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Left-digit pricing effects in a high-resolution examination of hypothetical operant demand for alcohol

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A R T I C L E I N F O

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A B S T R A C T

Behavioral economic measures have demonstrated marked success in the evaluation of consumer choice. Field-standard operant demand curve analyses provide a valuable model of resource allocation via responses to maintain "free-rate" commodity use or consumption. This demand analysis thereby provides a behavioral complement to consumer science techniques. Despite apparent congruence of operant behavioral economics and consumer science, the left-digit effect represents one area of research predominantly untouched by behavioral economic investigation. Previous efforts have applied the hypothetical purchase task to map the effect of a changing left-digit on subsequent purchase decisions. The current study extends investigation of the phenomenon to responding on the validated Alcohol Purchase Task. Introduction of a high-density price structure revealed evidence of digit sensitivity, wherein demand elasticity was disproportionately affected at and around whole-dollar changes. That responses were influenced by small shifts in pricing implies a possibility for policy-level modulation of alcohol ingestion without need to increase commodity price beyond unit elasticity. Capture of digit preference in a self-report framework speaks to the sensitivity of purchase task methodology to detect small, aberrant changes in consumer product perception. Behavioral economic researchers should consider this extent of sensitivity when interpreting results of hypothetical purchase task investigations.

1. Introduction

Since the early days of Behaviorism, the translation of psychological principles to marketing has been successful in rendering unique insight concerning consumer behavior (see Link, 1932). John B. Watson produced works and speeches arguing for the synthesis of behavioral science – concepts that embody behavior analysis – with advertising as a means of capturing a greater proportion of the consumer population as buyers for any given product (Kreshel, 1990). The pairing of social science with the body of knowledge already established in sales set the stage for a new strategic perspective that continues to advance market industry (e.g., Curry et al., 2010; Foxall, 1994; see also Foxall, 2016; Hantula and Wells, 2013).

The study of consumer choice from a behavioral perspective has since evolved – in part – to embody a behavioral economic framework (Foxall, 2017). Broadly, behavioral economics is an approach to consumer evaluation that considers the impact of relevant factors (e.g., response cost) on decision making (Thaler, 2015). Distinct traditions of behavioral economics have grown from these origins: a cognitive-perceptual approach made famous by Nobel Laureates like Daniel Kahneman and Richard Thaler (e.g., Kahneman and Tversky, 1979; Thaler, 1999) that focuses on concepts such as mental accounting and bounded rationality, and operant behavioral economics - an approach grounded in operant learning theory and initially theorized by operant scientists (e.g., Foxall, 1990; Green and Kagel, 1987; Hursh, 1984, 2014).

Application of operant behavioral economics and its respective analyses has historically been used to model choice related to consumer health and well-being, as well as outcomes that influence decision making in a range of samples, human and non-human (e.g., Bickel et al., 2016, 1999; Hursh, 1984, 2014; Lamb et al., 2016; Odum, 2011). Operant demand assessment – a method for predicting consumer valuation of a target commodity – models consumer choice via observed (i.e., revealed) or reported (i.e., stated) responses to defend and maintain "free-rate" obtainment of a commodity amidst escalating response requirements (Hursh, 2014; Hursh and Silberberg, 2008). Prototypical demand assays measure consumption across a range of prices and fit to quantitative models to render the demand curve. Resulting curves

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thereby provide point elasticity estimates across the entire range of potential prices. These curves are logarithmically scaled and characteristically model curvilinear exponential decay, where the left-most portion remains relatively stable (i.e., *inelastic demand*; < 1 unit change in consumption per 1 unit change in price) and the right-most portion diminishes quickly (with respect to increasing response cost; i.e., *elastic demand*; > 1 unit change in consumption per 1 unit change in price; Hursh and Roma, 2016; Hursh and Silberberg, 2008; Watson and Holman, 1977).

