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Happy Hour Drink Specials in the Alcohol Purchase Task

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There is strong evidence to suggest that happy hour drink specials are associated with undesirable outcomes such as increased amount of drinking, increased likelihood of being highly intoxicated, and increased likelihood of experiencing negative outcomes related to drinking (e.g., getting into fights). Public policy efforts have been made to ban or at least restrict alcohol drink specials. Research in behavioral economics—primarily demand curve analyses—has yielded valuable insights into the role of environmental effects on reinforcer consumption, especially within the context of alcohol reinforcement. The use of the Alcohol Purchase Task (APT), which asks respondents to report how many alcoholic drinks they would be willing to purchase at various prices, has contributed greatly to these efforts. The purpose of the current experiment was to determine whether self-reported consumption of alcohol on an APT changes when participants imagine a hypothetical "happy hour" scenario, akin to drink specials encountered in the real world. Results from the current experiment extend previous literature on APT vignette manipulations and provide implications for efforts to reduce problematic drinking.

Public Health Significance
This study examines the degree to which framing of common drink special scenarios impact relative hypothetical consumption of alcohol drinks in a commonly used purchase task. Results suggest that drink discount framing differentially affects hypothetical alcohol consumption and alcohol demand. Assessing effects of drink special framing, especially as it relates to happy hour specials, on alcohol demand may help provide novel insights into alcohol valuation, alcohol overconsumption, and broader policy impacts.

Keywords: behavioral economics, alcohol purchase task, drink specials, happy hour, demand curve

From 2006 to 2010, there was an annual average of 87,798 alcohol-attributable deaths and 2,500,000 years of potential life lost (Stahre, Roeber, Kanny, Brewer, & Zhang, 2014). During this time period, excessive drinking was responsible for one in 10 working age adults' (20–64 year olds) deaths. Binge drinking (4+/5+ drinks per occasion for women and men, respectively), heavy drinking (8+/15+ drinks per week for women and men, respectively), and drinking among individuals 21 years of age or younger defines excessive alcohol consumption (Centers for Disease Control and Prevention, 2016). Prolonged excessive alcohol consumption can lead to a number of health-related diseases such as high blood pressure, heart disease, stroke, various cancers, social and mental health problems, and alcohol dependence (World Health Organization, 2014). Apart from devastating health consequences, it is estimated that excessive alcohol consumption cost the United States $250 billion in 2010 (Sacks, Gonzales, Bouchery, Tomedi, & Brewer, 2015), an increase of more than $25 billion from the estimated $223.5 billion in 2006 (Bouchery, Harwood, Sacks, Simon, & Brewer, 2011). Various strategies recommended to reduce excessive alcohol consumption include increasing alcohol excise taxes (Elder et al., 2010), regulating the number and density of alcohol retailers in a given area (Campbell et al., 2009), holding alcohol-serving establishments responsible for harm and injury as a result of illegal service (e.g., serving intoxicated or underage individuals; Rammohan et al., 2011), and limiting days and hours of sales (Hahn et al., 2010; Middleton et al., 2010). Importantly, evidence suggests such policies are indeed effective in curbing excessive alcohol consumption (Brand, Saisana, Rynn, Pennoni, & Lowenfels, 2007).

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Research conducted during the past several decades has generally supported the notion that alcohol consumption is price sensitive (i.e., elastic demand). That is, alcohol consumption tends to increase as alcohol price decreases and vice versa (for an overview of this research, see Chaloupka, Grossman, & Saffer, 2002). The price of alcohol can be lowered due to reduced taxes, manufacturer and retail competition, and/or drink specials such as "happy hours." Happy hour " . . . is a term for a set period of time, often advertised, when an establishment serves alcohol at a discounted rate" (Baldwin, Stogner, & Miller, 2014, p. 18) and is considered a "discount drink policy" (Babor, Mendelson, Greenberg, & Kuehnle, 1978).

Research has examined how discount drink specials affect alcohol consumption, primarily among college-aged students and young adults. In terms of the effects of drink specials among college-aged participants, Kuo, Wechsler, Greenberg, and Lee (2003) found that college students' excessive drinking was sensitive to alcohol price and that alcohol specials were significantly related to greater alcohol consumption. Further, Baldwin et al. (2014) found that certain groups (e.g., women, underage drinkers, nonathletes, sorority/fraternity members) were more likely to increase their drinking habits during happy hour specials and those who reported increased drinking during happy hours were about two times more likely to drive and get into fights while intoxicated. Finally, Thombs et al. (2008) found that participants who reported taking advantage of a drink special were over four times more likely to be highly intoxicated and underage drinkers were nearly three times more likely to be highly intoxicated. Thus, research among college-aged participants suggests that changes in drinking patterns during happy hour specials significantly predict alcohol related problems and those who take advantage of these specials increase their drinking.

Among the adult population, Babor et al. (1978) recruited 34 non-alcohol-dependent adult males (casual and heavy drinkers) from the community to participate in alcohol research, where they lived in a clinical research ward for 30 days and earned points, which could be exchanged for money. For all participants, alcoholic drinks (12 oz can of beer, 1 oz liquor) were available for purchase at any time of day or night for $0.50 per drink and for approximately half of the participants, a happy hour condition was in place each day from 2 to 5 p.m. where drinks were available for purchase at $0.25 per drink. Both casual and heavy drinkers drank more during the happy hour condition and heavy drinkers drank more irrespective of condition, thus providing some additional confidence in the findings reported by Baldwin et al. (2014); Kuo et al. (2003), and Thombs et al. (2008).

