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Behavioral Economic Predictors of Substance-Impaired Driving among College Substance Users

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BEHAVIORAL ECONOMIC PREDICTORS OF SUBSTANCE-IMPAIRED DRIVING AMONG COLLEGE SUBSTANCES USERS

by

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Abstract

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Substance-impaired driving among college students represents a significant public health concern yet little is known about specific theoretical risk factors for driving after substance use among heavy drinking college students. The present study evaluated the hypothesis that substance users with elevated substance demand and steeper delay discounting would be more likely to report driving after substance use. Participants were 419 college students who reported at least one day of past month alcohol or marijuana use. Participants completed two Alcohol Purchase Tasks (APT), a Marijuana Purchase Task, a Delayed Discounting task, and a series of questions regarding driving after substance use. In binary logistic regression models that controlled for a number of covariates, participants who reported higher alcohol demand were more likely to report driving after drinking. Additionally, in a series of ANCOVAs, DD^{+} participants reported significantly less of a reduction in demand as a function of the driving scenario.

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Substance-impaired driving among college students represents a significant public health concern. Despite widespread prevention efforts, approximately 3.4 million (30%) college students report driving after drinking alcohol (Hingson, Zha, & Weitzman, 2009), with rates increasing significantly after the 21^{st} birthday (Beck et al., 2010; Fromme, Weatherill, & Neal, 2010; Quinn & Fromme, 2012). Among college drinkers, 41% report past-month driving after drinking, 17% report driving after consuming five or more drinks, and 43% report believing they can drive safely after consuming 2-4 drinks in one hour (Hingson, 2003). Though marijuana-impaired driving has received considerably less attention, recent data suggest that rates of drug and alcohol-impaired driving are similar among college students (Arria, Caldeira, Vincent, Garnier-Dykstra, & O'Grady, 2011). Consequences of substance-impaired driving can be fatal; 74% of alcohol-related student deaths result from alcohol-impaired traffic accidents and driving after marijuana use more than doubles the risk of being involved in a fatal crash (Brady & Li, 2013; Hingson et al., 2009). College students are more likely to drive after substance use than their same-aged peers who do not attend college; 34.2% of full-time college students report past year driving after drinking compared to 27.9% of nonstudents (Paschall, 2003).

Marijuana is the most prevalent illicit drug detected among drug-impaired drivers and the most frequently used illicit drug on college campuses (Arterberry et al., 2012; McCarthy, Lynch, & Pedersen, 2007). Though years of epidemiological and experimental research has demonstrated that marijuana use impairs driving ability and increases risk for traffic accidents (For reviews see: Kelly, Darke, & Ross, 2004; Moskowitz, 1985; Ramaekers, Berghaus, van Laar, & Drummer, 2004), college students perceive driving after marijuana use as more acceptable and less dangerous than driving after drinking (McCarthy et al., 2007), and this perception of lower relative risk may contribute to a permissive attitude towards driving after using marijuana (McCarthy et al., 2010).

Recent research indicates that polydrug use among college students is on the rise (Brady & Li, 2013; Substance Abuse and Mental Health Services Administration, 2012). Approximately a quarter of drivers injured in car accidents test positive for multiple substances, the most common combination being alcohol and marijuana. Combined use of drugs and alcohol is associated with greater psychomotor impairment (Kelly et al., 2004; Lamers & Ramaekers, 2001; Robbe, 1998); those who drive after the combined use of drugs and alcohol are 23 times more likely to be involved in a fatal car accident (Brady & Li., 2013). The combined effects of alcohol and marijuana have been shown to significantly impair driving performance, even at relatively low levels of blood alcohol concentration (Sewell, Poling, & Sofuoglu; 2009). Though other studies have examined rates of drug and alcohol-impaired driving among college students (Arria et al., 2010; Arterberry et al., 2012; McCarthy et al., 2007), to our knowledge no studies have determined rates or predictors of driving after combined alcohol and marijuana use in this population.

Demographic and Personality Predictors of Substance-impaired Driving

Predictably, heavy episodic drinking (i.e., 4/5 drinks or more per occasion for females/males) is a strong predictor of drinking and driving, accounting for over 80% of all driving occurrences (Flowers et al., 2008). Compared to students who did not engage in heavy episodic drinking (HED) over a two-week period, students who engaged in 3-4 HED episodes were 8 times more likely to drive after drinking (Paschall, 2003). Moreover, the number of drinks students estimate they can consume and still be able to drive safely and legally within an hour is predictive of alcohol-impaired driving (Hingson, 2003). Likewise, level of marijuana use is associated with marijuana-impaired driving (Arria et al., 2011). Considering the multitude of potential serious negative consequences associated with impaired driving, it is important to investigate whether there are individual difference factors associated with driving after substance use, above and beyond level of use, to elucidate why some young adult substance users drive after using substances while others refrain. Identifying such factors may inform targeted intervention efforts designed to reduce impaired driving among college students.

To date, researchers have identified several individual difference factors associated with substance impaired driving. Consistent findings throughout the literature reveal that young white males are more likely than others to drive after using substances (for review see Kelly et al., 2004). Fraternity or sorority membership (LaBrie, Napper, & Ghaidarov, 2012), living off-campus (Weschler, Lee, Nelson, & Lee, 2003), family history of alcohol problems (LaBrie, Kenney, Mizra, & Lac, 2011), and younger age of drinking onset (Hingson 2002, 2003) are associated with more frequent alcohol impaired driving. Additionally, stronger self-approval of substance impaired driving, stronger perception of peer approval of substance impaired driving, and decreased perceptions of risk of substance-impaired driving are associated with a higher likelihood of driving after drinking and marijuana use (LaBrie et al., 2012; McCarthy et al., 2007). Sensation seeking has also been shown to be associated with alcohol-impaired driving in both the general population and among young adults (for review see Jonah, 1997). The present study attempts to extend this literature by investigating whether or not two theoretically based variables that have shown robust relations with a variety of other indices of alcohol-related risk - behavioral economic measures of demand and delay discounting - predict risk for substance-impaired driving among young adult substance users above and beyond known covariates.

Behavioral Economics

Behavioral economics (BE) views drug consumption as choice behavior maintained by the reinforcing properties of drugs and assumes that substance misuse and ultimately addiction entails a consistent overvaluation of substance-related rewards relative to substance-free rewards (Bickel, Marsch, & Carrol, 2000; Bickel, Johnson, Koffarnus, MacKillop, & Murphy, 2014). Behavioral economic theory posits that the primary causes of excessive substance use are a) minimal constraints on drug use (high availability/low cost), b) low levels of substance-free reinforcement, and c) strong preference for immediate rewards rather than delayed rewards.

In terms of person-level factors, level of *demand* for a particular substance captures important intra-individual differences in reinforcing efficacy (the behavior-strengthening nature of a reinforcer) and *delay discounting* measures preference for smaller immediate rewards relative to larger delayed rewards. These two domains are theorized to be etiological markers in the development of substance use disorders and predict an individual’s current and future substance use patterns (Bickel et al., 2014).

Demand

Demand refers to the amount of a commodity purchased by an individual at a certain price and provides an index of an individual's valuation of a commodity. A multidimensional assessment of a commodity's relative value can be visualized by generating a demand curve, which plots consumption as a function of price. Hypothetical demand curve measures, such as the Alcohol Purchase Task (APT) and the related Cigarette, Marijuana, and Cocaine Purchase Tasks, are time and cost-efficient and have been used in clinical research to generate demand and expenditure curves that illustrate participants' hypothetical rate of consumption across a range of drink/drug prices (Bruner & Johnson, 2013; Collins, Vincent, Yu, Liu, & Epstein, 2014; Heinz, Lilje, Kassel, & de Wit, 2012; Mackillop & Murphy, 2007; Murphy & MacKillop, 2006). These indices are conceptually related yet empirically discrete and include intensity (consumption level when drinks are free), breakpoint (the price that suppresses consumption to zero), and O_{max} (maximum expenditure on alcohol). Individual differences in sensitivity to changes in price can be quantified by measuring elasticity of demand, which can range from elastic (sensitive to price) to inelastic (insensitive to price) and may reflect the "essential value" of the commodity (Hursh & Roma, 2013; Hursh & Silberberg, 2008; see Figure 1.)

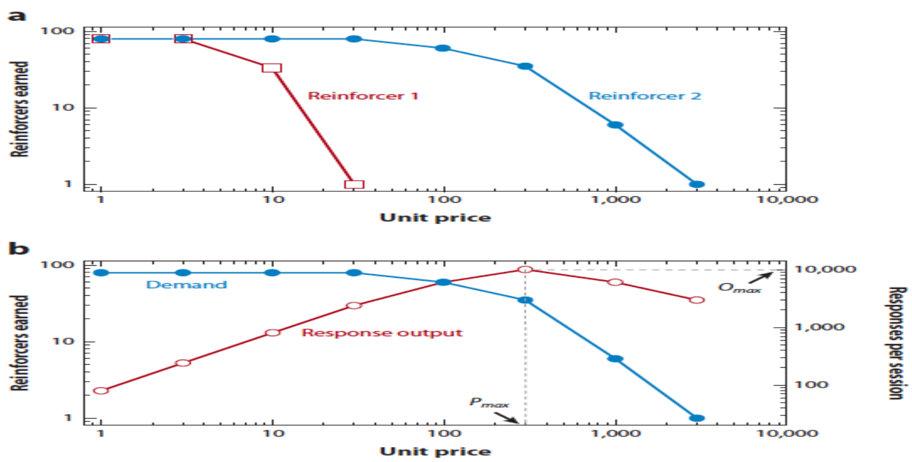

Figure 1. Demand curves for two hypothetical reinforcers.