Traditional operant demand assessments employ work tasks, during which organisms must meet effort requirements to defend consumption of a target commodity (Hursh, 1978). More recent work has advanced the use of the hypothetical purchase task (HPT) with a strictly human sample as means of more rapid – or ethical[1] – collection of consumer data (Jacobs and Bickel, 1999; Petry and Bickel, 1998; see also Roma et al., 2016, 2017). The HPT is a survey-type instrument through which participants report their anticipated resource allocation toward defending access to a target commodity at each of a number of ascending prices. To date, application of hypothetical purchase task methodology extends to a variety of commodities with abuse liability, not limited to alcohol (e.g., Murphy and MacKillop, 2006), cigarettes (e.g., MacKillop et al., 2008), cannabis (e.g., Aston et al., 2015), cocaine (e.g., Bruner and Johnson, 2014), opioid medication (e.g., Schwartz et al., 2019), internet use (e.g., Acuff et al., 2018), pornography (e.g., Mulhauser et al., 2018) and ultraviolet tanning (e.g., Reed et al., 2016). Many of these tasks have been shown to be commodity specific and are therefore sensitive to individual characteristics of the commodity of interest, such as dependence (see Aston and Cassidy, 2019).

Hypothetical demand measures have received a substantial degree of attention in the behavioral economic community for their reliability and validity (Amlung et al., 2012; Murphy and MacKillop, 2006). Specifically, Amlung et al. (2012) analyzed correspondence between hypothetical demand for alcohol and actual alcohol purchasing. Purchases reported on the demand assessment closely modeled choices made when presented outside the hypothetical circumstance, thereby demonstrating adequate predictive ability. Additionally, validity has been analyzed using a one-month follow up such that baseline intensity predicted alcohol consumption and subsequent problems (Murphy et al., 2015; Dennhardt et al., 2015). Indices derived from the APT also correlate with other types of self-report measures of alcohol consumption (MacKillop et al., 2010; Murphy and MacKillop, 2006; Bertholet et al., 2015). For a further review on the assessment of psychometric properties with the APT, see Kaplan et al. (2018). Subsequently, these methods influenced a growing body of literature concerning their implementation and expected outcomes (e.g., Stein et al., 2015). Ongoing investigation underscores the importance of clarity and consistency of task constraints to leverage the weight of possible framing-effects on respondent behavior (Gentile et al., 2012; Kaplan and Reed, 2018; Kaplan et al., 2017; Skidmore and Murphy, 2012; see also Moore, 2010; Urcelay and Miller, 2014; Weatherly, 2014).

One consumer decision influence remaining relatively unexplored is the *left-digit effect*, or the phenomenon in which disproportionately large magnitude differences in consumption occur proximate to price transition from one whole-dollar amount to the next. Left-digit effect changes are representative of characteristically irrational deviations from expected purchasing decisions, observable when the total change in response cost demonstrates just a small magnitude difference. The effect is hypothesized to occur as a result of greater attending to the left-most digit while at least partially ignoring the subsequent values (Lacetera et al., 2012; Thomas and Morwitz, 2005; Brenner and Brenner, 1982) and has been observed in decision making beyond monetary expense, suggesting some potential extension to other relevant domains (e.g., interpretation of odometer readings; Lacetera et al., 2012).

Marketing and consumer retail research has consistently demonstrated support for the importance of the left-digit effect in purchasing considerations (Gendall et al., 1997; Manning and Sprott, 2009; Schindler and Kibarian, 1996; Stiving and Winer, 1997; Thomas and Morwitz, 2005). The history and theories of left-digit sensitivity have differing origins (e.g., standardization of the British pound after the Civil War led to odd-pricing which became a status symbol of imported goods, compared to domestic goods; see Gendall et al., 1997 for theories) with little agreement; regardless, the effect appears to be pervasive as a market strategy for enhancing consumer perception of saleable goods (Gendall et al., 1997). With such persistence of left-digit-sensitive pricing in everyday sales, left-most price figures appear to exhibit greater control over behavior as values are paired with discounted goods. Such an effect could have strong implications for purchase task methodology, given the reliance upon respondent interpretation of the various media or structures by which price arrays can be arranged and presented (e.g., Reed et al., 2014; Roma et al., 2016). Further, capitalization upon price sensitivity in the global market may have implications for policy-enforced pricing of commodities with high abuse liability (see Hursh and Roma, 2013). The left-digit effect thereby embodies an important target for behavioral economic study – one that lends itself well to simulation in a hypothetical purchase task where prices can be manipulated without market disruption.