Given the relatively clear associations between happy hour drink specials and increased drink consumption and negative outcomes, the current study sought to provide an initial investigation on if and how framing of happy hour drink specials in a simulated operant assay, the APT (Murphy & MacKillop, 2006), would affect reported alcohol consumption. The APT emanates from the behavioral economic tradition that blends concepts from economic and operant frameworks (Hursh, 1984; Rachlin, Green, Kagel, & Battalio, 1976). Within the behavioral economic tradition are several frameworks for understanding health behaviors (Bickel & Vuchinich, 2002), drug use (Bickel, Johnson, Koffarnus, MacKillop, & Murphy, 2014; Bickel & Marsch, 2001; Hursh, 1991), and especially alcohol use (MacKillop, 2016; Vuchinich & Tucker, 1988). From the behavioral economic perspective, one way relative value is quantified is by measuring how consumption of a good (e.g., alcohol) varies with the price (e.g., price per drink) to obtain the good. A good whose consumption decreases relatively rapidly with increases in costs is inferred to have a lower value compared with a good whose consumption is "defended" in the face of increasing costs. Such quantification is achieved by way of the demand curve analyses where price is manipulated (in a simulated or experiential fashion) and resulting consumption is measured.

Historically, demand assays required that participants come into a laboratory setting and respond on manipulanda to earn and experience the commodity, akin to that of Babor et al. (1978). Recently, the field has increasingly employed hypothetical purchase tasks (HPTs; Jacobs & Bickel, 1999; Roma, Reed, DiGennaro Reed, & Hursh, 2017), such as the APT, wherein respondents answer how much of a commodity they would be willing to purchase and consume at various different prices; this approach permits a safe and efficient simulation of substance marketplaces. Specific versions of the purchase tasks have been tailored to certain commodities of interest including cigarettes (Cigarette Purchase Task; MacKillop et al., 2008), marijuana (Marijuana Purchase Task; Aston, Metrik, & MacKillop, 2015), nonmedical use of prescription drugs (Pickover, Messina, Correia, Garza, & Murphy, 2016), indoor tanning (Tanning Purchase Task; Reed, Kaplan, Becirevic, Roma, & Hursh, 2016), steroids (Pope et al., 2010), work tasks (Hypothetical Work Task; Henley, DiGennaro Reed, Kaplan, & Reed, 2016), Internet access (Broadbent & Dakki, 2015), and gambling (Weinstock, Mulhauser, Oremus, & D'Agostino, 2016).

Central to this study is the APT, which asks participants how many standard-sized drinks they would purchase at a range of prices, and the APT demonstrates favorable psychometric properties including validity and reliability (e.g., Amlung, Acker, Stojek, Murphy, & MacKillop, 2012; Kiselica, Webber, & Bornovalova, 2016; Murphy, MacKillop, Skidmore, & Pederson, 2009). Additionally, the APT has shown clinical translation in its ability to simulate situational modulators of drinking. For example, Gentile, Librizzi, and Martinetti (2012); Gilbert, Murphy, and Dennhardt (2014); Skidmore and Murphy (2011), and Teeters and Murphy (2015) demonstrated how next-day constraints affect drinking. In an additional extension, Kaplan et al. (2017) showed that differing durations of hypothetical access to alcohol (i.e., time at the bar drinking) affected responding such that demand values were lowest for the shortest duration and highest for the longest duration. Because the APT provides a method by which to explore how different situational factors affect alcohol consumption motivation, we chose to use the APT to simulate alcohol consumption in various happy hour scenarios. Given that much of the previous work examining drink specials have been conducted using college-aged participants, we sought to recruit a relatively diverse participant sample using the Amazon Mechanical Turk platform. We expected that framing of a happy hour drink special would result in increased consumption relative to responding on a standard version of the APT. We also expected that the full price group (who received the standard APT twice) would show little change in their self-reported consumption.

Method

Participants

We recruited a total of 1,104 participants from Amazon Mechanical Turk (mTurk; www.mturk.com) for a broader survey on alcohol use. MTurk is an online crowdsourcing platform where individuals (i.e., workers) complete tasks (termed human intelligence tasks or HITs) posted by requesters (Buhrmester, Kwang, & Gosling, 2011). In an effort to obtain relatively high-quality responses, workers were required to meet the minimum following qualifications: (a) have at least 100 approved HITs, (b) have at least 95% of their previous HITs approved, and (c) be located in the United States. Within the range of previous studies, (e.g., Horton & Chilton, 2010; Johnson, Herrmann, & Johnson, 2015; Kaplan et al., 2017; Reed, Becirevic, Atchley, Kaplan, & Liese, 2016; Roma, Hursh, & Hudja, 2016), workers were paid between $0.50 and $1.00 for their time. Average duration to complete the task was 11.38 min with a realized hourly wage of between $2.64 and $5.27 per hour.

Materials

All materials were created and distributed using Qualtrics Research Suite (www.qualtrics.com) web service. Participants answered general demographics related to their age, income, employment status, and smoking habits. The University of Kansas Institutional Review Board (IRB) approved all study procedures (IRB No. 20635).

Daily Drinking Questionnaire (DDQ). The DDQ (Collins, Parks, & Marlatt, 1985) assessed weekly alcohol use (both frequency and quantity) during a typical week in the past month. The DDQ resulted in three measures: (a) the number of days during the past month meeting binge drinking criteria (i.e., 4+/5+ drinks in a single occasion for women and men, respectively), (b) the number of drinks per week, and (c) the number of hours spent drinking per week.

APT. We constructed three versions of the APT. Based on our review of the literature, the most comprehensive APT vignette appears to be one used by Murphy et al. (2013; p. 131). This vignette is similar to the standard, validated version of the APT used by Murphy et al. (2009; p. 398) with the addition of the sentence, "Imagine that you do not have any obligations the next day (i.e., no work or classes)." Given the modified versions of the APT included wording related to a happy hour and that the mTurk population is, on average, older than the average-aged college student participant (Paolacci, Chandler, & Ipeirotis, 2010), we replaced the word "party" in the Murphy et al. (2013) vignette with the word "bar." Additionally, although happy hour specials may typically run for only a few hours in an evening, we sought to remain consistent with many previous versions of the APT by using the 5-hr drinking period from 9:00 p.m. until 2:00 a.m. Thus, the full vignette of the standard version reads as follows:

> 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 bar on a weekend night from **9:00 p.m. until 2:00 a.m.** 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 bar, and that you will not drink or use drugs after leaving the bar. You cannot bring your own alcohol or drugs to the bar. Also, assume that the alcohol you are about to purchase is for your consumption only. In other words, you cannot sell the drinks or give them to anyone else. You also cannot bring the drinks home and you have no other alcohol at home. Everything you buy is, therefore, for your own personal use within the **5 hour period** that you are at the bar. Please respond to these questions honestly, as if you were actually in this situation.
>
> To verify you understand the pretend scenario, you must correctly answer the next three questions before moving on in the questionnaire.