Although increases in price typically lead to decreases in demand, there are important individual differences reflected in the demand indices that may provide a unique measure of substance use severity. Elevated alcohol demand has been shown to be significantly associated with a variety of indices that are indicative of more severe alcohol use, including increased alcohol consumption (Murphy & MacKillop, 2006), impulsivity (Kiselica & Borders, 2013; Smith et al., 2011), drinking to cope (Yurasek et al., 2011), craving (MacKillop et al., 2010), increased alcohol problems (Murphy, MacKillop, Skidmore, & Pederson, 2009; Skidmore, Murphy, & Martens, 2014), depression and PTSD symptoms (Murphy et al., 2013), and poor response to treatment (MacKillop & Murphy, 2007). Additionally, elevated tobacco demand among young adults is associated with greater nicotine dependence, providing further support that drug demand plays a role in substance dependence (Chase, MacKillop, & Hogarth, 2013; Murphy et al., 2012). Behavioral economic theory would predict that drinkers with elevated demand would be less likely to modify their drinking in order to avoid the health and legal risks associated with substance impaired-driving. Although previous research indicates that elevated demand is associated with increased overall levels of drug and alcohol problems, only one published study has examined whether demand is associated with driving after alcohol use specifically.

Using a novel behavioral economic hypothetical demand curve paradigm, Teeters and colleagues (2014) examined whether or not driving after drinking is related to individual differences in alcohol demand among heavy drinking college students. Participants who reported higher demand were more likely to report driving after drinking. Specifically, in binary logistic regression models that controlled for drinking level, gender, ethnicity, age, and sensation seeking, participants who reported higher breakpoint, intensity, and O_{max}, and significantly less sensitivity to changes in price (elasticity) were more likely to report driving after drinking. These results provide support for behavioral economics models of substance abuse, which view elevated demand as a pathognomonic feature of substance misuse (Bickel et al., 2014) and extend previous research by indicating that elevated alcohol demand is associated with specific decisions to drive after drinking. Presumably, many heavy drinkers abstain from alcohol if they are in a situation where they would have to drive home. Individuals with elevated demand may be unwilling to abstain in these situations because their desire to consume alcohol outweighs concerns about the financial, legal, and health risks associated with drinking and driving.

However, this study leaves several important questions unanswered. Alcohol-impaired driving was assessed using a single item that asked participants whether or not they had driven after having had "too much to drink." Because previous research indicates that college students' perceptions of their level of intoxication are often inaccurate (Mallett, Turrisi, Larimer, & Mastroleo, 2009), participants in the sample may have driven with

BACs over the legal limit but may not have felt that they had “too much to drive.” The present study included a more detailed measure of impaired driving. Additionally, heavy episodic drinkers were included, limiting generalizability. The present study included a wider range of drinking levels to determine if demand is associated with driving after drinking more generally among college student drinkers. Furthermore, although rates of marijuana-impaired driving among college students are comparable to rates of alcohol-impaired driving, no research has examined whether or not increased marijuana demand is associated with driving after marijuana use. The present study examined whether individual differences in marijuana demand predict marijuana impaired driving.

Finally, the present study extends Teeters et al. by including a demand curve approach to directly model decisions concerning how much one would drink in a hypothetical situation where they have to drive. Using a demand curve approach, previous research has demonstrated that demand for alcohol decreases/becomes more elastic as a function of environmental contingencies, such as having a class or a test the next day (Gentile, Librizzi, & Martinetti; 2012; Skidmore & Murphy, 2011). The next-day responsibility can be conceptualized as an indirect method of increasing the “price” of drinking. In order to examine the relative sensitivity of alcohol demand to next-day responsibilities as a function of family history of problematic drinking, Murphy and colleagues (2014) created a “sensitivity to next-day contingency” index (percent change between two APT scenarios). A lower percent change among family history positive participants reflected less sensitivity to next-day responsibilities. Although driving after drinking represents a crucial environmental contingency, the effect of knowing one has to drive home after drinking on the number of drinks consumed has yet to be examined, and there are presumably individual differences in the extent to which the hypothetical contingency suppresses drinking. In the present study, a modified demand curve approach in which participants are explicitly told they were driving home is used to examine the relative sensitivity of alcohol demand in response to this important contingency.

Delayed Reward Discounting

Behavioral economic theory also predicts that substance use is related to strong preference for immediate rewards. Delayed reward discounting (DRD) is a behavioral economic index of impulsivity that describes the decrease in reward value as a function of delay (MacKillop et al., 2011; see Figure 2). Though individuals typically prefer larger immediate rewards over smaller delayed rewards, there are meaningful individual differences in the degree to which delayed rewards are discounted. Delayed reward discounting appears to model a cardinal feature of drug dependence: chronically choosing a smaller immediate reward (the drug) over larger but delayed rewards (improved health, employment, family life, etc.; Bickel, Yi, Mueller, Jones, & Christensen, 2010).

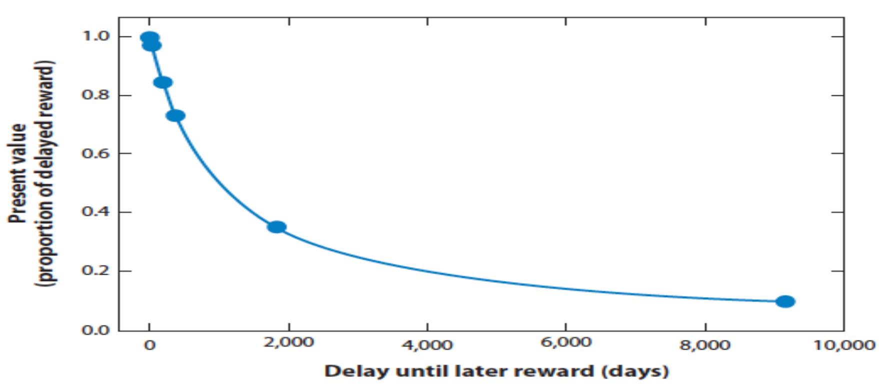

Figure 2. Hypothetical delay-discounting function. Reward value decreases in a hyperbolic fashion as delay until receipt of the reward increases (Bickel et al., 2014).

Numerous studies suggest that individuals who misuse alcohol discount delayed rewards significantly more steeply than individuals who do not abuse alcohol (See MacKillop et al., 2011 for review), and heavy drinking college students demonstrate greater discounting of hypothetical money than light/social drinkers (Vuchinich & Simpson, 1998). Additionally, studies that have calculated delayed reward discounting rates among individuals who abuse substances such as cocaine, (Coffey, Gudleski, Saladin, & Brady, 2003; Heil, Johnson, Higgins, & Bickel, 2006; Kirby & Petry, 2004), methamphetamine (Hoffman et al., 2006; Montessero et al., 2007), opioids (Kirby & Petry, 2004; Madden et al., 1997), and tobacco (Heyman & Gibb, 2006; Johnson et al., 2010) indicate that groups of drug users discount delayed rewards more steeply than controls. Moreover, greater DRD is associated with other clinically relevant drug and alcohol outcomes, such as lower likelihood to reduce or quit drinking (Tucker, Vuchinich, Black, & Rippens, 2006), relapse to smoking following treatment (MacKillop & Kahler, 2009), greater likelihood of passing out after drinking (Kollins, 2003), greater HIV risk among heroine abusers (Odum, Madden, Badger, & Bickel, 2000), and lower likelihood of condom use among cocaine abusers (Johnson & Bruner, 2012).

To date, few studies have examined discounting rates among marijuana users. Johnson and colleagues (2010) compared discounting rates among adults with current marijuana dependence, past marijuana dependence, and no history of marijuana use and found no significant differences between the three groups. However, a significant trend toward higher discounting rates in current marijuana dependent individuals was found. In a sample of adults receiving treatment for marijuana dependence, high delay discounting prior to treatment was associated with lower readiness to change, but not associated with treatment outcome (Peters, Petry, LaPaglia, Reynolds, & Carrol, 2013). Furthermore, in a clinical sample of marijuana dependent military veterans making a self-guided quit attempt, delay discounting did not predict cessation outcomes but was significantly correlated with higher craving for marijuana, younger age of first marijuana use, and earlier commencement of regular marijuana use (Heinz, Peters, Boden, & Bonn-Miller, 2013). These results suggest that although delay discounting may be related to initiation of marijuana use and readiness to change, the effect size of discounting for marijuana may be less than for other drugs.

Notably, results from a recent meta-analysis on DRD and addictive behavior (MacKillop et al., 2011) reveal significantly greater effect sizes in clinical samples relative to subclinical samples suggesting that DRD is related specifically to more problematic levels of alcohol, tobacco, or other drug use rather than merely substance *use*. This finding sheds light on the inconsistent results found in studies examining DRD and addictive behaviors in less severe (nonclinical) populations. Though significant differences in discounting rate in nonclinical samples of young adult drinkers have been found (Field, Christiansen, Cole, & Goudie, 2007; Vuchinich & Simpson, 1998), other studies have failed to find significant differences (Dennhardt & Murphy, 2011; MacKillop et al., 2007). These findings provide a rationale for examining DRD among a more high-risk group of collegiate drinkers/marijuana users, such as those who drive after substance use.

Substance impaired driving represents the choice of an immediate reward (e.g., convenience) over a delayed reward (e.g., keeping oneself and others safe, staying out of trouble with the law, avoiding possible fines). The hyperbolic discounting model accounts for the commonly observed dynamic inconsistencies in preference (*preference reversal)* from a larger delayed reward to a smaller immediate reward (Bickel et al., 2014). Specifically, when both a smaller and larger reward are available far into the future, an individual is likely to indicate a preference for the larger reward even if informed that the smaller reward were available sooner than the larger reward. As the time to receive the smaller sooner reward grows closer, however, the reward disproportionately gains value (MacKillop et al., 2011). Thus, when the smaller reward is made immediately available, an individual will often reverse his/her preference for the larger, delayed reward (Bickel et al., 2014; see Figure 3). Because the reinforcement associated with substance use, as well as the convenience of driving to a desired location, are relatively immediate, college students who overvalue immediate relative to delayed rewards may choose to drive after drinking and/or drug use rather than waiting for the larger, delayed reinforcement associated with safer options (even if they had initially planned not to drink and drive). Thus, steeper discounting of delayed rewards might lead to a pattern of heavy substance use and impaired driving putting the individual at risk for fatal consequences.