In their novel capture of left-digit effects by operant demand methodology, MacKillop et al. (2012) examined points of price sensitivity and insensitivity when consumers simulated purchasing decisions regarding cigarettes. The MacKillop et al. study used a high-density price sequence to yield a high-resolution view of consumer choice. Examination of unit elasticity revealed greater-than-average sensitivity to cigarette price when values escalated to the next whole-dollar amount – significantly fewer cigarettes purchases immediately followed a left-digit shift, despite the relatively small change in price (i.e., $0.20 or less). Such consumer decisions depict changes in reported purchases at rates that exceed the corresponding change in response cost. The authors conclude in favor of the highlighted phenomenon as a tool for use in public policy – carefully engineered price structures could reduce cigarette smoking in the general public, should regulation maintain market price at values just beyond the nearest whole-dollar amount.

Advancing the use of left-digit-sensitive pricing as a tool for socially meaningful change, MacKillop et al. (2014) extended their previous work (2012) by examining the influence of left-digit cigarette price changes in a high-resolution snapshot of self-reported motivation to quit habitual smoking. Participants moved through a high-density array of prices and, much like in a typical HPT, were prompted to imagine each value as reflecting real-world cigarette costs; instead of consumption, respondents reported their prospective desire to quit smoking under said imagined constraints. In addition to the expected positive relation between product pricing and the corresponding probability of smoking cessation, the authors observed – on average – significantly greater changes in reported quit probability following left-digit shifts as compared to the average change across prices.

The purpose of the current study is to further explore the influence of left-digit sensitivity from within a behavioral economic framework. We move to expand the demonstration of this effect to a novel commodity – alcohol – using the previously validated Alcohol Purchase Task (APT; Kaplan and Reed, 2018; Murphy and MacKillop, 2006; Murphy et al., 2009). Given the experimental validity of the APT (see review by Kaplan and Reed, 2018), studying the left-digit effect with alcohol may provide further evidence for the effect within highly dense price-sequences (MacKillop et al., 2012, 2014). Through application of methods similar to those used in past demonstrations, we hypothesized observation of greater than average reductions in alcohol purchasing at

[1] The hypothetical purchase task has demonstrated particular utility when assessing demand for substances with a relatively greater risk for abuse or user inebriation (e.g., heroin, alcohol) in that *hypothetical* consumers do not make contact with or ingest said substance.

or around whole-dollar price changes. As such, we expected irrationally greater sensitivity to price relative to other price changes in a high-resolution view of alcohol demand at values adjacent to each whole-dollar increment.

2. Materials and methods

Survey materials were created using Qualtrics® Research Suite (www.qualtrics.com/). Prior to accessing the assessment, an information statement briefed participants on the nature of the work and the anticipated time commitment. Mean duration to task completion was 5.15 min (SEM = 29.31 s), approximating an hourly wage of $5.83. All procedures were approved by the Human Subjects Committee-Lawrence Campus (HSCL).

2.1. Participants

The initial sample contained 127 participants recruited from Amazon Mechanical Turk (mTurk; www.mturk.com/), a platform that connects researchers to a large pool of potential research candidates filterable via experimenter-established criteria; this approach has rendered quality data in the social sciences (Buhrmester et al., 2011; Kees et al., 2017; Mason and Suri, 2012; Rouse, 2015), in addition to specific addiction studies (Strickland and Stoops, 2019), including those using the APT (Kaplan and Reed, 2018; Kaplan et al., 2017; Morris et al., 2017, 2018). Workers were eligible for participation if they had completed at least 100 human intelligence tasks (HITs; e.g., surveys) through mTurk with at least 95% of their work approved by HIT creators and worked from an IP address located in the United States. Participants received $0.50 upon HIT completion, verified by a unique code generated at survey termination. Of the 98 participants (mean age = 32.99 years) that completed the HIT (see section 2.3.1 for data exclusionary detail), 49 (50%) self-reported female identification.