In order to proceed, participants were required to correctly answer three multiple choice questions: (a) "In this pretend scenario, how many hours do you have to consume the drinks?", (b) "In this pretend scenario, how much did you drink before the bar?", and (c) "In this pretend scenario, what is the drink special?" Based on the standard version, two modified APTs relating to happy hour scenarios were constructed. To do this, the second sentence of the vignette (i.e., "Imagine that you and your friends are at a bar on a weekend night from 9:00 p.m. until 2:00 a.m. to see a band.") was replaced with the following sentences (note: the two wordings in brackets and separated by the "/" correspond with the two different versions):

> Imagine another typical weekend later the same month as the last scenario (same bar, same group of friends, etc.). Now imagine that from 9 p.m. until 2 a.m., the bar has a ***Happy Hour Drink Special where drinks are [1/2 off (50% off)/buy one get one free (BOGO)]***.

For the remainder of this paper, we refer to the half-price (50% off) condition as "HP," the buy one get one free condition as "BOGO," and the standard, full-price condition as "FP."

Regardless of version, below the vignette a statement read, "How many standard drink purchases would you make at each price:" A three-column table was displayed below this statement. The first (i.e., left) column presented a price and associated drink. The specific text differed slightly based on condition, however the same price sequence (indicated by the X.XX in the following) was displayed regardless of condition. In the unmodified (i.e., FP) version, the text read, "$X.XX per drink." In the HP version, the text read, "$X.XX per drink on sale for $Y.YY per drink" (where Y.YY was half the price of X.XX). Finally, in the BOGO version, the text read, "$X.XX per drink on sale for $X.XX per 2 drinks." Prices were the same price sequence used in Murphy et al. (2013): $0.00 (free), $0.25, $0.50, $1.00, $1.50, $2.00, $2.50, $3.00, $4.00, $5.00, $6.00, $7.00, $8.00, $9.00, $10.00, $15.00, and $20.00. The second (i.e., middle) column presented a heading that read (depending on condition), "Number of [standard/half price/buy one get one free] drink purchases you would make:" and presented boxes where participants typed in their responses. The third (i.e., right) column presented a heading that read, "Number of drinks you would consume:" and also presented boxes. Javascript coding was used to automatically populate these boxes when a participant entered a number into the box in the middle column of its respective row. The value that appeared was conditional on the vignette condition. In the FP and HP conditions, the calculated value was the same as that in the middle column. In the BOGO condition, the calculated value was double the value that the participant entered into the middle column (to disambiguate whether a single BOGO purchase resulted in 1 or 2 drinks).

Procedure

Upon selecting the HIT on the mTurk platform and clicking on the survey link, participants viewed an information statement, at the end of which they were able to either agree or disagree to participate. After agreeing, all participants completed the unmodified APT followed by the demographics form. Then participants completed one of the modified APTs or the unmodified APT (the group that completed the standard version twice served as the FP group). Presentations of the second APT (un/modified versions) were randomized across participants. Following a second presentation of the APT, participants completed the DDQ and additional alcohol and decision-making measures. After completing these questions, participants provided any comments to the researcher, the survey ended, and participants received a unique passcode, which they then entered into a box on the mTurk platform indicating their completion of the HIT.

Data Analysis

All data were analyzed in R statistical software (R Core Team, 2016) using the lme4 (Bates, Maechler, Bolker, & Walker, 2014) and beezdemand (Kaplan, 2017) packages. Data were flagged for unsystematic patterns of responding by applying the three criteria proposed by Stein, Koffarnus, Snider, Quisenberry, and Bickel (2015). The three criteria proposed by Stein et al. (2015) include: (a) trend (i.e., a global reduction in consumption; requiring at least a 0.025 log-unit reduction in consumption per log-unit range in price), (b) bounce (i.e., price-to-price increases in consumption; requiring less than or equal to 10% of prices increments resulting in consumption increasing no more than 25% of initial consumption), and (c) reversals from zero (i.e., requiring no instances of two consecutive zeros followed by a nonzero consumption value). To concretely illustrate these criteria, which primarily attempt to identify cases of inattention or response measurement error, imagine a participant who reports purchasing 10 drinks when drinks are free (i.e., $0.00; the first price). If this participant also reports purchasing 10 drinks when drinks are $10.00/per drink, the response pattern would meet the trend criterion. If the participant's responses "jump" at least twice, such that at any two consecutive prices the number of drinks *increases*, the response pattern would meet the bounce criterion. Finally, if the participant ceases purchasing (i.e., reports 0 drinks) at two consecutive prices but then reports nonzero purchasing at the next price, the response pattern would meet the reversals from zero criterion. Response sets that passed all three criteria were used for subsequent analyses; those not passing all three criteria were excluded listwise from both time points. In total, 383 (34.69%) data sets failed at least one criterion, leaving 721 participants for further analysis. These exclusions resulted in 317, 178, and 226 participants in the FP, BOGO, and HP groups, respectively.

We first converted all prices and consumption to "per drink" scales. Given differences in the price sequences expressed in this way, we focused analyses on the common prices: $0.00 (free), $0.25, $0.50, $1.00, $1.50, $2.00, $2.50, $3.00, $4.00, $5.00, and $10.00 (11 of the 17 prices used in the full sequence). We first ran a full, unrestricted generalized linear mixed model to predict consumption from the fixed-effect predictors price, time (i.e., first vs. second completion of the APT), and group, specifying both main and interaction effects. Given concerns of potential overfitting, we followed up this analysis with three generalized linear mixed models, one for each of the groups, with a fixed-effect interaction (including main effects) between price and time. All models specified a random intercept of individual to account for participants' responses during the first completion of the APT.

