Your income is identical to your current income.
- You have no access to these items outside of the context of purchasing them here.
- These items must be purchased for personal use, not to sell for profit later ***OR*** you may purchase these items to sell or give away later.

Assessment of Understanding:

What item are you purchasing?*

- [List of items, including target]

How many of this item are available for purchase?**

- [List of quantities, including target]

How long will this item be available for purchase?**

- [List of timeframes, including target]

When will items be delivered?***

- Immediately
- Next day
- Next week

Where are items being purchased from?***

- Outlet store
- Online retailer
- Grocery store

How much money do you have to purchase the item?***

- The same amount of money I have in real life.
- There are no limits to the amount of money I can spend.
- A fifty percent increase in my real life income.

Can you save, sell, or trade these items at a later time?***

- Yes
- No

*This question appeared on all assessments of understanding
**These questions appeared on all quantity assessments and time assessments, respectively.
***All of these questions appeared on the first assessment of understanding, and in all subsequent assessments, one of these questions was randomly selected from the list.

Appendix D

Debrief Survey

Would your probability of purchasing this item change if you were allowed to *sell it* or *give it away* later? Please explain.

- Yes
- No

[Text Box]

Would your probability of purchasing this item change if you had more money? Please explain.

- Yes
- No

[Text Box]

Were there any other restrictions that influenced the probability that you'd purchase this item? Please explain.

- Yes
- No

[Text Box]

The next question refers to your *real life* purchasing history for this item. Please indicate when you have most recently purchased this item.

- During the last *week*
- During the last *month*
- During the last *6 months*
- During the last *year*
- During the last *5 years*
- I purchased it *more than* 5 years ago.
- I've *never* purchased this item.

The next question refers to *real life* purchases of this item. Please provide information about your past and future purchases of this item.

- I have never purchased this item and do not plan to.
- I have never purchased this item but plan to purchase it in the future.
- I have purchased this item in the past and do not plan to purchase it again in the future.
- I have purchased this item in the past and plan to purchase it again in the future.

Please indicate your estimate of the true price (on average) of this item (rounded to the nearest dollar). (**This question was only given to participants after they completed the last HPT for the item.)**

Appendix E

WMU HSIRB Approval Form

WESTERN MICHIGAN UNIVERSITY

Human Subjects Institutional Review Board

Date: August 11, 2020

To: Anthony DeFulio, Principal Investigator
Haily Traxler, Student Investigator

From: Amy Naugle, Ph.D., Chair

Re: IRB Project Number 20-08-04

This letter will serve as confirmation that your research project titled "A Demand Analysis of Quantity and Time Restriction Frames" has been **approved** under the **exempt** category of review by the Western Michigan University Institutional Review Board (IRB). The conditions and duration of this approval are specified in the policies of Western Michigan University. You may now begin to implement the research as described in the application.

Please note: This research may **only** be conducted exactly in the form it was approved. You must seek specific board approval for any changes to this project (e.g., ***add an investigator, increase number of subjects beyond the number stated in your application, etc.***). Failure to obtain approval for changes will result in a protocol deviation.

In addition, if there are any unanticipated adverse reactions or unanticipated events associated with the conduct of this research, you should immediately suspend the project and contact the Chair of the IRB for consultation.

The Board wishes you success in the pursuit of your research goals.

A status report is required on or prior to (no more than 30 days) August 10, 2021 and each year thereafter until closing of the study. The IRB will send a request.

When this study closes, submit the required Final Report found at https://wmich.edu/research/forms.

Note: All research data must be kept in a secure location on the WMU campus for at least three (3) years after the study closes.

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