To date, only one published study has examined whether DRD is associated with alcohol impaired driving. McCarthy and colleagues (2012) conducted a within-subjects study in a community sample of 29 young adult drinkers to determine if drinking drivers exhibited greater levels of impulsivity while intoxicated. Delayed reward discounting (assessed using the Two Choice Impulsivity Paradigm; TCIP) of drinking drivers and non-drinking drivers was compared across alcohol and no-beverage sessions. In the no beverage (sober) session, drinking drivers and non-drinking drivers did not differ in the number impulsive choices made. In the alcohol session, drinking drivers made significantly more impulsive choices than non-drinking drivers. The authors concluded that alcohol influences preferences for immediate rewards and might affect decisions to drive after drinking. The authors note the measure of delayed reward discounting (the TCIP) as an important limitation and recommend that future research use alternative measures of delayed reward discounting. To our knowledge, no published studies have examined whether delayed reward discounting is associated with alcohol-impaired driving specifically among college students. In addition, the present study is the first to examine whether delayed reward discounting is associated with driving after marijuana use and driving after combined alcohol/marijuana use. The present study examines whether DRD predicts a) alcohol-impaired driving, b) marijuana-impaired driving, and c) combined alcohol/marijuana impaired driving.

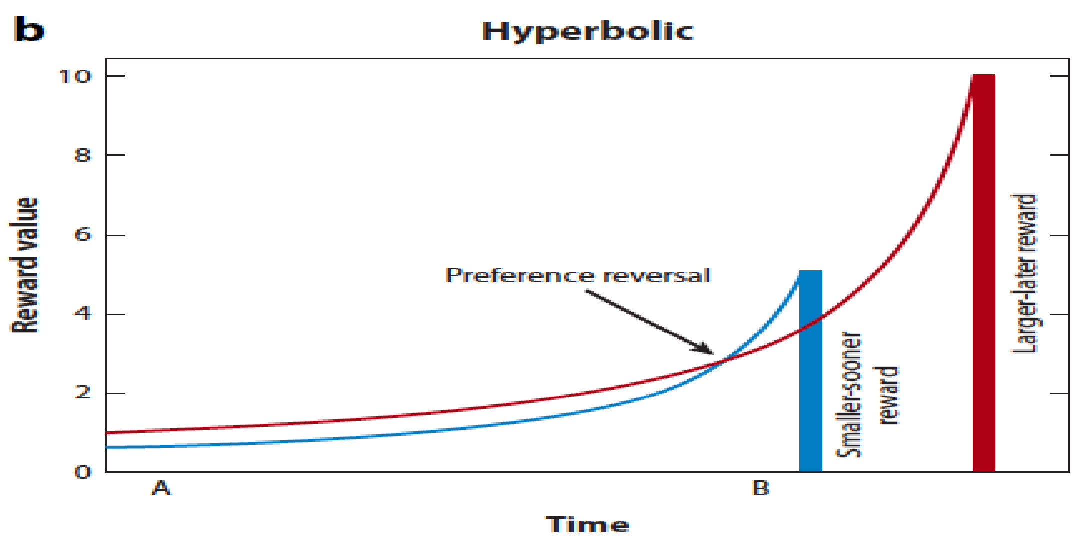

*Figure 3***.** Hyperbolic discounting function. Preference reverses from a larger later reward (at Time A) to a smaller sooner reward (Time B).

The present study aims to determine whether an association exists between two theoretically based variables that have shown robust relations with a variety of other indices of alcohol-related risk - behavioral economic measures of alcohol *demand* and *delay discounting*- and substance impaired driving. A secondary aim is to examine the relative sensitivity to an environmental contingency (knowing one has to drive home after drinking) on alcohol demand.

In order to determine the predictive value of demand and delayed reward discounting on substance impaired driving above and beyond known covariates, all analyses controlled for variables shown to covary with the dependent variable: gender, age, ethnicity, fraternity or sorority membership, sensation seeking, and level of use.

It is hypothesized that 1) elevated/inelastic demand will be associated with increased likelihood of driving after drinking and marijuana use, 2) overall alcohol demand will decrease as a function of knowing one has to drive home after drinking. However, 3) those who report past 3 month driving after drinking will show less of a reduction in demand than those who do not report driving after drinking, and 4) steeper discounting of delayed rewards will be associated with increased likelihood of driving after drinking, marijuana use, and combined alcohol and marijuana use.

Method

Participants

Participants were 419 undergraduate college students (75.9% women, 24.1% men; average age = 20.37, *SD* = 2.56, range = 18 – 39; 41.1% freshman, 26.5% sophomores, 17.2% juniors, and 14.2% seniors or above) from a large public university in the southern United States who reported past month alcohol or drug use. Students were eligible to participate if they were at least 18 years old. The sample was ethnically diverse: (59.8%

Caucasian, 32.6% African American, 2.8% Hispanic or Latino, 3.7% Asian, 2.1% American Indian, 0.7% Native Hawaiian/Pacific Islander, and the remainder not specifying their ethnicity). 17.2% (*n* = 72) were members of a fraternity or sorority.

Measures

Demographics. Participants completed a brief questionnaire regarding age, race/ethnicity, gender, and sorority and fraternity affiliation.

Alcohol use. Typical drinks per week was assessed by the Daily Drinking Questionnaire (DDQ; Collins, Parks, & Marlatt, 1985). Students were asked to estimate the total number of standard drinks they consumed on each day during a typical week in the past month. The DDQ is frequently used to assess alcohol consumption patterns among college students and is correlated with self-monitoring and retrospective drinking measures (Kivlahan, Marlatt, Fromme, Coppel, & Williams, 1990). A separate item was included to assess binge drinking. Students were asked to report how many times they had drunk 4 or more (if female) or 5 or more (if male) standard drinks in one occasion during the past month (Wechsler et al., 1995).

Driving after drinking. Driving after drinking was assessed with three questions adapted from prior studies that measured driving after drinking (LaBrie, Kenney, Mirza, & Lac, 2011). Participants reported how many times in the past 3 months they have driven within 2 hours of drinking 1-2 drinks, 3-4 drinks, and 5 or more drinks. Participants responded using a scale with the options of 0 (never), 1 (1-2 times), 2 (3-4 times), or 3 (5 or more times). Consistent with previous studies on driving after drinking (LaBrie et al., 2011, Labrie, Napper, & Ghaidarov, 2012), responses were coded into binary variables that indicate whether participants had driven after drinking three or more drinks (1 = yes, 0 = no). Those who reported driving after three or more drinks were labeled DD^+ and those who did not drive after three or more drinks were labeled DD^-.

Driving after marijuana use. Participants were asked how many times in the past 3 months they had driven within 2 hours of using marijuana. Participants responded using a scale with the options of 0 (never), 1 (1-2 times), 2 (3-4 times), or 3 (5 or more times). Consistent with previous studies on driving after marijuana use (McCarthy 2007, 2010), responses were dichotomized into “none” or “once or more.”

Driving after combined marijuana/alcohol use. Driving after combined use of marijuana and alcohol was assessed with a question asking participants to report how many times in the past 3 months they had driven within two hours of combined use of alcohol and marijuana. Participants responded using a scale with the options of 0 (never), 1 (1-2 times), 2 (3-4 times), or 3 (5 or more times). Responses were dichotomized into “none” or “once or more” (Arria et al., 2011).

Demand. Alcohol demand indices were derived from the Alcohol Purchase Task (APT; Murphy & MacKillop, 2006), a hypothetical measure that assesses alcohol consumption and expenditures over a range of 17 prices ($0.00 to $20.00 in the present study) and that can be used to generate alcohol demand curves. Participants were asked to indicate how many drinks they would purchase and consume at increasing monetary prices (e.g., “How many drinks would you have if they were $.25 each?”). They received the following instructions:

> *In the questions that follow we would like you to make decisions about how many drinks you would have in various situations. 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. ***<u>Please respond to these questions honestly, as if you were actually in this situation.</u>***

P*lease imagine that you and your friends are at a party from 9:00 PM until 1:00 AM. 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.*

Four observed indices (intensity, breakpoint, O_{max} and P_{max}) and one derived index (elasticity) were generated from the APT. Intensity was recorded as consumption at \$0.00. Breakpoint was recorded as the price that suppressed consumption to zero. O_{max} was recorded as participant's maximum expenditure on alcohol.

Elasticity was derived in the present study using GraphPad Prism v. 5.04 for Windows (GraphPad Software, San Diego, CA, USA, www.graphpad.com) and the macro available online through the Institute for Behavioral Resources website (www.ibrinc.org). Elasticity was generated from Hursh and Silberberg's (2008) exponential equation: $\log Q = \log Q_0 + k\,(e^{-\alpha P} - 1)$. In this equation, Q = quantity consumed, Q_0 = consumption at \$0.00, k = range of alcohol consumption in logarithmic units, P = price, and α = elasticity. In the present study, k was held constant across curve fits at 2.60. Larger values of α indicate greater elasticity (i.e., greater sensitivity to price). Consumption values of zero, which cannot be log transformed, and participant data in which less than five consumption values are provided and/or where missing data occurs for more than one price on the APT were eliminated prior to calculating elasticity. Hursh and Silberberg's (2008) exponential demand curve equation provided an excellent fit to the aggregated data (i.e., sample mean consumption values; R^2 = .98) and a good fit to the individual participant data (Mean R^2 = .87). Because there were numerous zero values in the driving contingency condition (which served to suppress demand), and because the curve fitting approach to generating elasticity estimates requires several non-zero consumption values to generate an adequate fit (Hursh & Silberberg, 2008; Yurasek et al., 2013), 30% of our sample did not have a valid elasticity value in this condition. This prevented us from computing percent reduction in elasticity for these participants. Therefore, only the three parameters that could be computed across both conditions for all participants (intensity, O_{max}, breakpoint) were compared.