In addition, we analyzed individual consumption at the common prices using two of the contemporary demand equations (Hursh & Silberberg, 2008; Koffarnus, Franck, Stein, & Bickel, 2015):

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

and

$$Q = Q_0 \times 10^{k(e^{-\alpha \cdot Q_0 \cdot C} - 1)} \quad (2)$$

where Q represents consumption, Q_0 is the amount of consumption at free price, k is a weighting parameter signifying the range of consumption in logarithmic units (in this case, the empirical range of mean consumption data + 0.5: 1.28), α is the rate of change in elasticity across the entire curve, and finally C is the price of the reinforcer (unit price; expressed in USD). For Equation 1 only, we omitted zeros completely given that the logarithm of zero is undefined. No changes were made for Equation 2. We obtained additional measures of P_{max} and O_{max} according to the specifications of the freely available Excel tool by Kaplan and Reed (2014). All demand indices reported hereafter are derived. Conceptually, the aforementioned demand measures each describe a different aspect of the demand curve. Here, Q_0 serves as the "intercept" or initial baseline quantity of alcohol demanded, α serves as the "slope" or the rate at which consumption declines in face of increasing costs, P_{max} is the price at which alcohol quantity decreases at a disproportionally greater rate than increases in price, and O_{max} is the total amount of money expended at P_{max}.

Results

Participant Demographics

Table 1 displays information related to participant demographics of the final sample. After exclusions, 721 participants' data remained for analysis. Demographic characteristics were similar to those of the general mTurk workforce (e.g., Paolacci et al., 2010). We found no differences in demographic variables between those participants included versus those excluded.

DDQ

Table 2 displays the results of participants' drinking patterns as measured by the DDQ. We found no statistically significant differences between the three groups in number of binges ($F(2,718) = 0.89$, $MSE = 17.97$, $p = .413$, $\eta_p^2 = .002$), total number of drinks ($F(2,718) = 1.65$, $MSE = 100.01$, $p = .193$, $\eta_p^2 = .005$), or total number of hours ($F(2,718) = 1.19$, $MSE = 129.70$, $p = .305$, $\eta_p^2 = .003$).

Table 1
Participant Demographics

Demographic variable	Overall (N = 721)
Age. Mean (*SD*)	35.50 (10.92)
Sex, *n* (%)	
Female	399 (55.3)
Male	321 (44.5)
Would rather not say	1 (.1)
Smoking status, *n* (%)	
Current smoker	164 (22.7)
Previous smoker	169 (23.4)
Never smoker	378 (52.4)
I don't smoke but use another form of tobacco	10 (1.4)
Income, *n* (%)	
<$20,000	118 (16.4)
$20,000–$29,999	91 (12.6)
$30,000–$39,999	99 (13.7)
$40,000–$49,999	77 (10.7)
$50,000–$74,999	162 (22.5)
$75,000–$99,999	79 (11.0)
>$100,000	86 (11.9)
Would rather not say	9 (1.2)
Education, *n* (%)	
High school/GED	74 (10.3)
Some college	173 (24.0)
2-Year college degree (Associates)	86 (11.9)
4-Year college degree (BA, BS)	288 (39.9)
Master's degree	67 (9.3)
Other	33 (4.6)
Employment, *n* (%)	
Employed	559 (77.5)
Unemployed	137 (19.0)
Retired	25 (3.5)
Profession, *n* (%)	
Business/marketing/accounting	90 (12.5)
Computer science/technology	92 (12.8)
Education	83 (11.5)
Health sciences/medicine/nursing	76 (10.5)
Retail	68 (9.4)
Other	312 (43.3)

Generalized Linear Mixed Models

Figure 1 displays hypothetical consumption of alcoholic drinks stratified by price per drink, time, and group. As depicted, responses by participants in the BOGO group tended to show relatively greater consumption in the presence of the BOGO framing as compared with the other two groups, and relatively greater consumption relative to the participants' initial responses. To analyze happy hour framing as a *between-subjects* effect, and to specifically compare changes in consumption in the happy-hour-framed groups *relative* to the FP group, Table 3 displays the results of the full, unrestricted generalized linear mixed model. As expected, the slope parameter (i.e., price; risk ratio [RR] = 0.85) was statistically significantly different from one indicating that for every unit increase in price, we expect to see consumption decrease by a factor of 0.85. We now interpret each parameter, starting with main effects and increasing in complexity (i.e., interaction terms). The Time 2 predictor (RR = 1.02) indicates no statistically significant difference in responses for the FP group between the first and second completions. With all else in the model being equal, responses in the BOGO condition were not statistically significantly different at Time 1 compared with the FP group (RR = 1.08), yet responses in the HP condition were higher at Time 1 as compared with the FP group (RR = 1.19) regardless of price. This suggests that at Time 1 there were group differences and that the randomization process, which does not always guarantee equality between groups, was not effective. Increasing in predictor complexity, there was a price by group interaction for the BOGO group such that at Time 1, participants' consumption in the BOGO condition decreased *at a slower rate* relative to the FP group (RR = 1.02). Additionally, we observed a Time × Group interaction indicating that compared with the FP group at Time 1, responses at Time 2 in the BOGO condition were significantly greater (a factor of 1.30 times). Finally, taking into account the significant Price × BOGO and Time × BOGO two-way interactions, we observed a three-way interaction between price, time, and group such that the BOGO frame resulted in greater consumption at low prices and that this difference went away at larger prices (RR = 0.97).