2.2. Measures

2.2.1. Alcohol purchase task

The APT is an assessment of operant demand for alcohol wherein participants self-report hypothetical purchases at each of a series of ascending prices (Murphy and MacKillop, 2006). Previous work has demonstrated predictive validity of the APT in its ability to model alcohol purchasing decisions made under typically experienced contingencies (see review by Kaplan and Reed, 2018). In an effort to impose these expected real-world constraints, participants are asked to report purchases reflective of decision making in an imagined scenario established by a vignette, identical here to that employed by Murphy et al. (2009:

> "In the questionnaire that follows we would like you to pretend to purchase and consume alcohol. Imagine that you and your friends are at a party on a weekend night from 9:00 pm until 2:00 am to see a band. Imagine that you do not have any obligations the next day (i.e., no work or classes). The following questions ask how many drinks you would purchase at various prices. The available drinks are standard size domestic beers (12 oz.), wine (5 oz.), shots of hard liquor (1.5 oz.), or mixed drinks containing one shot of liquor. Assume that you did not drink alcohol or use drugs before you went to the party, and that you will not drink or use drugs after leaving the party. You cannot bring your own alcohol or drugs to the party. Also, assume that the alcohol you are about to purchase is for your own consumption only. In other words, you can't sell the drinks or give them to anyone else. You also can't bring the drinks home. Everything you buy is, therefore, for your own personal use within the 5 -h period that you are at the party. Please respond to these questions honestly, as if you were actually in this situation."

To ensure participant attendance to relevant details, a set of multiple-choice questions pertaining to key vignette information (e.g., "What is the likelihood I will continue drinking after this time period?") followed an initial presentation of the vignette text; respondents were unable to progress with the assessment until all questions were correctly answered. Contingent upon passing these check questions, participants were again shown the full vignette body and were asked to imagine and provide the quantity of preferred alcoholic beverages they would purchase should they be priced at each of a series of ascending values. The assessment included a price sequence modified to yield a high-resolution view of alcohol demand within the value range thought to contain local market price (i.e., $2.00 - $6.00) determined from estimates of *Pmax* across studies in a systematic review by Kaplan et al. (2018) and by acquiring sample prices for a standard beverage from each geographical region in the United States. As such, participants saw 51 prices ranging from $0.00 (free) to $20.00, increasing by increments of $0.50 from $0.00 to $2.00, increments of $0.10 from $2.00 to $6.00, increments of $1.00 from $7.00 to $10.00, and $5.00 increments thereafter to the maximum assessed price of $20.00.

2.2.2. Daily drinking questionnaire

Participants answered questions regarding approximate historic alcohol consumption using the Daily Drinking Questionnaire (DDQ; Collins et al., 1985). The DDQ is a measure of alcohol consumption over an average week in the 30 days immediately preceding task completion (Collins et al., 1985; Kivlahan et al., 1990). Adaptations to the DDQ permit analysis of drinking habits for both females and males separately using the DDQ-F and DDQ-M, respectively.

2.3. Data analysis

Prior to analysis, data were assessed for quality responding according to criteria recommended by Stein et al. (2015). Preliminary examination focused on individual-level responding such that observed (i.e., values calculated without statistical modeling) intensity, breakpoint, and price of greatest expenditure were determined for each participant. Here, intensity was defined as the number of drinks reportedly purchased at free-price (Hursh and Silberberg, 2008).