A modified purchase task was included to assess marijuana expenditures (Marijuana Purchase Task; MPT). The same parameters derived from the APT can be derived from the MPT using the demand curve equation. The demand indices derived from the APT are correlated with alcohol consumption in a laboratory setting (Amlung, Acker, Stojeck, Murphy, & MacKillop, 2012) and with measures of alcohol consumption and related consequences (Murphy & MacKillop, 2006). Intensity and O_{max} have been shown to demonstrate excellent test-retest reliability (*rs* = .89 and .90, respectively) and breakpoint and elasticity have been shown to demonstrate good test-retest reliability (*r*s = .81 and .75, respectively; Murphy et al., 2009).

Demand in a hypothetical driving scenario. A revised alcohol purchase task was used to examine change in alcohol demand in response to an environmental contingency (having to drive home) relative to a standard drinking scenario. The instructions for the revised APT were modified by asking participants to report the number of drinks they would purchase and consume if they had to drive home at 2AM. They received the following instructions:

In the questions that follow we would like you to make decisions about how many drinks you would have in various situations. 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. Please respond to these questions honestly, as if you were actually in this situation.

Please imagine that you and your friends are at a party from 9:00 PM until 2AM. Assume that you did not drink alcohol or use drugs before you went to the party, and that you stopped drinking no later than 1:00 AM. Imagine that you were driving home at 2:00 AM (at least one hour after you stopped drinking).

Sensation-seeking. Sensation seeking was assessed using the sensation seeking subscale of the Urgency, (lack of) Premeditation, (lack of) Perseverance, and Sensation-Seeking Impulsive Behavior Scale (UPPS; Whiteside & Lynam, 2001). Participants were presented with 12 statements and were asked to rate each item in terms of how it aligned with their view of themselves. Response options ranged from 1 (not true of me) to 5 (very true of me). The Sensation Seeking subscale (α = .80) measures the degree to which individuals seek out activities that involve a sense of risk or thrill (e.g., "I'll try anything once"). Items are reverse scored and summed; higher total score indicates greater sensation-seeking. The subscales of the UPPS have demonstrated suitable convergent and discriminant validity (Whiteside & Lynam, 2001).

Marijuana-related problems. Drug-related problems were measured using the Marijuana Problems Scale (MPS; Stephens, Roffman, & Curtin, 2000). The MPS is a 19-item self-report measure that assesses problems experienced as a result of using different types of drugs in the past six-months. Individuals respond to the items on a three-point scale (*No Problem*, *Minor Problem, Serious Problem*).

Delay discounting. Rate of delay discounting was determined using a delay discounting task (MacKillop & Amlung, 2011) in which participants were presented with 60 hypothetical choices between a smaller monetary reward available today and a larger monetary reward available at some point in the future and asked to indicate their preference (e.g., "Would you rather have $70 today, or $100 in 3 months?" Monetary amounts and delays vary in magnitude and temporal distance. Discounting rate (*k*) was derived from choice patterns across all trials. Higher *k* is indicative of steeper discounting (i.e., greater reduction in the subjective value of a reward as a function of the delay to that reward) and greater behavioral impulsivity. Hypothetical choices between immediate and delayed monetary outcomes are valid and reliable approximations of real-world choices (Johnson & Bickel, 2002; Madden, Begotka, Raiff, & Kastern, 2003), and among college students, steeper discounting on hypothetical monetary choice tasks is associated with greater substance use severity and alcohol-related consequences (Kollins, 2003).

Procedure

Prior to the start of data collection, the protocol was reviewed and approved by the Institutional Review Board of the university. Participants were recruited from the undergraduate Psychology Department subject pool. All participants were provided with informed consent materials that highlight confidentiality of responses, a participant's right to quit at any time without penalty, and the voluntary nature of participation. Those who consented to participate were given the assessments. They completed the survey questionnaires in an online format for course credit. Only those who reported past month marijuana use were included in the marijuana impaired driving analyses and only those who reported past month alcohol use were included in the alcohol-impaired driving analyses.

Data Analysis Plan

Outliers were Winsorized using the method described by Tabachnick and Fidell (2013). Values exceeding 3.29 SDs above the mean were re-coded to be one unit greater than the greatest non-outlier value. In addition, distributions were checked for skewness and kurtosis and transformed as appropriate using log and square root transformations. The following variables were transformed: marijuana use days, intensity, breakpoint, O_{max}, elasticity, and *K*. Following these transformations, all final variables had acceptable levels of skewness and kurtosis (i.e., between -1 and 1). Pearson's correlations were used to analyze the associations between demographic variables (age, gender, ethnicity, fraternity or sorority affiliation), driving after substance use, alcohol consumption, sensation seeking, demand, and delay discounting

Raw consumption and expenditure values were used to plot consumption and expenditure demand curves for each participant. The curves were then used to generate intensity, O_{max}, and breakpoint values. As described above, Hursh and Silberberg's (2008) exponential equation was used to generate elasticity values. For all alcohol-impaired driving analyses, respondents were classified as a function of whether they drove after three of more drinks (1= yes, 0 = no) in the past 3 months.

To examine whether alcohol demand predicts alcohol-impaired driving, a hierarchical logistic regression model was tested using the dichotomized measure of alcohol-impaired driving as the outcome variable. Covariates (gender, race, age, fraternity or sorority membership, sensation seeking, and drinks per week) were entered in Step 1. In Step 2, the demand indices (intensity, breakpoint, elasticity, and O_{max}) derived from the Alcohol Purchase Task were entered individually to determine the predictive value of demand above and beyond known covariates. To examine whether marijuana demand predicted marijuana-impaired driving, a hierarchical logistic regression model was tested using the dichotomized measure of marijuana-impaired driving as the outcome variable. In Step 1, all covariates (gender, race, age, fraternity or sorority membership, sensation seeking, and drinks per week) were entered. In Step 2, the demand indices derived from the marijuana purchase task (intensity, breakpoint, elasticity, and O_{max}) were entered individually to determine the predictive value of demand above and beyond known covariates.

A "sensitivity to driving contingency" index was created by calculating the percent change between the two APT scenarios (the standard APT versus the driving APT) in order to examine the relative sensitivity of alcohol demand in response to having to drive home after drinking (Murphy et al., 2014). A lower percent change reflects less sensitivity to the driving contingency. An ANCOVA controlling for gender, race, age, fraternity or sorority membership, sensation seeking, and drinks per week was conducted to determine whether participants reported elevated demand in the non-revised (standard) condition relative to the revised (driving) condition. A series of independent-sample t-tests were used to determine if participants who drove after drinking reported significantly smaller reductions in demand as a function of the driving contingency. A separate ANCOVA (with identical covariates) was used to evaluate differences in percent reduction in the demand parameters as a function of the driving contingency.

Several hierarchical logistic regression analyses were run to examine whether DRD predicts a) alcohol-impaired driving, b) marijuana impaired driving, and c) combined alcohol/marijuana-impaired driving. In each of these analyses, covariates (gender, race, age, fraternity or sorority membership, sensation seeking, and drinks per week) were entered in Step 1. Delay discounting rate was entered in Step 2 to determine the predictive value of discounting rate above and beyond known covariates.

Results

Descriptive Statistics

In the past month, 81.6% (*n* = 342) of participants reported consuming alcohol. In the past three months, 56.5% (*n* = 231) of participants reported driving after drinking 1-2 drinks, 29.1% (*n* = 119) reported driving after drinking 3-4 drinks, 13.4% (*n* = 55) reported driving after drinking 5 or more drinks, and 19% (*n* = 79) reported driving after combined use of alcohol and another drug. In the past month, 43% (*n* = 176) of participants reported using marijuana. Among marijuana users, 69.9% (*n* = 123) reported driving after marijuana use and 37.4% (n = 67) reported driving after combined use of alcohol and marijuana. On average, drinkers reported consuming 8.54 drinks per week (*SD* = 8.37), and 2.40 heavy episodic drinking episodes per month (*SD* = 3.19) and marijuana users reported an average of 10.82 days of marijuana use (*SD* = 10.97). Descriptive data for drinkers as a function of driving status are in included in Table 1 and descriptive data for marijuana users as a function of driving status are included in Table 2.

Associations between Driving after Drinking, Demographic variables, Alcohol use, Alcohol Demand, and Delayed Reward Discounting

Pearson's *r* statistics were used to analyze bivariate associations between study variables (see Tables 3 and 4). The demand curve metrics intensity, breakpoint, elasticity, and O_{max} demonstrated significant associations with drinks per week, alcohol problems, and driving after drinking (r = .24 to .47). Sensation seeking was also positively associated with driving after drinking. Marijuana demand curve metrics intensity, breakpoint, elasticity, and O_{max} were significantly associated with frequency of marijuana use and intensity and breakpoint were associated with marijuana use problems. Though intensity of marijuana demand demonstrated a trend level association with driving after marijuana use (p = .054), none of the marijuana demand indices demonstrated significant associations with driving after marijuana use. Notably, none of the demand indices were significantly associated with average monthly income or average disposable income.

Multivariate Association between alcohol Demand and Driving after Drinking

To examine whether alcohol demand predicted alcohol-impaired driving, a series of hierarchical logistic regression model was tested using the dichotomized measure of alcohol-impaired driving as the outcome variable. Covariates (gender, race, age, fraternity or sorority membership, sensation seeking, and drinks per week) were entered in Step 1. Demand indices (intensity, breakpoint, elasticity, O_{max}) derived from the Alcohol Purchase Task were entered individually in Step 2 to determine the predictive value of demand above and beyond known covariates.