Due to concerns of overfitting and differences between the FP and HP groups at Time 1, we followed up the full, unrestricted model with three generalized linear mixed models—one for each group (Table 4). These models allow us to ask about the *within-subject* effects of the happy hour framing. These results were consistent with the findings from the full model. No statistically significant differences in consumption between the two time points were observed in the FP group (Time 2 RR: 1.02). For the HP group, the model indicated a statistically significant effect of time (Time 2 RR: 1.05), but no Time × Price interaction (RR: 1.00). Finally, for the BOGO group, the model indicated a statistically significant effect of time (Time 2 RR: 1.33) and Time × Price interaction (RR: 0.97). This indicates that consumption as a whole was greater in the BOGO-framed APT (as compared with the initial standard version) and that as price increased the difference in consumption between the two versions decreased.

Demand Curve Analyses

Across both time points, a total of 77 (10.68%) and 28 (3.88%) participants' data sets were unable to be fit by either Equation 1 or Equation 2, respectively, with discrepancies due to too few consumption values to be fit using Equation 1. Of those data sets that did successfully converge, we conducted a series of paired *t* tests to determine differences in demand measures at Time 1 compared with Time 2. Prior to conducting the *t* tests, we examined histograms of the indices and used transformations to approximate a normal distribution. As a result, we log-transformed α, P_{max}, and O_{max}. Goodness-of-fit measures were similar using the two equations. For Equation 1, the mean individual R^2 at Time 1 was 0.79

Table 2
Participant Drinking Tendencies

Group	*n*	Binges, *M* (*SD*)	Total drinks, *M* (*SD*)	Total hours, *M* (*SD*)
FP	317	2.42 (4.57)	8.17 (10.48)	8.28 (13.46)
BOGO	178	2.69 (4.56)	9.80 (10.62)	9.60 (10.78)
HP	226	2.12 (3.41)	8.33 (8.73)	7.90 (8.25)

Note. FP = full-price condition; BOGO = buy one get one free condition; HP = half-price condition.

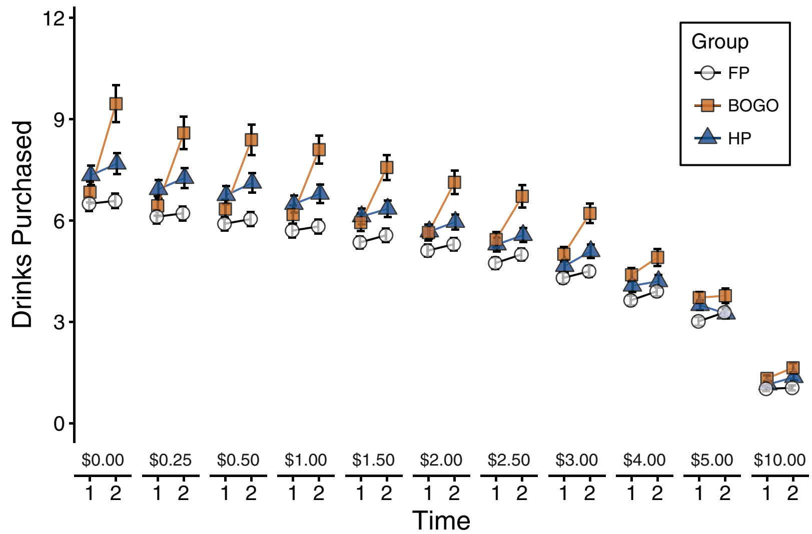

Figure 1. Mean number of drinks (hypothetically) purchased as a function of price per drink (unit price in USD) stratified by time. Circles indicate full-price (FP) group, squares indicate buy one get one free (BOGO) group, and triangles indicate half-price (HP) group. Error bars represent SEM. All Time 1 points indicate completion of the standard Alcohol Purchase Task. Notice that at low prices the BOGO group displays the greatest increase in consumption between Time 1 and Time 2; however, this difference tends to diminish at increasing prices. See the online article for the color version of this figure.

(median = 0.83; interquartile range [IQR] = 0.71–0.90) and at Time 2 was 0.79 (median = 0.83; IQR = 0.70–0.89). For Equation 2, the mean individual R^2 at Time 1 was 0.79 (median = 0.81; IQR = 0.71–0.89) and at Time 2 was 0.79 (median = 0.81; IQR = 0.71–0.89).

Q_0. Comparisons of derived Q_0 at Time 1 and Time 2 for all three groups were statistically significant, regardless of equation. For the FP group, difference in mean Q_0 was statistically significant for both Equation 1 (M_d = 0.24, 95% CI [0.14, 0.35], $t(277) = 4.47$, $p < .001$) and Equation 2 (M_d = 0.12, 95% CI [0.05, 0.20], $t(308) = 3.26$, $p = .001$). Similarly, for the HP group, difference in mean Q_0 was statistically significant for both Equation 1 (M_d = 0.55, 95% CI [0.28, 0.81], $t(211) = 4.06$, $p < .001$), and Equation 2 (M_d = 0.41, 95% CI [0.20, 0.63], $t(218) = 3.79$, $p < .001$). Differences in mean Q_0 for the BOGO group were larger and also statistically significant for both Equation 1 (M_d = 2.79, 95% CI [2.07, 3.52], $t(153) = 7.59$, $p < .001$) and Equation 2 (M_d = 2.70, 95% CI [2.04, 3.36], $t(164) = 8.06$, $p < .001$). Thus, results indicated that reported drinks purchased when free (i.e., $0.00 per drink) were higher during the second completion of the APT and that the largest mean difference in Q_0 was observed in the context of the BOGO framing condition.