Responses were aggregated across participants and described using Hursh and Silberberg's (2008) exponential demand model:

$$\log Q = \log Q_0 + k(e^{-\alpha(Q0)C)} - 1) \quad (1)$$

where Q is consumption expected at price C, Q_0 is consumption expected at free-price (i.e., C = $0.00, substituted with the nominal value $0.01 to permit plotting of the consumption at this price on the log-scaled ordinate axis), α is a parameter quantifying the *sensitivity* of the consumer to increasing price, and k is a scaling factor corresponding to the range of reported consumption and is thus expressed in logarithmic units. Generation of a best-fit regression line using Eq. (1) permitted derivation of a precise point of unit elasticity (i.e., *Pmax*) and corresponding expenditure value (i.e., *Omax*). For the described analyses, Q_0 and α were left unconstrained, while k was constrained to a value between 0 and 5.

Drawing from previous behavioral economic work examining left-digit effects (i.e., MacKillop et al., 2012, 2014), we used a within-samples ANOVA with Greenhouse-Geisser correction (to account for lack of sphericity) to check for meaningful differences in reported consumption across assessed price points; effect sizes in the form of Cohen's d_z – a derivative of Cohen's d that controls for within-subject comparison (i.e., correlated measurements; Lakens, 2013) – provide further interpretability for the influence of increasing cost on reported alcohol consumption. To demonstrate statistical support for the role of left-digit transitions, we conducted a paired-samples t-test to compare average changes in consumption between left-digit and non-left-digit transitions.

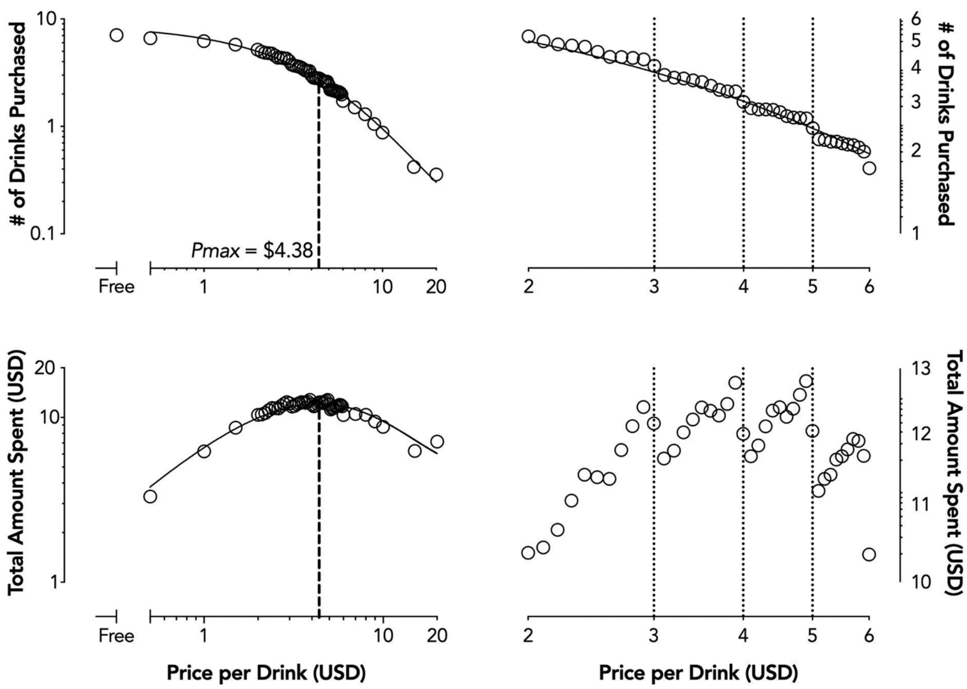

Fig. 1. Top-left: Aggregate (n = 98) reported consumption across all assessed price values. Top-right: A high-resolution view of reported consumption within the range of market price. Bottom-left: Aggregate reported expenditure corresponding to each assessed price point. Output is greatest at and around *Pmax* (i.e., *Omax*; $12.09). Bottom-right: A high-resolution view of reported expenditure within the range of market price.