Unstandardized regression coefficients, Wald statistics, odds ratios, and 95% confidence intervals for odds ratios for each predictor are shown in Table 5. According to the Wald criterion, intensity, breakpoint, O_{max}, and elasticity significantly predicted engaging in alcohol-impaired driving. Participants reporting higher intensity (odds ratio [OR] = 1.56, 95% CI [1.04, 2.34]), breakpoint (OR = 1.67, 95% CI [1.23, 2.28]), O_{max} (OR = 1.26, 95% CI [1.03, 1.53]), and lower elasticity (OR = .39, 95% CI [.15, 1.02]) were more likely to report driving after drinking (Figure 4).

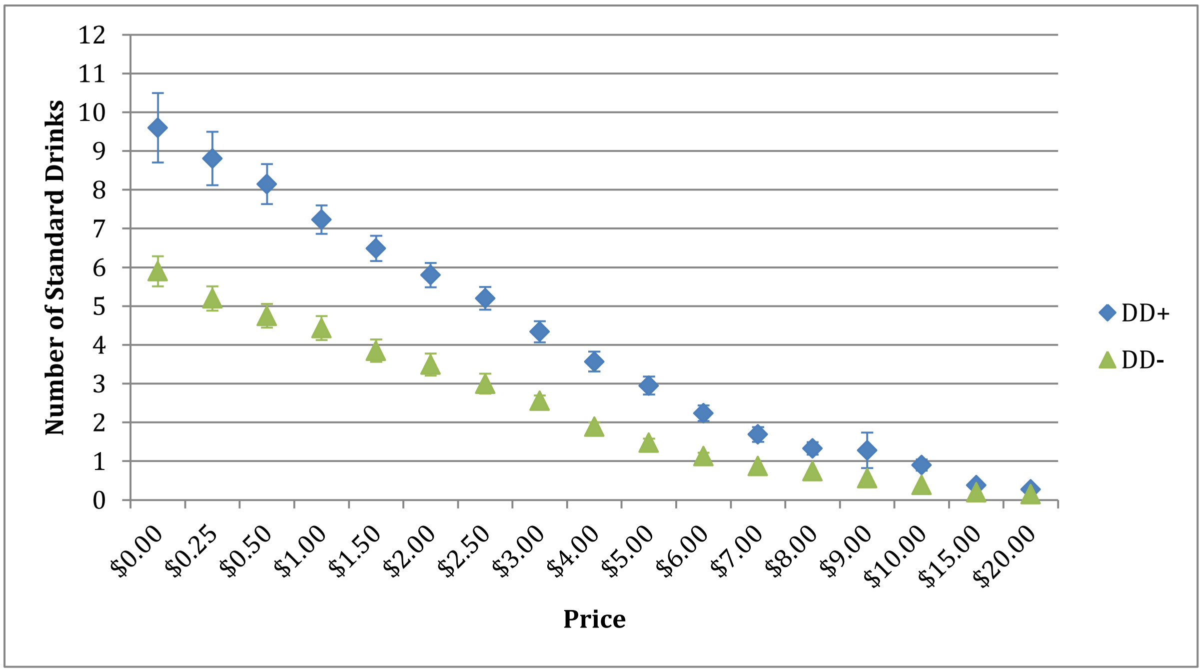

Figure 4. Depicts the mean (± 1 Standard Error of the Mean; SEM) number of drinks (hypothetical) that DD^+ (*n* = 107) and DD- (*n* = 221) would purchase as a function of price.

Multivariate Association between Alcohol Demand and Driving after Marijuana Use

To determine whether marijuana demand is associated with marijuana-impaired driving, a series of hierarchical logistic regression models were tested using the dichotomized measure of marijuana-impaired driving as the outcome variable. All covariates (gender, race, age, fraternity or sorority membership, sensation seeking, and drinks per week) were entered in Step 1. In Step 2, the demand indices derived from the marijuana purchase task (intensity, breakpoint, elasticity, and O_{max}) were entered individually to determine the predictive value of demand above and beyond known covariates.

Multivariate Association between Alcohol Demand and Driving after Marijuana Use

To determine whether marijuana demand is associated with marijuana-impaired driving, a series of hierarchical logistic regression models were tested using the dichotomized measure of marijuana-impaired driving as the outcome variable. All covariates (gender, race, age, fraternity or sorority membership, sensation seeking, and drinks per week) were entered in Step 1. In Step 2, the demand indices derived from the marijuana purchase task (intensity, breakpoint, elasticity, and O_{max}) were entered individually to determine the predictive value of demand above and beyond known covariates.

Unstandardized regression coefficients, Wald statistics, odds ratios, and 95% confidence intervals for odds ratios for each predictor are shown in Table 6. According to the Wald criterion, none of the demand metrics significantly predicted engaging in marijuana-impaired driving above and beyond known covariates (Figure 5). Although no significant associations were found in the multivariate model, individuals who drove after using marijuana reported higher marijuana intensity values.

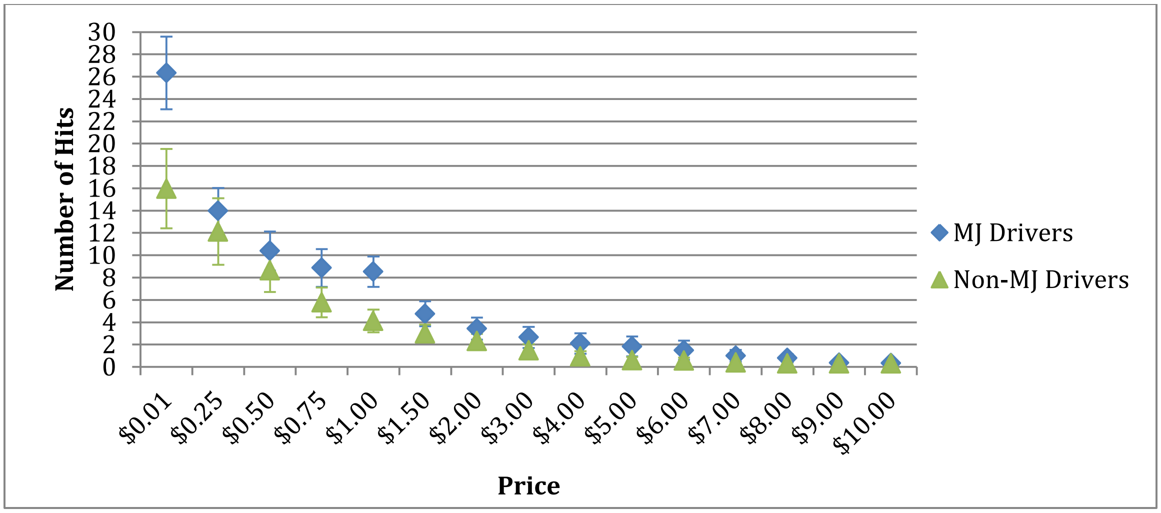

Figure 5. Mean (± 1 Standard Error of the Mean; SEM) number of (hypothetical) hits that a student would take as a function of price and driving status.

Reductions in Demand as a Function of a Driving Contingency

Figure 6 plots raw demand curve consumption values across the 17 prices and the driving condition (standard alcohol purchase task vs. revised alcohol purchase task). Across both conditions, reported alcohol consumption exhibited a decelerating curve in response to increasing price. As can be seen in Figure 6, there were significant reductions in demand between the standard and revised (driving) alcohol purchase task. In the driving alcohol purchase task condition, mean consumption at no cost (intensity) was 4.42 drinks (SD = 4.01), mean lowest price at which participants reported they would stop consuming drinks (breakpoint) was \$7.90 (SD = 6.58), and mean maximum expenditure (O_{max}) was \$12.39 (SD = 13.50). The mean reported reduction of demand intensity as a function of the driving contingency test was .369 (SD = .34), indicating a 36.9% reduction or a change from 7.28 to 4.59 drinks consumed when drinks are free. O_{max} was reduced by 24.6% (SD = .47) and breakpoint by 17.8% (SD = .33). See Table 7 for descriptive data on drinking and demand curve parameter values (intensity, breakpoint, O_{max}) across the two demand curve conditions, and the percent reduction in demand scores as a function of driving contingency by substance-impaired driving status.

Reductions in Demand as a Function of a Driving Contingency

Figure 6 plots raw demand curve consumption values across the 17 prices and the driving condition (standard alcohol purchase task vs. revised alcohol purchase task). Across both conditions, reported alcohol consumption exhibited a decelerating curve in response to increasing price. As can be seen in Figure 6, there were significant reductions in demand between the standard and revised (driving) alcohol purchase task. In the driving alcohol purchase task condition, mean consumption at no cost (intensity) was 4.42 drinks (*SD* = 4.01), mean lowest price at which participants reported they would stop consuming drinks (breakpoint) was $7.90 (*SD* = 6.58), and mean maximum expenditure (O_{max}) was $12.39 (*SD* = 13.50). The mean reported reduction of demand intensity as a function of the driving contingency test was .369 (*SD* = .34), indicating a 36.9% reduction or a change from 7.28 to 4.59 drinks consumed when drinks are free. O_{max} was reduced by 24.6% (*SD* = .47) and breakpoint by 17.8% (*SD* = .33). See Table 7 for descriptive data on drinking and demand curve parameter values (intensity, breakpoint, O_{max}) across the two demand curve conditions.