α. For the FP group, difference in mean log(α) (where a negative mean difference indicates smaller log(α) at Time 2) was statistically significant for both Equation 1 (M_d = −0.05, 95% CI [−0.10, −0.01], $t(277) = -2.30$, $p = .022$) and Equation 2 (M_d = −0.08, 95% CI [−0.12, −0.05], $t(308) = -4.84$, $p < .001$). Interestingly, for the HP group, there were no statistically significant differences in mean log(α) for either Equation 1 (M_d = −0.03, 95% CI [−0.09, 0.03], $t(211) = -0.84$, $p = .404$) or Equation 2 (M_d = −0.03, 95% CI [−0.09, 0.04], $t(218) = -0.88$, $p = .382$). Differences in mean log(α) for the BOGO group were only statistically significant for Equation 1 (M_d = −0.09, 95% CI [−0.17, −0.01], $t(153) = -2.35$, $p = .020$) but not Equation 2 (M_d = −0.05, 95% CI [−0.12, 0.02], $t(164) = -1.30$, $p = .196$).

$P_{\mathbf{max}}$. For the FP group, difference in mean log(P_{max}) was statistically significant for Equation 2 (M_d = 0.07, 95% CI [0.04, 0.11], $t(308) = 3.97$, $p < .001$) but not Equation 1 (M_d = 0.02, 95% CI [−0.03, 0.07], $t(277) = 0.96$, $p = .338$). For the HP group,

Table 3
Generalized Linear Mixed Effect Model

Variable	Risk ratio [95% confidence interval]	*p* value
Fixed effects		
(Intercept)	5.46 [5.05, 5.91]	<.001
Price	.85 [.84, .86]	<.001
Time 2	1.02 [.99, 1.05]	.130
BOGO	1.08 [.95, 1.23]	.260
HP	1.19 [1.06, 1.35]	.004
Price × Time 2	1.01 [1.00, 1.02]	.203
Price × BOGO	1.02 [1.01, 1.04]	<.001
Price × HP	1.00 [.99, 1.01]	.791
Time 2 × BOGO	1.30 [1.24, 1.36]	<.001
Time 2 × HP	1.02 [.98, 1.07]	.337
Price × Time 2 × BOGO	.97 [.95, .98]	<.001
Price × Time 2 × HP	.99 [.98, 1.01]	.430
Random effects		
$\tau_{00,\ id}$	.464	
N_{id}	721	
Intraclass correlation$_{id}$	.317	
Observations	15,862	
Deviance	7,639.057	

Note. BOGO = buy one get one free condition; HP = half-price condition.

Table 4
Generalized Linear Mixed Effect Models (One per Group)

Variable	FP: Risk ratio [95% CI]	FP: *p* value	HP: Risk ratio [95% CI]	HP: *p* value	BOGO: Risk ratio [95% CI]	BOGO: *p* value
Fixed effects						
(Intercept)	5.45 [5.02, 5.92]	<.001	6.55 [6.04, 7.10]	<.001	5.88 [5.27, 6.56]	<.001
Price	.85 [.84, .86]	<.001	.85 [.84, .85]	<.001	.87 [.86, .88]	<.001
Time 2	1.02 [.99, 1.05]	.131	1.05 [1.01, 1.08]	.008	1.33 [1.29, 1.38]	<.001
Price × Time 2	1.01 [1.00, 1.02]	.203	1.00 [.99, 1.01]	.939	.97 [.96, .99]	<.001
Random effects						
$\tau_{00,\ id}$	.517		.352		.516	
N_{id}	317		226		178	
Intraclass correlation$_{id}$	.341		.260		.340	
Observations	6,974		4,972		3,916	
Deviance	3,385.891		1,936.685		2,317.204	

Note. CI = confidence interval; FP = full-price condition; BOGO = buy one get one free condition; HP = half-price condition.

there were no statistically significant differences in mean log(P_{max}) for either Equation 1 (M_d = −0.02, 95% CI [−0.09, 0.05], $t(211) = -0.62$, $p = .535$) or Equation 2 (M_d = −0.01, 95% CI [−0.09, 0.06], $t(218) = -0.36$, $p = .717$). Differences in mean log(P_{max}) for the BOGO group were statistically significant for Equation 1 (M_d = −0.16, 95% CI [−0.25, −0.08], $t(153) = -3.72$, $p < .001$) and Equation 2 (M_d = −0.21,95% CI [−0.28, −0.14], $t(164) = -5.68$, $p < .001$). Interestingly, whereas P_{max} increased at Time 2 in the FP group, P_{max} decreased at Time 2 in the BOGO group. And there was not a statistically significant difference for the HP group.

***O*$_{max}$.** For the FP group, difference in mean log(O_{max}) was statistically significant for both Equation 1 (M_d = 0.05, 95% CI [0.01, 0.10], $t(277) = 2.30$, $p = .022$) and Equation 2 (M_d = 0.08, 95% CI [0.05, 0.12], $t(308) = 4.84$, $p < .001$). For the HP group, there were no statistically significant differences in mean log(O_{max}) for either Equation 1 (M_d = 0.03, 95% CI [−0.03, 0.09], $t(211) = 0.84$, $p = .404$) or Equation 2 (M_d = 0.03, 95% CI [−0.04, 0.09], $t[218] = 0.88$, $p = .382$). Differences in mean log(O_{max}) for the BOGO group were statistically significant for Equation 1 (M_d = 0.09, 95% CI [0.01, 0.17], $t(153) = 2.35$, $p = .020$) but not Equation 2 (M_d = 0.05, 95% CI [−0.02, 0.12], $t(164) = 1.30$, $p = .196$). Contrasted with the analyses of P_{max}, we observed increases in O_{max} for both the FP and BOGO groups. Results were consistent, however, for the HP group showing no statistically significant differences.

Discussion

The goal of the present study was to examine the effects of a hypothetical happy hour drink special on responding on an APT. Two different hypothetical drink special scenarios were constructed by slightly modifying the wording and price structure of the APT: BOGO and HP. The prices per drink in both drink special groups were equivalent. We found that participants in the BOGO group reported more drinks primarily at the lower prices relative to their initial responding. The FP group showed no statistically significant differences between the two APT versions, whereas the HP group showed slightly more purchases in the HP-framed APT compared with the standard version. At the $5.00 and $10.00 prices, levels of consumption at Time 2 were nearly indistinguishable between the three groups.