2.3.1. Data exclusions

Of the 127 participants initially recruited, 15 (11.8%) were excluded for leaving survey materials incomplete. An additional 10 participants (7.87%) were excluded for reporting nonsystematic consumption data – seven individuals were eliminated based on trend (i.e., ΔQ; 0.025), one was eliminated for bounce (i.e., local increase in demand from one price to a subsequent price is no more than 25% of the lowest reported consumption; B; 0.10), and two were removed for reporting consumption values which reversed from zero (e.g., reporting consumption after an initial, preceding breakpoint$_0$; Stein et al., 2015). Three additional participants were excluded for reporting consumption only at free price. One final exclusion was made based on extreme reported consumption values at free-cost, where an outlier was defined as a z-score $+/-3.29$ (Tabachnick and Fidell, 2013). Cleaning and application of all exclusionary criteria resulted in the flagging and removal of 29 (22.83%) data sets.

3. Results

Based on responding to the DDQ, the average weekly consumption of alcohol for females was 6.08 drinks (SD = 7.15 drinks), with 25 (51.0%) reports of at least one binge drinking episode (i.e., four or more drinks in a single occasion) within the preceding 30-day span. Seven (14.3%) of these women were classified as heavy drinkers, defined as at least five binge drinking sessions in a 30-day period. For males, the average weekly consumption of alcohol was 9.6 drinks (SD = 11.68 drinks). Twenty-five (51.0%) men indicated at least one binge drinking episode (i.e., five or more drinks in a single occasion) in the most recent 30-day span, and eight men (16.3%) fit the *heavy* drinker criteria of five or more binge drinking episodes in a 30-day period. Taken together, results of the DDQ suggest the sample proxies the broader population of drinkers and is not disproportionally comprised of participants with alcohol use disorder or dependence.

Visual analysis of alcohol consumption as measured by the modified APT identified a systematic reduction in self-reported purchasing with respect to increasing cost. Eq. (1) fit an aggregate of collected data well (R^2 = .99; see Fig. 1); model fitting proceeded using a best-fit k = 1.986 and Q_O = 8.816 drinks, yielding an estimated aggregate consumer sensitivity to price, α = .0076. By taking the first derivative of Eq. (1) (informing direction and intensity of the sloping regression line; Chiang and Wainwright, 2004) and solving for price to yield a slope-coefficient of -1.0 (i.e., the point of unit-elasticity on a graphic demand depiction bearing logarithmically scaled axes; Watson and Holman, 1977; see also Gilroy et al., 2019)[2], we generated a precise *Pmax* of $4.38 and a corresponding *Omax* of $12.09.

Visual analysis of the demand curve in Fig. 1 (top panels) identified marked reductions in average consumption – deviant as compared to the overall trend – following left-digit transitions. Interestingly, the left-digit effect appears most robust within the range of expected market prices ($2.00 to $6.00; top right panel of Fig. 1), suggesting consumers may allocate more attention to prices most relevant to their experiences in marketplace settings. In further analysis of the pertinent price range, Fig. 2 portrays relative decreases in reported purchasing of alcohol from within the high-resolution view of market pricing. Reported consumption also decreases markedly at price transitions following whole-digit shifts (i.e., $$Y$.00–$Y$.10, where Y is a whole-dollar value).

A within-samples ANOVA with Greenhouse-Geisser correction examining all assessed price points revealed a statistically significant, moderate magnitude effect of price on reported consumption, F(2.64, 253.46) = 113.582, $p <$ .001, η_p^2 = .542. Effect sizes for adjacent price points varied within the price sequence (range d_zs = .0000–.6644), but strongest effects were found at or around left-digit shifts (see Table 1). A comparison of average change at left-digit shifts (M = .2764, SD = .2380), relative to non-left-digit-shifts (M = .0894, SD = .0863), revealed a statistically significant difference, t(97) = 6.892, $p <$ .001, d = .6961, suggesting the possible influence of left-digit sensitivity on assessment responding.

4. Discussion

The goal of the current study was to extend the demonstration of the left-digit effect to a validated purchase task for alcohol. Similar to prior operant demand studies assessing left-digit sensitivity, responding on the current study exhibited localized elasticities < -1.00 around whole-dollar shifts and thus provides support for the role of the effect's

[2] Where the first derivative $= -\alpha Q_0 P(\ln[k])e^{-\alpha Q_0 P}$.