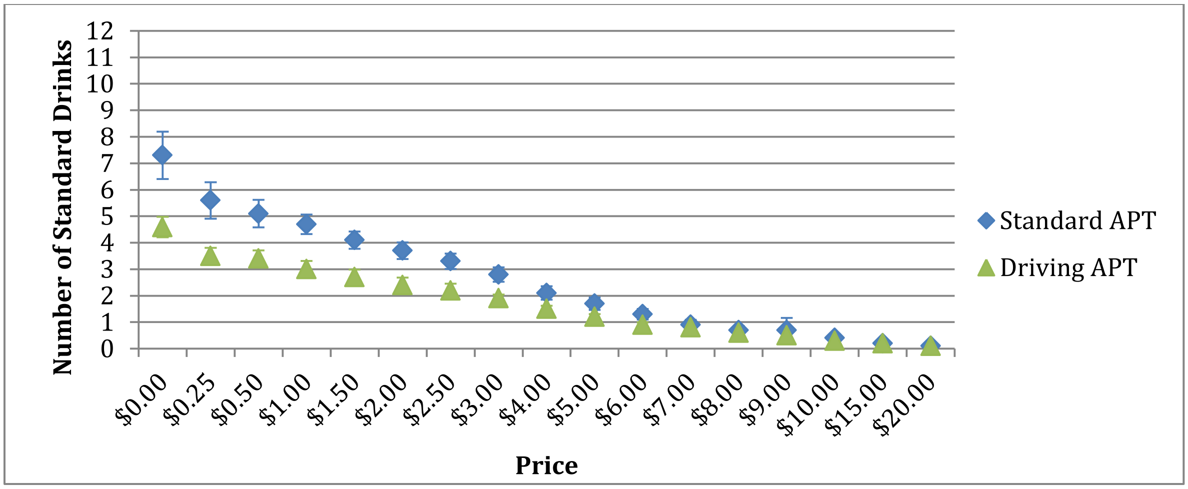

Figure 6. Depicts the mean (± 1 Standard Error of the Mean; SEM) number of drinks (hypothetical) that participants would purchase as a function of price by APT scenario.

Effects of Impaired Driving Status on Alcohol Demand and Sensitivity of Alcohol Demand to Driving Contingency

Figure 7 plots the mean percent reduction in raw demand curve consumption values as a function of next-day contingency, across the 17 demand curve prices, for participants with and without a previous history of driving after drinking. A series of independent sample *t*-tests indicated that impaired-driving participants reported significantly smaller reductions in demand as a function of the next-day test at eleven price increments ($0 - $6 increments; all tests were two-tailed). A series of ANCOVAs that controlled for gender, ethnicity, and typical weekly drinking were conducted to determine whether impaired driving participants reported elevated demand in the driving condition. Compared to participants who did not report driving after drinking in the past three months (DD^-), participants who reported past three month driving after drinking ($DD^{+)}$ reported significantly greater intensity $F(1, 277) = 16.53$, $p < .01$, $\eta_p^2 = 0.06$ and O_{max} $F(1, 276) = 18.72$, $p < .07$, $\eta_p^2 = 0.07$. To determine if DD^+ participants exhibited significantly less of a reduction in demand as a function of the driving contingency, three ANCOVAs (with identical covariates) were conducted to evaluate differences in percent reduction in the demand parameters as a function of the driving contingency. DD^+ participants were less sensitive to the driving contingency than participants who did not report past alcohol impaired driving on the indices reflecting percent reduction in intensity of demand, $F(1, 316) = 16.27$, $p < .01$, $\eta_p^2 = 0.05$, breakpoint, $F(1, 316) = 3.92$, $p = .05$, $\eta_p^2 = 0.01$, and O_{max}, $F(1, 317) = 15.43$, $p < .01$, $\eta_p^2 = 0.05$ (See Figure 7).

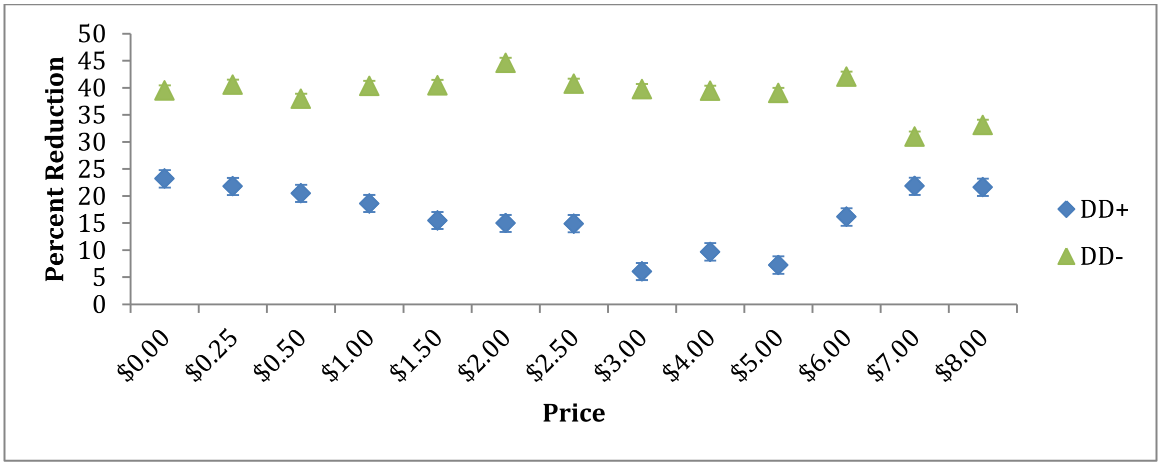

Figure 7. Mean (± 1 Standard Error of the Mean; SEM) reduction in number of drinks (hypothetical) that a student would purchase as a function of price and driving status.

Multivariate Association between Demand, Delayed Reward Discounting, and Driving after Drinking and Marijuana Use

Several hierarchical logistic regression analyses were run to examine whether DRD predicts a) alcohol-impaired driving, b) marijuana impaired driving, and c) combined alcohol/marijuana-impaired driving. In each of these analyses, covariates (gender, race, age, fraternity or sorority membership, sensation seeking, and drinks per week) were entered in Step 1. Delay discounting rate was entered in Step 2 to determine the predictive value of discounting rate above and beyond known covariates. Unstandardized regression coefficients, Wald statistics, odds ratios, and 95% confidence intervals for odds ratios for each predictor are shown in Table 8. According to the Wald criterion, delayed reward discounting did not predict engaging in alcohol-impaired, drug-impaired, or combination alcohol/drug impaired driving.

Discussion

Driving after substance use is a significant public health concern and there remains a need to identify theoretical and individual difference risk factors for substance-impaired driving above and beyond level of use and demographic variables. The present study used a novel behavioral economic paradigm to determine whether or not elevated substance demand and delayed reward discounting were associated with driving after substance use in a sample of college substance users. Key findings include: a) participants who reported higher alcohol demand were more likely to report driving after drinking, b) Participants with a recent history of driving after drinking are less sensitive to a hypothetical driving contingency than those who did not report driving after drinking in the past three months, and c) delay discounting rates are not associated with driving after alcohol, marijuana, or combined alcohol/marijuana use.

Participants whose demand curves showed higher alcohol intensity, breakpoint, and O_{max} and lower elasticity of demand (less price sensitivity) were more likely to report driving after drinking. Notably, these results suggest that those who drive after drinking report greater demand for alcohol *independent* of drinking level and several other known covariates (gender, age, ethnicity, sensation seeking, and fraternity or sorority affiliation).

Theoretical and laboratory research on behavioral economics suggests that elevated/inelastic demand reflects a stronger and more persistent motivation to consume alcohol (Bickel et al., 2000, 2013; Hursh & Silberberg, 2008). In line with the behavioral economic framework, the present results suggest that elevated demand is associated with specific decisions to drive after drinking. Presumably many drinkers will abstain from alcohol if they are in a situation where they would have to drive home. However, a subset of individuals with elevated demand may be unwilling to abstain in these situations; their desire to consume alcohol may outweigh "costs" such as concerns about the financial, legal, and health risks associated with drinking and driving. Because demand is not influenced by the many contextual features that limit drinking among young adults (e.g., drinking age, cost, peer influence, etc.), it may provide a clean and useful measure of strength of desire for alcohol.

In the present study, peak consumption at lowest price (intensity), the first price that suppressed consumption to zero (breakpoint), maximum expenditure on alcohol (O_{max}), and sensitivity to price (elasticity) demonstrated predictive utility for driving after drinking. For example, drinkers who reported driving after drinking reported maximum alcohol expenditures that were on average $7.00 greater, maximum consumption levels of four drinks greater, and breakpoint values that were $3 more than drinkers who did not drive after drinking.

These findings replicate and extend the results found by Teeters and colleagues (2014) by demonstrating that elevated demand is not only associated with drinking and driving among college binge drinkers but also among a wider range of college drinkers. The current findings add to a growing literature suggesting that elevated/inelastic demand is uniquely associated with of a variety of clinically-relevant alcohol-related outcomes including drinking to cope (Yurasek et al., 2011), craving (MacKillop et al., 2010), alcohol problems (Murphy et al., 2009), impulsivity (Kiselica & Borders, 2013), depression and PTSD symptoms (Murphy et al., 2012), acute stress (Amlung & MacKillop, 2014), and poor response to treatment (MacKillop & Murphy, 2007).