The results of the current study contribute to the growing literature on APT vignette manipulations. Previous research has demonstrated differential responding in the context of academic constraints (Gentile et al., 2012; Gilbert et al., 2014; Skidmore & Murphy, 2011), driving after drinking (Teeters & Murphy, 2015), and differing durations of hypothetical access to alcohol (Kaplan et al., 2017). Continued examinations of vignette or other structural manipulations of the APT, and the HPT more generally (e.g., Roma et al., 2016), may be beneficial for several reasons. First, the degree to which participants' responses change in the context of vignette manipulations may provide some insight into individuals' decision making related to the commodity under study. For example, Teeters and Murphy (2015) examined the effects of a driving after drinking manipulation of the APT. They found that participants who self-reported driving within two hours after drinking three or more drinks during the past three months showed significantly smaller reductions in demand compared with participants who reported less than three drinks. Given that the goal of the current study was an initial investigation as to whether the APT would be sensitive to drink special and drink price manipulations, future research should specifically investigate associations between drink special framing and clinically relevant alcohol measures, and among samples of problematic or heavy drinkers.

Second, that the BOGO group showed the largest differences in responding (see Table 4) even when examined as a function of equivalent unit prices is an interesting finding, given work from the human operant literature examining unit price (Bickel, DeGrandpre, Hughes, & Higgins, 1991; DeGrandpre, Bickel, Hughes, Layng, & Badger, 1993; Madden, Bickel, & Jacobs, 2000). Some have argued that consumption should be examined as a function of the cost-benefit ratio, or unit price; that is, the work required or spent per unit of the commodity (Hursh, Raslear, Shurtleff, Bauman, & Simmons, 1988). For example, both Bickel et al. (1991) and Madden et al. (2000) found that cigarette consumption (i.e., number of puffs) was similar under identical unit prices even when the costs (response requirements) and benefits (reinforcer magnitude) of the unit price ratio were different. Differences in consumption between the happy hour groups in the current study may be due to the framing of the price sequence specifying two drinks. In the BOGO condition, an example price point read, “$1.00 per drink on sale for $1.00 per 2 drinks,” whereas in the HP condition the same price read, “$1.00 per drink on sale for $0.50 per drink.” In the latter scenario, unit price per drink was explicit and is more similar to the standard version that read, for example, “$1.00 per drink.” Although the following comparison should be taken with caution as there are a number of differences between the studies, Madden et al. (2000) found that when smokers were given the choice of responding on alternatives with equal unit price, participants tended to favor the alternatives that resulted in more cigarette puffs (i.e., greater benefit) and required more responses (i.e., greater cost) at *low unit prices*. Preference shifted toward the alternatives that resulted in fewer puffs and required fewer responses at *higher unit prices*. They concluded that, “. . . when both response requirements were relatively small, the difference in reinforcer magnitude outweighed the proportionally equivalent difference in response requirement” (Madden et al., 2000, p. 58).

It is possible that amount (i.e., number of drinks) may have exerted a relatively greater influence on responding and could account for the differences observed at free price. For this, the three prices read, “$0.00 per drink,” “$0.00 per drink on sale for $0.00 per drink,” and “$0.00 per drink on sale for $0.00 per 2 drinks,” for the FP, HP, and BOGO versions, respectively. That participants in the BOGO condition consumed more drinks even at equivalent unit prices is consistent with the findings by Wilson, Stolarz-Fantino, and Fantino (2013). In their study, participants made a series of repeated decisions for hypothetical drink purchases (i.e., soda) in the context of different drink menus, one of which contained a bundle (defined as the “sale of two or more separate products in one package”; Stremersch & Tellis, 2002). Even though unit price was held constant across the three different drink sizes, the bundled menu resulted in participants buying significantly more ounces of soda compared with the unbundled condition and the condition with only one size option available. These results are also generally consistent with consumers’ perceptions of quality and value of products associated with promotions.

Both the bundling and the buy one get something free promotions are considered “value-added” and consumers generally tend to favor these types of promotions over other promotions (e.g., discounts; Hardesty & Bearden, 2003; Krishna, Briesch, Lehmann, & Yuan, 2002; Raghubir, 2004). Economists and behavioral economists have theorized that such bundling and value-added framing effects may be considered a cognitive bias (Gilbride, Guiltinan, & Urbany, 2008), and thereby sensitive to widely researched cognitive biases such as mental accounting (Thaler, 1985) and prospect theory (Kahneman & Tversky, 1979). While we did not set out to examine price bundling within the theoretical framework of cognitive biases, we believe such an account is viable and ought to be researched more directly in future studies.

Although they did not evaluate bundles, per se, Darke and Chung (2005) compared participants’ perceptions of a product (i.e., headphones) under different promotional conditions (i.e., no discount, standard discount, free-gift offer). Participants in the free-gift offer not only rated the product as higher quality, they also rated the value of the deal higher. Participants in the standard discount offer group rated quality the lowest, and there were no differences in ratings of value compared with the control conditions. Further support for general preferences for BOGO promotions come from a non-peer-reviewed report based on a proprietary shopping panel (http://www.ala-national.org/assets/research_center/Hot_Topic_BOGO_freeFINAL.pdf). Out of 673 respondents, they report 93% of them have taken advantage of a BOGO offer and 66% of them preferred BOGO promotions over other promotions. Pulling from psychology’s “behavioral economic” literature, individuals tend to respond in seemingly “irrational” ways when something is marketed as “free” (Ariely, 2008). For example, Shampanier, Mazar, and Ariely (2007) asked participants to make hypothetical purchases between two types of chocolates at different prices. When both chocolates cost money, neither was chosen more often than the other, but when each was discounted such that one option was free nearly all (90%) participants chose the free chocolate. Shampanier et al. (2007) found consistent results (an increase in purchases of the free alternative) in a follow-up experiment when participants made actual purchases.