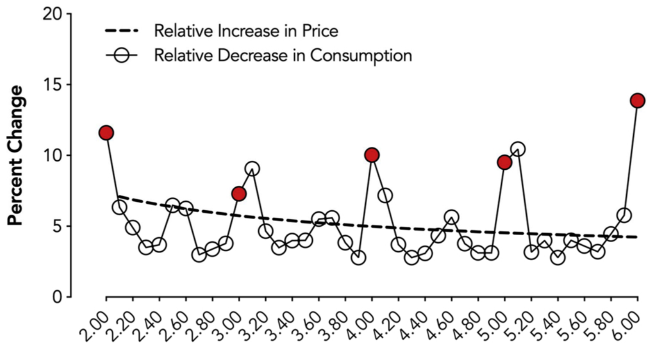

Fig. 2. Relative change in aggregate reported alcohol consumption with respect to change in price within the high-resolution view of market price. Points at which changes in consumption exceed the relative change in price represent elastic demand, or prices at which there is a disproportionately greater change in consumption relative to change in price. Aggregate reported consumption appears most elastic at or immediately following changes in whole-dollar amounts (indicated via filled points).

influence on consumer decision making. Put simply, participants reported a disproportionally large decrease in consumption at and around whole-dollar changes, relative to what is expected with respect to relative price increases.

In our findings, the left-digit effect presents within the range of typical market pricing of alcohol ($2.00 to $6.00), which may suggest consumers allocate attention to prices most relevant to their experiences in marketplace settings (DelVecchio et al., 2007; Mazar et al., 2014; Zhou, 2011). However, further research is required due to the high-density price assessment only within those values, potentially masking left-digit effects beyond local market price values. Interestingly, we also found some carryover effects of left-digit pricing in the price transitions immediately *following* the whole-digit shift. Although not discussed in previous behavioral economic investigations of left-digit sensitivity (i.e., MacKillop et al., 2012, 2014), we hypothesize that effects of these latter price transitions are typical for values that *just* exceed whole-dollar amounts, due in part to consumer preference for "round" prices (i.e., values ending in 0 or 5; Aalto-Setälä and Halonen, 2004; Kandel et al., 2001; Lynn et al., 2013), an effect that may serve to compound the demonstrated influence of left-digit transitions. We emphasize that our hypothesis is pure speculation, given that these findings were unexpected; because these were unexpected results, our study did not feature purchase tasks with requisite pricing sequences to enable specific analysis of these effects. Future research should design experimental purchase tasks to examine prices just exceeding whole-dollar amounts, assessing these pricing effects in high-resolution sequences.

Overall, the data suggest consumer sensitivity to the price structuring of purchase tasks. Responding on the employed high-density APT furthers MacKillop et al. (2014) observation that not all price arrays yield similar results – hypothetical purchase tasks are sensitive enough to capture minute changes in consumption when the price structure is dense. Researchers must be cognizant of the structuring of HPTs to avoid inadvertently inviting digit preference or introducing other unintended framing effects. On the other hand, these small but significant decreases in consumption around the whole-dollar change mirror effects observed in microeconomics and marketing literature and lend support for the use of HPTs in research pertaining to consumer behavior analysis (Thomas and Morwitz, 2005). Operant behavioral economics should continue to attempt to bridge the gap to traditional economic theory in order to best capture socially significant consumer phenomena. Demand analyses capable of successfully modeling digit preference offer one such way for behavioral researchers to study behavioral phenomena of interest to economists.

The results of the current study suggest it may be possible to reduce demand for commodities through application of digit-preference effects. This observed reduction in consumption without extreme price increases could be a popular option for consumers and policymakers alike in that taxation or aversive "push" methods may not be necessary to address unfavorable purchasing habits. This method has potential for extension to other commodities or for use in circumstances when moderation is desired over cessation (e.g., internet/video game use regulation, consumption of high caloric or sugar-sweetened potables and edibles, etc.).