Although we hypothesized that marijuana demand would predict marijuana-impaired driving among marijuana users, none of the demand indices derived from the marijuana purchase task were associated with driving after marijuana use. Though marijuana-impaired drivers indicated they would take more hits of marijuana when free (26 vs. 16 hits; $F(1, 151) = 3.75$, $p = .054$, $\eta_p^2 = 0.02$), would spend more overall on marijuana ($11.82 vs. $9.59), and would continue spending at higher prices ($3.15 vs. $2.58) than non-marijuana impaired drivers, these differences were not statistically significant. Only one previously published study has used an experimental purchasing task to examine marijuana demand among young adults. Collins and colleagues (2014) examined marijuana demand in a sample of 59 young adult regular marijuana users and found that intensity, O_{max}, and elasticity were associated with real-time marijuana use. In the present study, intensity, O_{max}, breakpoint, and elasticity were associated with frequency of marijuana use and intensity and breakpoint were associated with marijuana problems, but none of the demand indices were associated with driving after marijuana use. Lack of sample variability in marijuana use frequency may have limited the ability to detect a significant difference between drivers and non-drivers. Demand is a continuous variable that reflects strength of desire for a substance and is meant to map on to a continuum of desire as reflected by varying amounts of substance use. In the current sample, drinking level (average drinks per week) had a normal distribution allowing for appropriate sample variability in demand. However, marijuana use (number of days using marijuana) did not show the same level of sample variability. In the past month, 53% of participants reported 5 or fewer days of marijuana use and 27% reported more than 20 days of past month marijuana use. Greater sample variability would likely have been found if the number of joints smoked per marijuana use episode had been measured (Collins et al., 2014) rather than the total days of past month use. Furthermore, over 50% of the sample ceased purchasing when the price of marijuana reached $2.00. Perhaps using a purchasing task with a greater number of lower price points would have resulted in more variability. Given the prevalence of marijuana impaired driving, it is important that future studies utilize precise marijuana use measures and marijuana purchase tasks that are able to tap the continuum of marijuana use. Though is difficult to make comparisons across purchase tasks due to differences in dosing, it appears that overall demand for marijuana is lower than demand for alcohol even among users. However, it is possible that demand for marijuana is lower than for alcohol as marijuana is a less potent reinforcer with less abuse potential.

This study also used a behavioral economic demand curve paradigm to directly model decisions concerning how much one would drink in a hypothetical situation where he/she has to drive home from a party. Though driving after drinking represents a crucial environmental contingency, this is the first study to examine the effect of knowing one has to drive home on the number of drinks consumed at escalating prices. We hypothesized that overall demand would decrease in response to the driving contingency and that drinkers with a history of driving after drinking would report greater reinforcing efficacy for alcohol and less sensitivity of alcohol demand to the driving contingency. As hypothesized, there were significant sample-level reductions in demand between the standard and revised (driving) alcohol purchase task, thus providing further validation for the hypothetical scenario (Skidmore & Murphy, 2011; Gentile et al., 2012; Murphy et al., 2014). Also as hypothesized, DD^+ participants reported significantly smaller reductions in demand than DD^- participants. Specifically, in multivariate models that controlled for drinking level, age, gender, and ethnicity, participants who reported past three month drinking and driving showed significantly smaller reductions in maximum consumption levels when drinks were free (intensity), maximum price paid for a single drink (breakpoint), and maximum overall expenditure (O_{max}) as a function of the driving contingency. Thus, participants with a recent history of drinking and driving appeared to have a harder time decreasing demand in response to the driving contingency as evidenced by significantly less of a reduction in demand.

These results suggest that even when made explicitly aware of having to drive, college drinkers with a recent history of drinking and driving may choose to consume significantly more drinks when free, to spend significantly more money on alcohol (O_{max}), and to continue drinking at significantly greater prices (breakpoint) than college drinkers without a recent history of drinking and driving. Due to the financial, legal, and health risks associated with drinking and driving, one might expect that having to drive home would minimize the role of price when deciding how much alcohol to consume. For example, a designated driver might be expected to set a limit of zero drinks regardless of drink price. However, previous studies have shown that many designated drivers do not abstain from alcohol and some choose to drive with average BACs above the intoxication level shown to impair driving skills (Barry, Chaney, & Stellefson, 2013; Timmerman, 2003). Notably, college drinkers who reported driving after drinking in the past three months reported that they would drink an average of seven drinks when drinks were free, regardless of the fact that they would have to drive home within one hour of consuming their last drink. Though there are a number of factors that contribute to BAC (e.g., weight, gender, food consumed, type of drink), consuming seven drinks in less than four hours would most likely result in a BAC well over the U.S. legal limit for adults 21 and over. However, the majority of participants who reported drinking after driving (n = 202; 60%) were under 21 years of age and cannot legally drive after consuming any amount of alcohol.

The results of the present study suggest that drink price has a major impact on consumption in the context of driving after drinking. Even when made explicitly aware of having to drive home, low drink prices lead to risky drinking. Though previous research has shown that drink price is an important risk factor for heavy drinking and alcohol consequences more generally (Barnett, Orchowski, Read, & Kahler, 2013; Read, Merrill, & Bytschkow, 2010; Thombs et al., 2009) the results of the present study provide evidence that drink specials and free/low cost alcohol (e.g. “pregaming”, college parties, open bar events) are risk factors specifically for drinking and driving. Strong desire for alcohol may make the perceived benefits of drinking more salient than the price of drinks. Due to elevated demand for alcohol, participants with a recent history of driving after drinking may be unwilling to abstain from drinking despite the financial, legal, and health risks associated with drinking and driving. Their desire to consume alcohol may outweigh these potential “costs.”

Previous research suggests that raising alcohol excise taxes would effectively reduce risky drinking and alcohol-related problems, including alcohol-related motor-vehicle crashes (Chaloupka, Grossman, & Saffer, 2002; Cook, 2007). A review of studies evaluating the effect of alcohol price and taxes on motor vehicle crashes found a consistent inverse relationship between drink prices and taxes and alcohol-impaired driving as well as a significant relationship between alcohol prices/taxes and alcohol impaired motor-vehicle injuries and fatalities (Elder et al., 2010). The results of the present study provide further evidence of the significant relationship between drink price and driving. Thus, raising alcohol prices and alcohol excise taxes may be one potential way of reducing drinking and driving among college students. As can be seen in Figure 6, participants reported they would drink an average of 3 drinks before driving home if drinks cost $1 versus an average of 1.5 drinks before driving home if drinks cost $4.

The present study also sought to determine whether delayed reward discounting (DRD) was associated with driving after drinking, marijuana use, and combined alcohol/marijuana use. In contrast with prior findings, no association was found between delayed reward discounting and alcohol-impaired driving (McCarthy et al., 2012). In a community sample of 29 young adult drinkers, McCarthy and colleagues (2012) found that after consuming alcohol, drinking drivers made more impulsive choices on an experimental delay discounting task (the Two Choice Impulsivity Paradigm; TCIP) on both the ascending and descending limb of the blood alcohol concentration curve than non-drinking drivers. However, consistent with the results of the present study, discounting rates (amount of impulsive choices made) of drinking drivers and non-drinking drivers did not differ in the sober (no beverage) condition. Thus, preference for immediate verses delayed rewards appears to be exacerbated by the effects of alcohol. Perhaps differences in delayed reward discounting rates between drinking drivers and non-drinking drivers would have emerged in the present study if the discounting task had been given to participants while intoxicated. Future research is necessary to determine whether delayed reward discounting rates differ as a function of blood alcohol concentration (BAC) between college students who have previously driven while intoxicated and those who have not.

Although many studies have found delayed reward discounting to be related to substance use and problems (see MacKillop et al. for review) among clinical samples, several studies among college students have failed to find a relationship between these constructs (e.g., Dennhardt & Murphy, 2011; MacKillop et al., 2007). This suggests that perhaps discounting is only weakly and inconsistently related to drinking in college. Additionally, findings from prior studies examining discounting rates among marijuana users suggest that discounting rates do not differ between adults with current or past marijuana dependence and adults with no history of marijuana use (Johnson et al., 2010) and are not associated with treatment or cessation outcomes (Heinz et al., 2013; Peters et al., 2013). Though students who drive after alcohol/marijuana use represent a more high-risk group of collegiate drinkers/drug users, discounting rates among these students likely differ from clinical samples.

These results provide further evidence that drinkers with elevated demand should be prioritized for brief interventions services, ideally with a focus on decreasing alcohol-impaired driving. For example, the interventionist and student could collaboratively calculate approximate BACs after consuming seven drinks to demonstrate the student's level of impairment. As noted above, previous research suggests that elevated demand is also associated with a host of other risky outcomes related to drinking, and there is thus a strong rationale for prioritizing drinkers with elevated demand for intervention services. However, elevated demand also predicts poor response to standard single-session brief alcohol interventions (MacKillop & Murphy, 2007), which suggests that students with elevated demand may require supplemental intervention approaches that focus specifically on reducing demand and impaired driving (Murphy et al., 2012).

Several limitations should be considered when interpreting these findings. Participants were not asked whether or not they had access to a car or had any opportunities to drive in the past three months. Thus, some students with a lifetime history of substance impaired driving who are likely to drive after substance use in the future may not have been classified as impaired drivers because they did not have access to a car. In addition, participants were classified as drinking drivers if they reported driving within two hours after consuming three drinks. Depending on the student's weight, gender, rate of consumption, food consumed, total time drinking, etc., he or she may or may not have been above the legal intoxication limit. Future research should aim for a more precise assessment of a participant's (BAC) prior to driving. Similarly, participants were classified as marijuana-impaired drivers if they reported driving within two hours of using any type, quality, or amount of marijuana. This classification did not account for amount used, potency, or route of administration (e.g., eaten vs. smoked), all of which may render a driver more or less impaired. Differentiating between levels of marijuana consumption is a common limitation noted in marijuana studies (McCarthy et al., 2007, 2010), and future research would benefit from utilizing more precise methods of measuring marijuana impairment. Alcohol and marijuana demand metrics were obtained using a hypothetical purchase task as opposed to actual alcohol and marijuana consumption and expenditures. However, this concern is mitigated by the fact that hypothetical purchase tasks generate demand parameters that are reliable and correspond with actual laboratory consumption/expenditure choices (Amlung et al., 2012; Correia & Little, 2006). Additionally, the cross sectional design does not allow us to demonstrate whether or not elevated demand is a prospective risk factor for driving after drinking. Prospective research is also required to determine if interventions that successfully reduced demand would reduce risk for driving after drinking.