Given the construction of the BOGO-framed APT, it is difficult to discern whether increased consumption in that condition was attributable to the framing of getting another drink for free (as was displayed in the vignette) or to the price structure that specified two drinks rather than one. Future studies may attempt to investigate the relative contributions of these two variables on APT responding. For example, instead of specifying that one drink is free, a vignette could simply indicate either a bundled version or a “two-for-one” version. Likewise, another version would omit the quantity aspect and instead specify a BOGO purchase (e.g., $1.00 per drink on sale for $1.00 buy-one-get-one-free).

One strength of the current study is the use of crowdsourced participation, thereby adding to a small, but growing, literature on crowdsourced—employing a broad demographic sample from around the United States—investigations of alcohol demand using the APT (see also Kaplan et al., 2017; Morris et al., 2017). Much of the prior APT research and research examining drink specials and alcohol consumption (e.g., Baldwin et al., 2014; Kuo et al., 2003; Thombs et al., 2008) have used college or undergraduate participant samples. Although still a convenience sample, participants in the current study were demographically diverse and reflective of the mTurk workforce (Paolacci et al., 2010). Participants in each of the three groups were similar on the demographic variables and there were no group differences in typical alcohol consumption as measured by the DDQ.

A limitation of the current study is the relative price sequences used in the standard and modified APTs. The price sequence (i.e., price per drink) used in the standard version of the APT is the same as what has been used in previous APT research (e.g., Amlung, Yurasek, McCarty, MacKillop, & Murphy, 2015; Murphy et al., 2013; Tripp et al., 2015), while the prices in the modified versions were half the standard sequence. And while the number of prices used was in line with recommendations by Roma et al. (2016), analyses had to be restricted to those per-drink prices common among the three versions. That is, out of the 17 prices used in the full price sequence, we only analyzed 11. Had the upper price limit for the modified APT been higher, this might provide increased sensitivity to detect differences. We note, however, that this would be more problematic if demand indices were computed directly from the observed data; rather, we determined all demand indices using nonlinear curve-fitting techniques. Future studies examining framing effects or other APT manipulations should ensure price sequences have equivalent upper bounds.

The APT used in the current preparation differed from previous forms in that participants responded with how many purchases they would make and a separate column automatically populated with the number of drinks they would consume. Previous research using the APT typically describe the question as, "How many drinks would you purchase and consume if they were $__?" or "How many drinks would you consume if they were $__?" We specifically integrated this aspect into the task because of the inherent differences in "drinks obtained" between the happy hour scenarios (e.g., in BOGO scenarios, customers receive two drinks whereas in other scenarios customers receive only one drink). In order to control for this aspect as a confounding variable, the automatic calculation of drinks consumed was kept constant across all versions of the APT. Although a limitation to this aspect lies in the fact that the survey software we utilized does not record data on whether participants changed their responses after seeing the automatically calculated value, all participants were at least exposed to this feature during their first completion of the APT (which was identical for all groups before exposure to the drink special manipulation). Future research may examine if information in terms of drinks consumed affects participant responses. With that noted, the current study did integrate attending questions, which may have increased responding to relevant stimuli. Specifically, participants were required to correctly identify assumptions specified in the vignette (e.g., the happy hour special). Future research could investigate whether attending questions result in a greater proportion of systematic responding or increase the likelihood of responses being under the control of relevant stimuli (e.g., cue-reactivity paradigms).

Another limitation is that the BOGO drink special was the only option available to participants in that group. As a result, drink consumption was necessarily calculated in multiples of 2s. This type of scenario, where only one drink special is available, may not be reflective of what is actually encountered in the real world. If participants were given the opportunity to distribute responses among BOGO and regularly priced drinks, total drink consumption may not have increased to the extent observed. It would also be interesting to provide concurrently available alternatives with equivalent unit price (e.g., HP and BOGO), akin to that of Madden et al. (2000).

We used two of the contemporary demand equations to investigate the effects of the happy-hour-framed vignettes. Goodness-of-fit measures were similar and results of the *t* tests comparing differences in Q_0 were statistically significant for all three groups, regardless of equation; however, mean differences (expressed in drink units) for the FP (M_d = 0.24; 0.12) and HP groups (M_d = 0.55; 0.41) were rather small relative to the BOGO group (M_d = 2.79; 2.70). This suggests that Q_0 may be the demand metric most sensitive to APT manipulations. Convergent evidence supporting this possibility comes from a recent meta-analysis (Kiselica et al., 2016), which found that, among several demand indices, Q_0 demonstrated the strongest relations with alcohol measures including alcohol consumption, binge/heavy drinking, alcohol problems, and alcohol use disorder symptoms. Notwithstanding the above findings, there were several instances where results of the *t* tests comparing demand indices were discrepant between the two equations (i.e., α, P_{max}, O_{max}), yet the *direction* of results was consistent for both equations. An explanation of the discrepant *t* test results is beyond the scope of this paper, but such findings highlight a need for additional investigation into the conditions under which these two equations perform similarly (and differently).

As with much of the APT research, the current study relied solely on self-report measures. However, past research suggests consistency between responses on the APT with hypothetical outcomes and with experienced outcomes (Amlung et al., 2012; Amlung & MacKillop, 2015) and various validity and reliability measures have been established (for an overview, see Reed, Kaplan, & Becirevic, 2015). Further demonstrations of consistency between responses on hypothetical and experiential versions of the APT would add value to the literature, especially in the context of vignette manipulations.

Conclusion

The APT has garnered increased use in understanding aspects related to alcohol use disorder and the task has shown favorable psychometric properties (e.g., reliability, validity). In recent years, studies have begun to evaluate how vignette framing can simulate alcohol consumption under various real-world conditions (e.g., Gentile et al., 2012; Gilbert et al., 2014; Skidmore & Murphy, 2011; Teeters & Murphy, 2015). The current study extends this research by demonstrating sensitivity of the APT to simulate potential alcohol consumption under various happy hour specials. The APT seems especially fit to simulate various other potential policies, regulations, or marketing tactics (Hursh & Roma, 2013; Roma et al., 2017), with and without framing manipulations.

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