More broadly speaking, alcohol is a commodity of interest due to the liability for abuse and other alcohol related problems (MacKillop and Kahler, 2009; Murphy and MacKillop, 2006; Murphy et al., 2009; Teeters and Murphy, 2015). Researchers often evaluate prospective policy changes on the purchase habits of different commodities (e.g., MacKillop et al., 2012), and alcohol is no exception. The current study focused exclusively on left-digit changes to alcohol pricing on demand. However, these effects, as well as the experimental approach used in this study, could be extended to other pricing manipulations used for alcohol control, such as happy hour restrictions (Kaplan and Reed, 2018), minimum unit pricing (e.g., Holmes et al., 2014), and taxation (e.g., Pogue and Sgontz, 1989). Moreover, examining local elasticities around left-digit price changes could be extrapolated to health economic analyses such as reducing health and economic burdens associated with alcohol consumption – such analyses are outside the scope of the current dataset.

As noted, single drinks are often priced at whole-dollar increments at bars and establishments that sell alcohol for immediate consumption.

Table 1
A depiction of price sensitivity at whole-dollar changes within the range of assessed high-resolution price values. Note that rounding error may prevent identical correspondence between values.

Prices	Average Consumption	Cohen's d_z	Absolute Decrease	% Decrease Q	% Increase C	%ΔQ/%ΔC	Price Sensitivity
Illustrative Left-Digit Transitions							
$2.00–$2.10	5.18-4.97	.3401	0.21	4.13%	5.00%	0.83	Inelastic
$2.80–$2.90	4.33-4.28	.1934	0.05	1.18%	3.57%	0.33	Inelastic
$2.90–$3.00	4.28-4.05	.4604	0.23	5.25%	3.45%	1.52	Elastic
$3.00–$3.10	4.05-3.76	.2938	0.29	7.30%	3.33%	2.19	Elastic
$3.80–$3.90	3.28-3.28	.0000	0.00	0.00%	2.63%	0.00	Inelastic
$3.90–$4.00	3.28-3.00	.3935	0.28	8.41%	2.56%	3.28	Elastic
$4.00–$4.10	3.00-2.85	.2363	0.15	5.10%	2.50%	2.04	Elastic
$4.80–$4.90	2.62-2.61	.1010	0.01	0.39%	2.08%	0.19	Inelastic
$4.90–$5.00	2.61-2.41	.4504	0.20	7.81%	2.04%	3.82	Elastic
$5.00–$5.10	2.41-2.19	.4100	0.22	8.90%	2.00%	4.45	Elastic
$5.80–$5.90	2.05-1.98	.2171	0.07	3.48%	1.72%	2.02	Elastic
$5.90–$6.00	1.98-1.72	.4696	0.26	12.89%	1.69%	7.60	Elastic

Note: Q = Consumption, C = Price.
Elastic = Slope > −1, Inelastic = Slope < −1.

Prices for the same brand or type of alcohol may also vary from bar to bar within a single community. Alcohol as a commodity under study for the left-digit effect could thus be a limitation due to these variable prices and common whole-dollar price structures. The effects of left-digits may vary with commodities that remain stable across locations and with commodities available for purchase at values just below left-digit change. Future research should extend this work beyond alcohol and tobacco to other commodities where policy-level economic effects of pricing would be of interest (e.g., marijuana legalization, fuel, e-cigarettes).

5. Conclusions

A better understanding of the factors that influence consumer decision making – both in the marketplace and in experimental frameworks – is critical for a better synthesis of knowledge between marketing and behavioral science. Such a pairing has demonstrated a capability to heavily influence consumer responding and can thus prove impactful across a number of issues in which excessive or ill-allocated consumption is problematic (e.g., substance abuse; ecological responsibility). This study serves as further validation of HPT methodology in its ability to model aberrant decision making and its sensitivity to phenomena like the left-digit effect. Behavioral science would do well to continue broadening the scope of the HPT to fully understand the range of its acuity and to further promote the development of a tool applicable for use in many contexts.

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