Despite these limitations, this study has both theoretical and public health relevance in that it identified that elevated/inelastic alcohol demand is associated with driving after drinking and demonstrated that drinking drivers show less of an ability to decrease demand in response to a driving contingency. These results provide support for behavioral economics models of substance abuse, which view elevated demand as a pathognomonic feature of substance misuse (Bickel et al., 2014). Results from laboratory studies suggest that alcohol demand is malleable (Mackillop, Amlung, Acker, & Stojek, 2010). Because BMIs attempt to highlight costs and consequences of substance use in order to increase motivation to change and have been shown to reduce substance misuse among a variety of populations (Moyer, Finney, Swearingen, & Vergun, 2002), demand may decrease following a successful impaired-driving intervention In addition, multiple studies utilizing behavioral economic theory have shown that increasing access to non-alcohol related reinforcers generally reduces alcohol use and problems and increases likelihood of changing use successfully (Higgins et al., 2004; Murphy et al., 2005;

Murphy et al., 2012). Therefore, potential interventions that manipulate the full range of behavioral economic variables (substance free activities and desire to obtain a substance reflected in proximal changes in demand) might be effective in reducing alcohol demand and specific risk behaviors such as drinking and driving.

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Table 1
Descriptive Data on study variables for DD+ vs. DD-

	DD+ (n = 107)	DD- (n = 221)	Statistical Test χ^2	Φ

Gender			4.28*	-.11
Male	*n* = 34 (31.8%)	*n* = 47 (21.3%)		
Female	*n* = 73 (68.2%)	*n* = 174 (78.7%)		
Ethnicity			11.30**	.18
White	*n* = 81 (75.7%)	*n* = 125 (56.6%)		
Non- White	*n* = 26 (24.3%)	*n* = (43.4%)		
			Statistical Test	
			t	*df*
Age	20.56 (2.64)	20.38 (2.62)	-1.37	289
Drinks Per Week	13.00 (10.39)	4.57 (5.77)	-9.21**	326
Demand Metrics				
Intensity	9.46 (6.38)	5.75 (4.49)	-5.93**	309
Breakpoint	11.62 (6.05)	8.50 (6.04)	-4.28**	309
O_{max}	20.83 (14.63)	13.14 (12.01)	-4.93**	309
Elasticity	0.007 (0.005)	0.013 (0.011)	4.56**	267
Delay Discounting (*K*)	.056 (.095)	.080 (.113)	1.60	222
Sensation Seeking	34.32 (5.46)	35.36 (5.56)	1.61	359

Note. *$p < .05$. **$p < .01$.

Table 2

Descriptive Data on study variables for marijuana impaired drivers vs. non-marijuana impaired drivers

	MJ+ Drivers (*n* = 123)	MJ- Drivers (*n* = 53)	Statistical Test	
			χ^2	Φ
Gender			2.37*	-.14
Male	*n* = 45 (36.6%)	*n* = 11 (20.8%)		
Female	*n* = 78 (63.4%)	*n* = 42 (79.2%)		
Ethnicity			.18*	.04
White	*n* = 78 (63.4%)	*n* = 27 (49.1%)		
Non- White	*n* = 45 (36.6%)	*n* = 26 (50.9%)		
			Statistical Test	
			t	*df*
Age	20.19 (2.31)	20.10 (2.74)	.21	171
Marijuana Use Days	13.80 (11.12)	6.98 (8.52)	-3.97*	174
Demand Metrics				
Intensity	26.44 (33.85)	15.96 (25.17)	-2.05	151
Breakpoint	3.15 (3.21)	2.58 (2.82)	-.68	149
O_{max}	11.82 (23.08)	9.59 (18.99)	-.60	152
Elasticity	0.015 (0.021)	0.026 (0.015)	1.72	94
Delay Discounting (*K*)	.081 (.179)	.103 (.217)	.53	102
Sensation Seeking	34.73 (5.16)	35.45 (6.32)	.85	138

Table 3

Pearson Correlations among alcohol use, psychological, and demographic variables (drinkers)

	1	2	3	4	5	6	7	8	9	10	11
1. Drinks Per Week	1										
2. Age	-.02	1									
3. Greek Affiliation	.16**	-.23**	1								
4. Driving after Drinking	.46**	.06	.10	1							
5. Driving after Alcohol/Drug Use	.31**	-.02	.04	.47**	1						
6. Breakpoint	.19**	.18**	-.06	.24**	.09	1					
7. O_{max}	.34**	-.15**	-.01	.25**	.19**	.59**	1				
8. Intensity	.50**	-.02	-.04	.32**	.21**	.15**	.38**	1			
9. Elasticity	-.34**	-.19**	-.04	-.29**	.15*	-.66**	-.70**	-.28**	1		
10. Delay Discounting	-.06	-.03	-.05	-.08	-.02	-.11**	-.09	-.10	-.08	1	
11. Sensation Seeking	-.13*	.02	.110	-.12*	-.04	.03	-.01	.01	-.06	-.16*	1

Driving after Drinking (No, Yes)

Note. *p < .05. **p < .01.

Table 4

Pearson Correlations among marijuana use, psychological, and demographic variables (marijuana users)

	1	2	3	4	5	6	7	8	9	10	11
1. Marijuana Use Days	1										
2. Marijuana Problems	.33**	1									
3. Greek Affiliation	.04	.02	1								
4. Driving after Marijuana Use	.29**	.06	-.10	1							
5. Driving after Combination Use	.24**	.12	-.18*	.42**	1						
6. Intensity	.49**	.17*	.10	.16	-.05	1					
7. O_{max}	.38**	.13	-.09	.05	.05	.41**	1				
8. Breakpoint	.30**	.18*	-.01	.08	.14	.64**	.58**	1			
9. Elasticity	-.32**	-.14	-.02	-.18	-.06	-.32**	-.32*	-.40**	1		
10. Delay Discounting	-.07	-.05	-.07	-.05	.04	.14	.19	-.20*	-.12	1	
11. Sensation Seeking	-.05	-.03	.15	-.06	-.01	-.12	-.10	-.02	.05	-.25*	1

Driving after Using Marijuana (No, Yes)

Note. **p* < .05. ***p* < .01.

Table 5

Logistic Regression Model Estimating Effects of Gender, Age, Drinks per Week, Sensation Seeking, and Demand on Drinking and Driving

Variable	*B*	*Wald X^2*	*OR*	*95% C.I.*
Step 1				
Gender	.13	.12	1.14	0.55– 2.36
Age	.10	2.61	1.11	0.98– 1.25
Ethnicity	.54	2.61	1.72	0.86– 3.44
Drinks per week	.13*	22.01	1.13	1.08 – 1.96
Greek Affiliation	.12	.09	1.12	0.52 - 2.42
Sensation seeking	-.02	.62	.98	0.92 - 1.03
Step 2				
Intensity	.44	4.63*	1.56	1.04 – 2.34
Step 2				
Breakpoint	.51	10.54*	1.67	1.23 - 2.28
Step 2				
Omax	.23	5.19*	1.26	1.03 – 1.53
Step 2				
Elasticity	-.94	3.72*	.39	0.15 - 1.02

*$p < .05$.

Table 6

Logistic Regression Model Estimating Effects of Gender, Age, Marijuana Use Days, Sensation Seeking, and Demand on Marijuana-Impaired Driving

Variable	*B*	*Wald* X^2	*OR*	*95% C.I.*
Step 1				
Gender	-.90	2.58	.41	0.14– 1.21
Age	-.20	3.70	.82	0.67– 1.00
Ethnicity	.31	0.50	1.36	0.58– 3.19
Greek Affiliation	-.02	0.46	.81	0.13 – 5.16
Marijuana Use Days	.07	6.27*	1.07	1.02 – 1.13
Sensation seeking	-.02	.33	0.98	0.90 - 1.06
Step 2				
Intensity	-.03	.17	.99	0.98 - 1.01
Step 2				
Breakpoint	-.03	.10	.97	0.82 – 1.15
Step 2				
Omax	-.01	1.06	.99	.97 – 1.01
Step 2				
Elasticity	.03	.04	1.03	.79 – 1.33

*p < .05.

Table 7

Mean Scores on Alcohol Related Variables and Demand Curve Indices for impaired drivers vs. non-impaired drivers (with Standard Deviations in Parentheses)

	DD+ (*n* = 107)	DD- (*n* = 221)
Drinks Per Week	14.09 (10.08)	5.92 (5.93)
Standard APT Demand Metrics		
Intensity	9.46 (6.38)	5.75 (4.49)
Breakpoint	11.62 (6.05)	8.50 (6.04)
O_{max}	20.83 (14.63)	13.14 (12.01)
Driving APT Demand Metrics		
Intensity	7.41 (7.42)	3.17 (2.90)
Breakpoint	10.16 (6.08)	6.65 (6.55)
O_{max}	18.27 (13.28)	8.68 (10.01)
Percent Change in Intensity	0.22 (0.26)	0.39 (0.36)
Percent Change in Breakpoint	0.02 (0.70)	0.25 (0.47)
Percent Change in O_{max}	0.07 (0.42)	0. 34 (0.48)

Table 8

Logistic Regression Model Estimating Effects of Gender, Age, Marijuana Use Days, Sensation Seeking, and Delay Discounting on Alcohol, Drug, or Combined Substance Impaired Driving

Variable	***B***	***Wald X^2***	***OR***	***95% C.I.***
Step 1				
Gender	-.40	.89	.67	0.29– 1.53
Age	.09	1.42	1.09	0.95– 1.25
Ethnicity	.26	.43	1.30	0.59 - 2.88
Greek affiliation	.15	.14	.10	0.45 – 3.01
Sensation seeking	-.06	1.38	.94	0.84-1.04
Step 1				
Drinks per week	.16	26.1	1.17*	1.10 – 1.25
Drug use days	.08	27.9	1.08*	1.05 – 1.11
Step 2: (Alcohol-Impaired Driving)				
Delayed Reward Discounting	-.71	.47	.49	0.06 – 3.79
Step 2: (Marijuana-Impaired Driving)				
Delayed Reward Discounting	-.47	.24	.63	0.95 – 4.14
Step 2: (Combined Alcohol/Marijuana-Impaired Driving)				
Delayed Reward Discounting	-.10	260	.91	0.12 – 7.08